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UNLEASHING THE POTENTIAL OF PRECISION AGRICULTURE

ABSTRACT BOOK

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UNLEASHING THE POTENTIAL OF PRECISION AGRICULTURE

2-6 July 2023, Bologna, Italy

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Abstract

The 14th European Conference on Precision Agriculture will showcase the ongoing research and applications in precision agriculture. Organized by the Department of Agricultural and Food Sciences of the University of Bologna, under the auspices of the International Society of Precision Agriculture (ISPA), the ECPA sessions will present Precision Agriculture from the perspective of scientists, crop consultants, advisors, extension personnel, agronomists, producers, and other practitioners.

This volume collects the 2-page extended abstracts of the Posters and Side-event contributions presented at the conference, which took place in Bologna, Italy, from July 2-6, 2023.

The oral presentations are published in full in an edited book published by Wageningen Academic Publishers.

Acknowledgements

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ECPA Posters

P1 – Future Crop Farming

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Introduction

As crop robots are finding their ways onto farms, they are largely heralded for cost efficiency due to substituting labor-intensive tasks [1]. Despite the advantage of a lower weight than tractors and the option to equip crop robots with precision farming tools, the mere implementation of crop robots in existing plant production systems will not realize their potential. Thus, the established way of farming must also be reconsidered. Ecological issues like the risk of soil erosion and the loss of biodiversity may be addressed in small-scale, highly diversified agricultural systems [2,3]. Such systems include the cultivation of multiple crops in the same field, e.g., in the form of strip intercropping. In addition to ecological benefits, intercropping approaches may improve the economic resilience of farms against external shocks [4], which, however, stands in contrast to cost inefficiencies resulting from small-scale structures. The role of crop robots in future farming systems is thus a field to be studied, also from a social perspective: crop robots' ecological and economic benefits face farmer adoption hesitancy due to uncertain societal reactions [5].

Objectives

To understand the potential of crop robots for future-proof agriculture, a systems-oriented evaluation is necessary. The project Future Crop Farming in south-eastern Germany is designed to address this nexus of technology, ecology, and economics under consideration of the underlying social framework by applying the Actor Network Theory. In addition to the agronomic analysis of the crop production system, the field lab will also serve as a platform for communication with different groups of society.

Materials and methods

A 12 ha plot was converted to a strip-intercropping field lab, presenting six blocks of seven crop strips each, surrounded by a headland of grass-clover. The crop rotation consists of sugar beet, winter wheat, lupin, winter barley, soy, corn, and winter rye. The crops are grown in 15 m-wide strips orthogonal to the slope of the field, with each block separated from the next by 6 m-wide beetle banks. Beetle banks are raised, dam-like structures within fields serving as habitat for various insects [6]. In the field lab, they were planted with perennial gras and flower mixes. Management of the blocks alternates between an integrated, good agricultural practice approach and reduced input of pesticides with a strong focus on crop robots, allowing for a statistical analysis of differences in yield, edge effects, and labor input due to management.

The data thus generated permits an economic evaluation of the strip-intercropping field design under consideration of both novel and established technology. This perspective is complemented by analysis of the design's ecological impacts: specific foci lie on insect populations compared to larger field structures as well as effects on soil erosion risk. The latter is particularly relevant to the region where the field lab is located but also with respect to herbicides being replaced by (robotic) mechanical weeding in the reduced variant.

Designed as a 'living lab', the project also comprises empirical social and sociological research. Quantitative general population and specific target group surveys on the acceptance of crop robots for the purpose of more biodiversity in agriculture will be conducted. Societal structures underlying farming will be evaluated based on qualitative interviews with farmers and other actors in the sector by means of the Actor Network Theory, which considers human, institutional, and natural actors. The findings will be developed into an educational trail around the field, aiming to address both agricultural and non-agricultural communities in an effort to illustrate the conflicts of interests within agricultural production.

Results

The first season of Future Crop Farming was completed in 2022. The weather conditions during the vegetation period resulted heavy weed competition in both the integrated and the reduced variants, especially in sugar beet and lupin. However, robotic weeding in the reduced variant proved somewhat more effective than the use of herbicides in the integrated variant in both crops.

Positive effects of the field design were observed on biodiversity in the whole system, as expected, and on soil protection, which became evident after heavy rains in spring that caused strong erosion in the region, yet not on the field lab. Insights from modelling the field indicate that the soil protective effect can be traced back to the beetle banks.

A comparison of labor input for robot-executed tasks and conventional technology use does not yet show the expected results as preparatory work for robotic tasks resulted in higher labor input.

From a social perspective, there was a strong interest in the project from regional, national, and international groups, with local farmers tending to be more skeptical. A discussion group with farmers indicated that acceptance of novel farming systems was heavily influenced by family and regional traditions. The sociological research provided the basis for the educational trail conceptualization.

Discussion and conclusions

Beginning in 2023, the reduced variant will be managed using the crop robots Farmdroid FD20 and AgXeed AgBot 5.115T2, which will replace the AgroIntelli Robotti used in 2022. This switch in technology will allow the robotization of more tasks than sowing and weeding. The economic analysis of all three robots may contribute to the generalization of labor requirements when using crop robots. Further online and in-field surveys will be implemented in summer 2023 to investigate the reception of the crop production system in combination with crop robots among both the farming community and the general population. The insights thus generated may prove useful to both farmers and policymakers for communication about crop robots to the general public. Additionally, knowledge transfer activities will be expanded from on-site field visits to a simultaneous establishment of the educational trail both on-site and online on the project website. The future crop farming field lab serves as stimulus for rethinking crop production systems with the help of precision agriculture tools.

Acknowledgements

This project was funded by the Bavarian State Ministry for Food, Agriculture and Forestry (A/21/17). The field lab is also part of the Horizon Europe project Digitalisation as an Enabler of Agroecological Farming Systems (HORIZON-CL6-2021-FARM2FORK-01-03).

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P2 – Data and Connectivity to Foster Smallholder and Urban Farming. Farmer Charlie

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Introduction

Producing a third of the world's food [1], smallholder farmers need to obtain accurate, useful data to improve their activities and make informed decision in real time in order to avoid wastes that amount to 40% or more in cases (from discussions with cooperatives). This is even more crucial when they live in isolated or remote areas, with scarce or absent connectivity (in 2022, 2.7bn of people were not yet connected to the Internet, according to ITU data). Farmer Charlie is a smart agriculture IoT platform created to meet these needs. In 2022, a prototype testing in Sicily, Italy, confirmed the efficiency and effectiveness of our product. Additional research on urban farming led to identify a market of private and smallholder farmers (gardens and allotments) in Europe, which could benefit from remote monitoring of soil and weather information to manage their crops and plan irrigation, input and sustainable growth of their crops at a convenient cost.

Objectives

Our research showed that there are over 570 million small farms globally (FAO), with 360 million in emerging economies. Besides, 40% of the world population still does not have internet access, even more in rural areas. Research started to devise a low-cost solution, affordable for these farmers and helpful to bring data and agronomic information they cannot access. Farmer Charlie was created to bridge that gap. Last year, Farmer Charlie bootstrapped its own prototype development and testing in Sicily, Italy, where its technology was tested on horticultural products and citrus fruit trees.

The feedback received from Sicilian farmers was very positive and showed a market opportunity for Farmer Charlie in Europe, as an easy to use, easy to install low-cost solution addressing small and private farmers' needs. Through discussions and investigations with allotment owners and garden farmers, Farmer Charlie appears to be also suited to city farming. R&D features include compatibility with 5G, satellite and other IoT radio-technologies, optimisation of the telecom network (e.g., data transfer rates). Low cost has always been considered an essential requirement.

Materials and methods

Farmer Charlie is made of the following subsystems: in-field sensors to detect soil values such as humidity, pH and temperature; a connectivity module; a user-friendly application; support systems including a battery/solar panel. Our approach relies on optimising the system in order to address the farmers' need for receiving crucial data and information on the crops even remotely. The inclusion of different connectivity technologies in our service opens new opportunities to adapt Farmer Charlie to European market, but this is developed in a way which need to remain cost-effective.

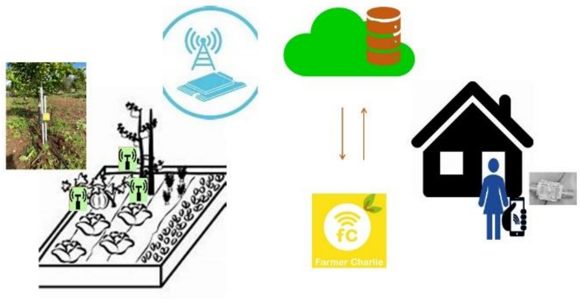
Results

Our target was to develop sensors which were good quality, at a very low cost and with a long life. We were pleased to have achieved success against our objective to develop a robust, interoperable, and low-cost system.

The equipment measured humidity and temperature in the field and were connected to a weather station. The radio-module is based on a managed LoRA protocol, to bring efficiencies to our system.

Our data rate is narrow band, but we can also rely on radio modules which can transmit in broadband, would we require video, for instance.

Figure1. Farmer Charlie - System



Source: Farmer Charlie, 2023.

Discussion and conclusions

Further to our research and development activities and the deployment of our system in Sicily, we have now identified the following challenges which we have addressed:

- the battery system needs to be optimised and coupled with a solar panel in order to increase the duration of sensor over more than 3 years.
- the measurement of humidity and temperature is valuable for the control of irrigation systems, and the better use of water, a scarce resource.
- there is a further need to measure nutrients in soil, luminosity and other parameters. Addressing these needs requires a trade-off in measuring all with one unique sensor (our sensor has four entries) or individual sensors.

We address the need of monitoring vegetable gardens and citrus fruits remotely, as the farmer (private or smallholder) cannot always oversee their growth in person. Knowing soil and weather condition in real time can assist with better practice and improved yield. Controlling the use of water and limiting fertilizers and pesticides, our system is also aimed at reducing waste in farms (current estimate of waste is 15% [2]).

Acknowledgements

Thanks to Innovate UK for their continuous advice and encouragement, and for funding our research and development projects to develop and implement Farmer Charlie.

Thanks to all the partners, collaborators and farmers who offered their knowledge, commitment and enthusiasm during the conception and development of Farmer Charlie's activities.

We would like to thank the International Society for Precision Agriculture for accepting our abstract and inviting us to present at the 14th European Conference for Precision Agriculture. This has been a fantastic opportunity to reflect on our work and to (proudly) realize how much we have achieved, despite the challenges posed by the pandemic, technical issues and limited funding and staff.

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P3 - Developing a continuum of education and training pathways in integrative precision agriculture

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Introduction

The University of Georgia (UGA) is a public teaching, research, and outreach institution located in the state of Georgia, USA. It was founded in 1785 making it the oldest public university in the USA. Agriculture contributes approximately USD69.4 billion annually to Georgia's economy and is the largest business sector in Georgia. The 2020 total farm gate value for the state was USD12.2 billion with more than 4 million hectares in production [1]. Georgia is the U.S. state that produces the most peanuts, broilers (chickens), pecans, blueberries and spring onions and ranks in the top five for cotton (#2), watermelon, peaches, eggs, cucumbers, sweet corn, bell peppers, tomatoes, cantaloupes, rye and cabbage [2]. Farmers in the state are under ever-increasing economic pressure from rising input costs and competition from countries with lower wages and are turning to the technological solutions offered by precision agriculture to improve their efficiency and profitability.

Based on the strength of Georgia's agricultural industry, the extensive history of precision agricultural research at UGA, the expertise present in College of Agricultural and Environmental Sciences (CAES) and the College of Engineering (CoE), the University Provost's Taskforce on Academic Excellence in 2019 identified Integrative Precision Agriculture (IPA) as one of five areas of research for UGA to increase investment and build excellence. The investment in IPA consisted of two thrusts: the establishment of nine new IPA faculty positions and the formation of the Institute for Integrative Precision Agriculture (IIPA).

The IIPA was launched in 2022 to serve as a conduit to connect agricultural technology research, education and outreach within UGA and with outside partners such as other universities and agribusiness. This is accomplished through networking events, joint infrastructure and seed grant programs, among other efforts.

Educational initiatives

The IIPA will not offer new academic degrees in the short term. Instead, it will focus on developing a continuum of education and training from the secondary (high school) to the tertiary level (university) that will develop market-ready graduates with knowledge and skills to develop and apply IPA solutions when they enter the workforce. Market-ready graduates with these types of skills are currently the limiting factor in the development and expansion of companies that offer IPA services and technologies in rural Georgia. To achieve this goal, the IIPA is developing multiple educational pathways for students that lead to associate of science (A.S.) or bachelor of science (B.S.) degrees that match industry needs for training and education in IPA. The IIPA is working closely with industry partners to identify these needs. For example, the IIPA hosted an international IPA conference during May 2023 during which there was a panel discussion on industry workforce needs and how academia can create curricula and attract students to meet needs. The panel was composed of IPA leaders from industry and academia.

In many states of the USA, students are able to take university level courses while still in high school. This is commonly referred to as dual enrollment as the credits also count towards high school graduation requirements. For example, a student may take a first-year university chemistry course which also fulfils a high school science course requirement. In Georgia, students are allowed to accumulate up to 30 dual enrollment credits while in high school which is approximately 25% of the credits needed to graduate with a 4-year bachelor degree from a public university in Georgia. Dual enrollment with a public institution is at no cost to the student. This provides students with an opportunity to complete their university degree in three rather than four years but also significantly reduces the cost of a university education.

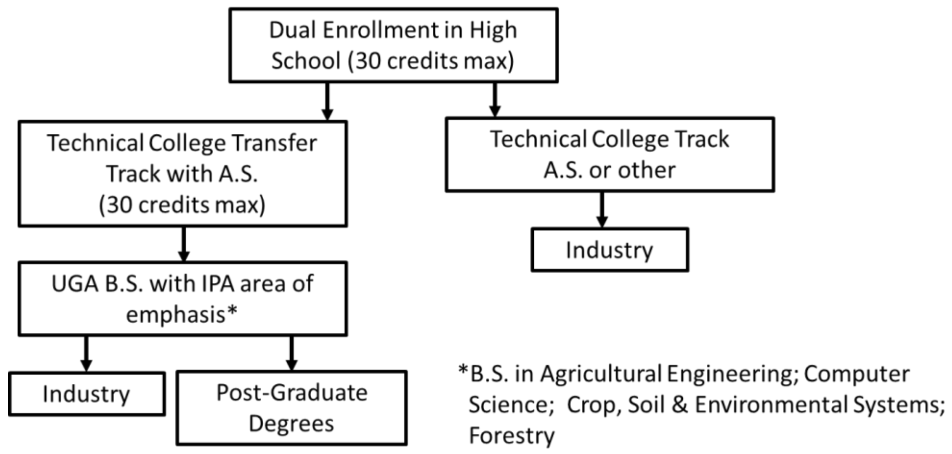
In Georgia, there are two types of public tertiary education – that offered by the University System of Georgia (USG) and that offered by the Technical College System of Georgia (TCSG). The USG consists of 25 colleges and universities all of which offer bachelor degrees, many offer masters degrees, and a few offer doctoral degrees. TCSG consists of 23 technical colleges which provide technical education, adult education, and customized business and industry training programs. Many technical colleges have campuses in rural areas and because of that, have begun offering dual enrollment courses to serve high school students living in these areas. Dual enrollment courses from technical colleges are eligible for transfer to USG institutions. Within the last few years, technical colleges have also begun offering 2-year A.S. degrees.

The educational IPA pathways are being developed in partnership with rural high schools and technical colleges with a large footprint in rural Georgia and take advantage of dual enrollment. In this model, students are recruited for an IPA pathway while in high school during which they pursue academic credits via dual enrollment with the technical college. After high school, they enroll at the technical college where they pursue an A.S. in IPA. The A.S. in IPA are new degrees with that will be offered by a small group of technical colleges in rural areas and will be developed in conjunction with UGA. The A.S. will have two tracks. One track results in a terminal A.S. that leads to direct employment with industry in technical support roles. The second track includes the core science, technology, engineering and mathematics (STEM) courses needed to pursue a B.S. at UGA. When students arrive at UGA they are essentially third-year students and are able to complete a B.S. in two years. Figure 1 shows the educational pathway options in graphical form.

Feedback from industry has clearly indicated that the ideal graduate is one who can apply traditional knowledge in agricultural sciences, data science, and engineering to develop IPA solutions to current and anticipated problems. Because of this, the IIPA is not developing a new IPA degree at UGA. Instead, the IIPA is developing IPA areas of emphasis within existing STEM disciplines. An area of emphasis is a concentration of courses that provides a student with competence in a specific area of knowledge and is explicitly identified on students' transcripts. As one example, the B.S. in Crop, Soil and Environmental Sciences (CSES) includes an IPA area of emphasis. Although some IPA-related courses such Principles of Precision Agriculture and Geographic Information Systems as are required of all students pursuing the CSES degree, students pursuing the area of emphasis are required to take four additional IPA-related courses and have the option of taking even more as electives. The suite of available IPA courses will increase as the new IPA hires develop and begin to offer new courses in their areas of expertise.

At the time of this writing, areas of emphasis are being developed for the agricultural engineering, computer science, and forestry degrees in addition to the one described in the previous paragraph. Others are under consideration. The IPA educational pathways are currently under development with the goal of being implemented for the 2024-2025 academic year.

Figure 1. IPA workforce development educational pathways in graphical form.



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P4 - Extended Classroom in Precision Agriculture as a Tool for Engineering Education

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Introduction

The curriculum of the Electrical Engineering, Electronic Engineering and Agroindustrial Engineering programs at the Universidad Pontificia Bolivariana (UPB) in Medellín, Colombia, has been continuously evolving since their creation in 1950, 1970 and 1994, respectively. Throughout their history, these programs have been characterized by offering training tailored to the social needs of the environment, focusing on the region, but without losing sight of the global environment, to the point that many of their graduates are working in companies abroad [1].

This spirit of permanent updating has been oriented, in recent years, from the perspective of the CDIO model and the ABET model. Currently, the need to incorporate Competency Based Learning (CBL) and Problem Based Learning (PBL) perspectives is reinforced. The CDIO model seeks to provide engineering students with training within four fundamental frameworks: Conceive, Design, Implement and Operate [2], that can be strengthened through CBL and PBL methodologies. These methodologies state that, by using problems or projects as a stimulus for learning, students develop their competencies better and in a more comprehensive manner [3].

Materials and methods

The training process of an engineering student traditionally begins with a mathematical foundation, useful to form in the student's mentality the logical reasoning skills that will allow him/her to generate solutions inspired by mathematical and algorithmic bases in the future. Within their training cycle in mathematics, and according to the experience of the teachers, one of the main concerns of the students is how and when they will begin to develop the competencies of their career and area.

At UPB, the Technologies in Urban Agriculture Research Program is being carried out, which beyond the direct research products that may be produced, leaves as a result an extended classroom in Precision Agriculture implemented in a Greenhouse built at UPB, whose functionalities include an automated irrigation system, which is expected to serve as a platform for the development of classroom projects for the formation of competencies among undergraduate students. This extended classroom is implemented in the aforementioned Greenhouse, with technologies oriented to Artificial Intelligence (AI), such as: Machine Learning (ML), Fuzzy Logic (FL) and Internet of Things (IoT), for the development of intelligent irrigation systems [4]. The analysis and implementation of this project allows establishing the connection between the competencies proposed in different courses of the Electronic Engineering program of the Universidad Pontificia Bolivariana and their development and strengthening through problem solving, in this particular case, in Precision Agriculture. Likewise, to evaluate the current state of the engineering schools and to give support to build methodological structures based on learning, implementing the CDIO and ABET initiative, based on CBL and PBL, for the training of future engineers [5].

To carry out these processes, competencies are identified in the Electrical, Electronic and Agroindustrial Engineering programs at UPB in order to evaluate the current state of the engineering school and determine those competencies that can be developed with urban agriculture methodologies. Then we seek to propose training activities in selected or elective subjects, incorporating technologies and teaching tools, strengthening research and innovation and methodological structures with clear objectives, practical activities and appropriate evaluation. Create collaborative learning environments and continuously monitor student performance and effectiveness of methodological structures [6].

With the above, competency-based models are proposed for UPB engineering students to acquire knowledge in Precision Agriculture. Priority competencies include research, communication and teamwork, leadership and entrepreneurship, social and environmental responsibility, and rigorous logical reasoning. These skills are combined with interpersonal and cross-cutting competencies that are crucial for students to excel in their field of study and contribute significantly to the development of precision agriculture [6].

Results

As mentioned above, a Greenhouse was built and implemented at UPB (Figure 1), which will be used as an extended classroom to train new engineers, who will acquire skills to use precision agriculture to propose methodologies and activities to develop competencies defined in the aforementioned engineering programs.

Figure 1. UPB Greenhouse

These competencies are based on Accreditation Board of Engineering and Technology (ABET) criteria that are aligned with the 1999 Bologna Process [6].

In order to train new engineers with competencies in which methodologies and activities are proposed to develop them, defined in the engineering programs already mentioned in the extended classroom, it is sought that they can acquire them through methodologies based on experiments, in which through the obtaining of soil moisture retention curves with metric potential sensors, models can be obtained, which can be used to perform continuous irrigation control [7].

These models will be obtained in the Continuous Control course and will be implemented through a Programmable Logic Controller (PLC) in the Programmable Logic Control course of the Electrical and Electronic Engineering programs, acquiring the competency of research, communication and teamwork and the competency of rigorous logical reasoning. These activities, incorporated into elective courses, can attract students from other engineering careers, such as: Agroindustrial Engineering, Mechanical Engineering and Industrial Engineering.

In addition to this, we want this training to have a remote operation scope by using a web platform, such as Ubidots, which allows visualizing variables such as Ambient Temperature, Relative Humidity, Soil Moisture, among other variables; so that students can visualize them, and with this data, analyze and use them to carry out the control of an irrigation system, either by making manual or automated irrigation decisions [8]. This training with remote operation scope, will be implemented in courses such as Agricultural Production or in elective courses such as Non-Food Technologies (Digital Agribusiness) of the Agroindustrial Engineering program, acquiring the competence of social and environmental responsibility and research, communication and teamwork.

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P5 – Resilient Smart Farming a conceptual and technological opportunity to strengthen resilience

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Introduction

The process of agricultural production is undergoing progressive digitalization worldwide, which is referred to as digital farming or smart farming [1,2], i.e., the share of software-based tools and purely software-based processes such as planning tasks is demonstrably increasing steadily [1,2]. Agriculture is an essential part of Critical Infrastructure as it is essential for global food production. This becomes especially important in times of diverse crisis events such as: War, Pandemics and Climate Change. Centralized and internet-dependent software-based infrastructures and applications are then particularly vulnerable. The concept and technological possibilities as well as the current developments of Resilient Smart Farming (RSF) show how data management can be designed according to the offline-first principle. A central building block here is Resilient Edge Computing (REC) and the developed HofBox: a mini-server that takes over data management on the farm and implements it with innovative, open source-based container technology Open Horizon [3,4,5].

Objectives

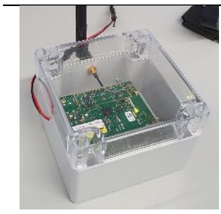
The central question here is: (How) Can decentralized data management with hybrid IT infrastructure be implemented and at the same time support the economic and ecological benefits of smart farming applications and increase resilience? Can the concept of Resilient Smart Farming provide a conceptual and technological way to strengthen resilience of digital infrastructures in agriculture?

Materials and methods

For the practical implementation of Resilient Smart Farming in the form of Resilient Edge Computing, a so-called HofBox was used as a miniserver with the hardware of a Raspberry Pi 4, 4GB with LoRa board in the first step. This simple and commercially available hardware could be manually integrated into the Open Horizon infrastructure. The LoRa board is used as a gateway for an autonomous sensor network on the farm. In the second prototype, a HofBox 2.0 with x86 and Secure Device Onboarding (SDO) was used for automated deployment of software containers.

At the infrastructure level, Resilient Edge Computing is deployed via the open source framework Open Horizon [3,4] at the professional level as IBM Edge Application Manager. The software used to deploy software containers in the project is open source software in the first step, such as Libre Office, MQTT broker or the GeoBox application. The Long Range Wide Area Network is supported, among other things, by its own gateways, which store the sensor data via the commnitiy-based and central platform The Things Network and make it available via APIs. You can see the different variants of the HofBoxes in (Table 1).

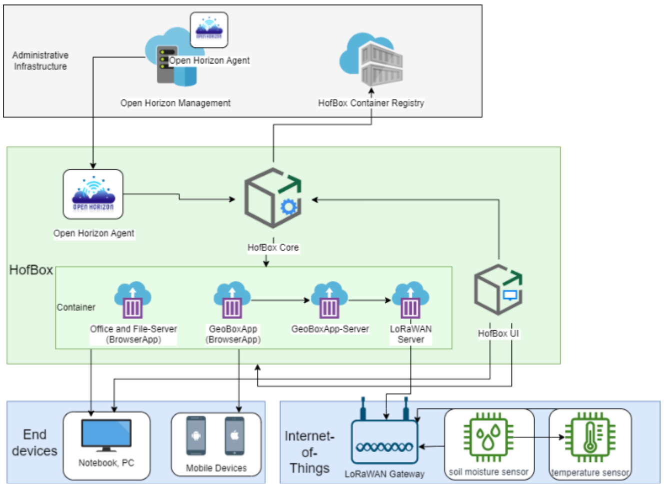
Table 1. Two different HofBox hardware were used

HofBox 1.2	description	HofBox 2.0	description
	Our first usable prototype of HofBox 1.2 was based on a Raspberry Pi 4 with 4 GB RAM and an extension of a LoRa-Board		The second usable prototype of HofBox 2.0 is a x86 with a secure device onboarding (SDO)

Results

The HofBoxes are initialized, installed and updated without user interaction (zero touch) via the open source edge computing platform "Open Horizon". The application layer applications shall be containerizable" to run in the data center, cloud-based or locally on the HofBox.

Figure 1. IT-Architecture for Resilient Smart Farming



The applications should be usable by means of a standard Internet browser, i.e. without additional software, accessible via a special start page on the HofBox and basically functioning without connection to the Internet. Furthermore, additional applications can be installed via the integration of an app store if desired by the user. To support the daily work, an (extendable) basic software (GeoBox app) is supplied as standard. The hofbox is a dedicated, self-contained, ruggedized compute server delivered to the farm, managed remotely, and providing localized workload ad data processing services to the farmer. In order to realize resilient smart farming into practiice, farmers data will be on the hofbox edge device. Only by agreeing, the data can be sent and stored elsewhere. The solution is fully resilient, because of a hybrid-cloud architecture which means that the solution is cloud agnostic.

Resilient smart farming thru rersilient edge computing is a role model for critical infrastructures.

Discussion and conclusions

The solution we designed and developed to strengthen digital resilience in agriculture, Resilient Smart Farming, is technologically feasible and can be tested in practice in the future. This will show whether the solution is also successful under the conditions of agricultural practice. We were able to practically demonstrate the technological feasibility with Resilient Edge Computing, as described above. We expect containerized software to be increasingly used in agriculture in the coming years. Under Open Horizon, we show that these can also be managed and administered.

Acknowledgements

For the text body, please use the style “Text”. Here you can acknowledge the contribution of other people, conflicts of interest statements, or any information about funding.

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P6 – Enhancing Production Efficiency and Farm Profitability through Participatory Research

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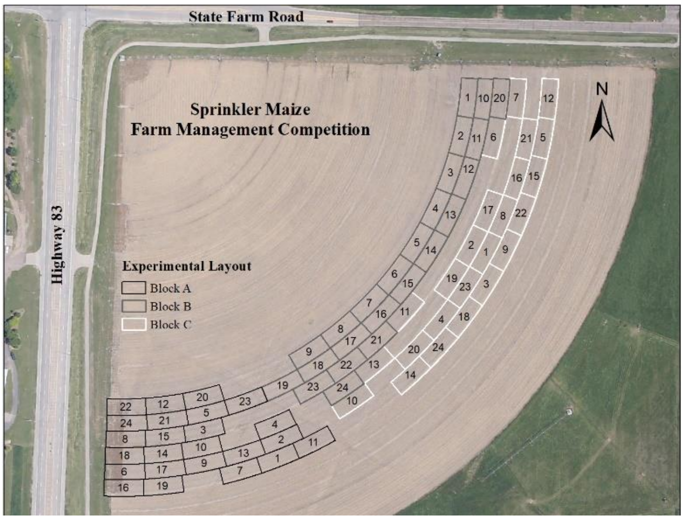
Introduction

Agricultural producers continue to evolve due to education, information accessibility, communication technology, societal expectations, regulatory increases, equipment sophistication, changes in production systems, productivity changes, and ever-escalating capital needs and intensity [1]. To remain relevant and effective, the space and methods in which research professionals engage growers and landowners on the use of best management practices in agriculture must be just as dynamic. However, outreach programs have traditionally relied on lecture presentations, field tours, fact sheets, and on-station demonstrations. These methods tend not to provide the experience that growers require to become comfortable adopting innovative solutions, whether it be new management practices or the use of new technology. To this end, the Testing Agricultural Performance Solutions (TAPS, https://tapsprogram.org/) program was developed.

The TAPS program is characterized by its innovative approach that combines interactive, "citizen-science" learning with interdisciplinary research. It revolves around annual farm management competitions hosted at university research farms, where participants make real-world management decisions, such as crop cultivar and seeding rate, irrigation and nitrogen amount, timing, and method, crop insurance, and marketing, which are then implemented side-by-side in replicated plots on the same field (Figure 1). This unique setup allows for TAPS researchers to directly compare and evaluate the influence of management decisions on production, efficiency, and economic outcomes void of farm and regional-level differences, including soil type, weather conditions, and equipment availability. Furthermore, by providing a controlled environment for testing different management methods using new and emerging technologies, TAPS enables participants to evaluate practices without exposing their own farm operations to unnecessary risks.

Figura 1. Experimental layout for the 2019 sprinkler irrigated maize competition held at the West Central Research, Extension, and Education Center in North Platte, NE, USA.



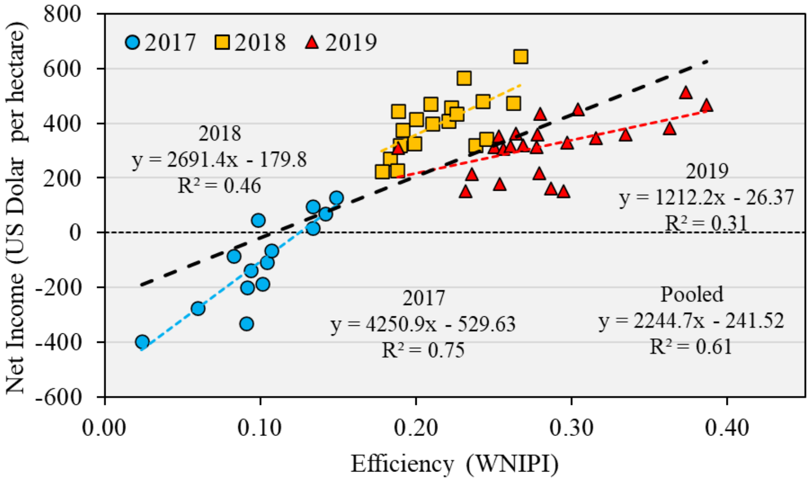
TAPS has expanded from a single competition of 15 teams comprised of 18 producers and two student groups in North Platte, NE, USA, to eight competitions across four states consisting of 156 teams made up of producers, student groups, agency personnel, and researchers. Each competition is uniquely designed and implemented to address local needs, constraints, and opportunities.

Extensive data is generated on the TAPS plots to inform operational performance of water conservation technologies and practices. Each team has access to real-time data from commercially available soil water sensors, plant and canopy sensors, aerial/satellite imagery, field level weather stations, irrigation and nitrogen management models, soil and plant analysis, scouting reports, marketing tools, among others. Each team accesses this information via the competition website, which also contains informational videos, user tutorials, and insights into how to use the technology. In addition, supporting data is collected to understand production responses and to provide validity to commercial technologies marketed for agricultural production. For example, neutron attenuation and infrared thermometry (Apogee Instruments, Logan, UT) are used to assess soil water availability, and soil and plant tissue sampling and canopy reflectance via Crop Circles (Holland Scientific, Lincoln, NE) are used to assess nutrient availability and uptake.

Results and Discussion

The project team has observed that efficient users of water and nitrogen fertilizer as measured by the Water and Nitrogen Intensification Perfromance Index (WNIPI) [2] also tend to be more profitable. The relationship between WNIPI and net income of the 2017 to 2019 TAPS sprinkler irrigated maize competition in North Platte, NE, USA, is presented in Figure 2. A positive, linear correlation with a pooled R^2 of 0.61 was observed. Thus, promoting the adoption of conservation, resource efficient oriented practices can align with farm profitability. Each year the participants are surveyed to evaluate the impact of the program on adoption of practices and technology. In 2018, 68% of the participants increased their confidence in irrigation technologies [1], and in 2019, 69% and 76% of participants were thinking about adopting one or more irrigation and nitrogen management tools, respectively.

Figure 2. Profit (US Dollar per hectare) versus input use efficiency as measured by Water-Nitrogen Intensification Performance Index (WNIPI) for the 2017 to 2019 Sprinkler Irrigated Maize Farm Management Competition in North Platte, Nebraska, USA.



Acknowledgements

The TAPS program is supported, in part, by the USDA Natural Resources Conservation Service (NRCS) under Award No. NR203A750013G011 ("Accelerating Adoption of Water Conservation Technologies and Management Practices through Innovative Engagement Programming"), by state and national commodity boards, including the Nebraska Corn Board, the Nebraska Sorghum Board, and the National Sorghum Checkoff Program, and by a multitude of various organizations and entities.

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P7 – Tractor Guidance Improves Environmental and Economic Gains for Pasture and Smallholder Farmers

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Introduction

Tractor guidance (TG) systems are a type of precision agriculture technology that uses global navigation satellite systems (GNSS) to mechanically steer tractor paths during field operations. Spatially precise applications of nitrogen (N) and phosphorus (P), through the use of auto-guidance systems, improve crop production and reduce non-point source pollution across agricultural landscapes, relative to non-GNSS enabled technologies (Shockley et al., 2011). Specifically, Kharel et al. (2020a) reported 6 and 16% reductions in input overlaps (double applications) and gaps (no application), respectively, via TG systems. Greater effective spatial coverages can translate to less labor, lower greenhouse gas emissions and non-point source pollution, and greater cost savings per unit area (Lindsay et al., 2018). However, in a follow-up study, Kharel et al. (2020b) found that factors such as terrain attributes (increased slope, variable topography) and field shape and irregularity drive the extent of these efficiency gains relative to non-TG systems. Other important factors, such as operator experience level for the non-TG comparison, likely also affect efficiency gain estimates; however, evaluations of driver experience have not been done to date.

Previous work by Ashworth et al. (2018) found that TG led to total farm-level carbon equivalent emission reductions of 15.7, 3.5, and 9.6 Mg for cotton (*Gossypium hirsutum* L.), soybean [*Glycine max* (L.) Merr.], and cotton–soybean mixed operations, respectively. These results highlight that emission reductions are crop, amount, and agro-input specific. Additional work by Ashworth et al. (2022) found that fertilizer source (organic vs. inorganic) greatly affected environmental benefits from TG via a life cycle assessment. In this assessment, poultry litter had fewer environmental gains than inorganic N, owing to the rate of volatilization for poultry litter under IPCC Tier 1 methods being twice that of synthetic sources, as well as fewer yield gains under the organic source. This study set out to explore the effect of operator experience level (0–1, 2–3, 6+ yr) during fertilizer (organic and inorganic) and herbicide applications and based on terrain attributes, relative to precision guidance tools. We predicted that the greatest operator experience level (6+ yr) scenario would have the fewest overlaps and gaps and, consequently, the least environmental gains during agro-input applications relative to precision guidance systems.

Objectives

The use of precision agriculture tools like tractor guidance (TG) improves production efficiencies by reducing overlaps and gaps and consequently reducing environmental impacts from over-applying fertilizers and herbicides in agricultural systems. However, the relationships between terrain attributes (slope, field shape irregularities, pass length), drivers experience level (0–1, 2–3, 6+ yr), and system (farm size, crop type, etc.) impact efficiency gains for precision agriculture tools are lacking. Therefore, in a series of studies, authors tested these factors by comparing TG (where a predefined field path was followed) and without TG (manually driven).

Materials and methods

This study was conducted at Booneville, AR, USA (35.087723 N, 93.993740 W) in 2018 and 2019. The details of the field study, data collection, and overlap estimation methodology for 2018 data are available in Kharel et al. (2020a, 2020b). A New Holland 7040 (NH7040) tractor was used without TG (manually driven) in six fields (11.7– 22.5 ha) with a 10-m fertilizer spreader and a 13-m boom sprayer from 2018–2019. Three operator experience levels where Operator A had 6+ yr tractor driving experience, Operator B had 2–3 yr experience, and Operator C had 0–1 yr experience were used for this study. Operator A applied fertilizer in 2018, Operator B applied herbicide in 2019, and Operator C applied fertilizer in 2019 for the same six pasture fields. Intelliview IV display (CNH), 372 receiver, and RTX signal (Trimble Navigation Ltd.) with 15-cm pass to pass accuracy as a navigation system were used by each operator. Kharel et al. (2020a) reported that there was no statistical difference in overlap and gap due to operation (fertilizer and herbicide application); hence, we combined these datasets from both operations to evaluate the effect of driver experience. Overlap and gap information were calculated as described in Kharel et al. (2020a, 2020b). Briefly, data points (tractor location recorded each second during field operations) showing more than 35° difference in heading direction were assigned a new pass number in increments. A line feature was created for each pass and a buffer polygon around the line feature was developed using equipment width. For each operation within a field, individual pass polygons were sequentially evaluated with the rest of pass polygons and overlap polygons calculated for further analysis. Gap area was then calculated by subtracting pass polygon and overlap polygon area from the field boundary area as shown by Equation 1 in Kharel et al. (2020a). Both overlap and gap area were expressed relative to field boundary area in percentage for statistical analysis. Since gap area was calculated for whole field and no gap polygons were created within a field, the majority of analysis on this paper focuses on overlap polygons.

Results

We estimated economic and environmental implications of TG using TGA for smallholder farmers. Adoption of TG systems has increased by 50–60% for major row crops in the United States; however, to date TG technologies are not widely used for either smaller-scale production or pasture-based systems, and more information is needed regarding how efficiency estimates from TG in pasture systems are affected. Results showed that operator experience level is critical when making efficiency gain estimates and operators with 6+ yr of experience reduced overlap 7.7 and 20.6% compared with 2–3 yr of experience and new operators, respectively. N fertilizer savings via TG lead not only to substantial energy savings during its manufacture but also to rather large reductions in N_2O emissions, which vary based on farm size, crop type, field shape, and terrain.

Discussion and conclusions

In a series of studies, authors tested these factors by comparing TG (where a predefined field path was followed) and without TG (manually driven). Studies found that operator experience level (for non-TG comparison) was inversely related to TG- driven efficiency gain improvements and that overlaps increased with increasing field irregularities (6 to 11% field area), shorter pass lengths (2 to 19m2), greater slope (17 to 53m^2), and roughness index (13 to 38m2) per grid cell. In addition, TG was profitable and led to farm level carbon equivalent (CE) emission savings of 15.7, 3.5, and 9.6 Mg for cotton, soybean, and ‘Mixed’ operations, respectively. These results highlight CE savings that are i) crop specific; ii) scale dependent; and iii) equipment/input-use specific. Overall, auto-guidance systems on tractors leads to more targeted nutrient and input applications, which leads to more sustainable production of food.

Acknowledgements

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P8 – Legal challenges about the use of drones in PA

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Introduction

Precision Agriculture (PA) represents a huge opportunity but also a challenge that the entire agri-food supply chain must face to make the food production process sustainable, both in environmental and economic terms.

This also challenges the legal environment because many profiles are linked to the aspects that emerge from using drones and precision mechanical means used in PA [1].

In European regulatory terminology, drones are included in the group of unmanned aircraft (UAS – unmanned aircraft system). Their tremendous flexibility allows their employment in an increasing number of activities and sectors, such as agriculture, resulting in interesting technology and extraordinary development opportunities. At the same time, it requires an urgent intervention on the legal side [2].

Objectives

The research aims to illustrate the European and national regulatory framework regarding the use of UAS systems, including drones, in agriculture.

Results

According to the EU Reg. 2018/1139 and EU Reg. 2019/947, as amended by EU Reg. 2020/639, UAS operations are divided into three categories, depending on the parameter of the risk associated with the operations, distinguishing them in open, specific and certified.

In PA, you can operate through the first two categories, with a preference for the open one because it does not require any prior authorisation, reducing costs and organisational effort, while for the specific category, technical capabilities are needed (EU Reg. 2019/945, as amended by EU Reg. 2020/1058, lays down the technical standards and classes of the UAS for each category).

Despite the strong impact in agriculture that the use of drones would lead, both in terms of necessary investments and the development of new agricultural services, there are advantages to be considered, such as the ability to perform multispectral scans on crops, reduce operating costs, respond quickly to intervention needs and optimise production efficiency.

However, several legal aspects need to be considered: security and insurance issues, civil liability relating to accidents, and the technical and social aspects arising from data collected by the UAS by remote sensing.

Regarding the national legal framework, the navigation code in article 734 states that the concept of aircraft covers civil aerial drones, as the unmanned aircraft systems are also regarded as aircraft, according to national special laws, ENAC Regulations and, for military ones, the decrees of Ministry of Defense.

Italy was the first EU country to adopt a targeted legal discipline in this matter thanks to ENAC Regulation 2013 about unmanned aircraft systems, revised and amended several times to adapt the internal technical legislation to ICAO (International Civil Aviation Organizations) guidelines; and finally replaced by Regulation ENAC UAS-IT 2021, currently in force.

The European Union is still acting on the evolution of the regulatory framework of unmanned aircraft systems, committing to ensuring standards for drones and providing the necessary services to guarantee the sustainable development of a rapidly growing market.

One of the sensitive aspects that can arise from the use of the technologies in question concerns the civil liability of goods and people on the surface; the EU itself has shown that it is aware of the problem, in fact, the «Declaration on remotely piloted aircraft (drones). Framing the future of aviation» (Riga, 2015) established that «the drone operator is responsible for its use» as one of the fundamental principles to be followed in the future regulation of flight with remotely piloted aircraft.

The most recent sources of European law have chosen not to define a special civil liability regime but to mitigate the risk by providing a registration system for unmanned aircraft systems and a general liability insurance obligation towards third parties [3].

The CE Reg. 2004/785 introduced a harmonised regime on minimun insurance requirements for air carriers and aircraft operators concerning insurance of passengers, baggage, cargo and third parties; the same Regulation applies to unmanned aircraft systems but not to aircraft with a maximum take-off mass of less than 20 kilos.

The absence of uniform European legislation on this point leads to interpretative doubts and presents a regulatory framework full of application uncertainties.

The use of drones may, in addition, generate substantial interference with the protection of the right to privacy and the protection of personal data; this worrying invasiveness has led to the emanation of the UE Reg. 2016/679 (GDPR) that treats the personal data generated during agricultural activities about the farmer, the agricultural workers and the subjects involved in the same activities [4].

Another profile concerns the aspects related to the protection, exchange and ownership of non-personal data, referring to agricultural activity: in this case, takes action the EU Reg. 1807/2018 «Free Flow Data Regulation» FFD, that is trying to create a Digital Single Market for the free movement of non-personal data within the EU, in association with the provisions of the GDPR (examples of non-personal-data in the FFD include those on precision agriculture).

The EU Commission, on 24 February 2022, introduced the proposal for a European law «EU Data Act», as part of the European Data Strategy to create a single European Data Market, trying to set out a cross-sectoral governance framework for data access and use, by physical persons, organisations and European public authorities.

Discussion and conclusions

Despite the initiatives aimed at encouraging the development of the PA and the digitalisation of the agricultural sector, it seems appropriate to face, in institutional headquarters, the regulatory and legal obstacles that hinder the dissemination of innovations in support of sustainable use of resources: such as the prohibition of the use of drones for the spraying of plant protection products [5].

In this perspective, it could be a relevant solution to provide framework legislation on agronomic data and their governance, but also on the use of drones that, otherwise, will continue to be valid only for topographical surveys and aerial documentation, not taking advantage of the additional opportunities of reduction of the factors of pollution and contribution to the ambitions of sustainability, according to the EU policy.

Although the EU Reg. 2022/425, amending EU Reg. 2019/947, extending the transitional periods for the use of drones in the open category, and the Easy Access Rules for UAS, a manual drawn up by EASA on the European regulation of drones, the current legislation is not yet responsive to the needs of the agricultural sector: this could compromise the proper development of the market, which can no longer be separated from smart agriculture.

Acknowledgements

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P9 - Small robot for localized spraying using ISOBUS protocol

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Introduction

Weeds and other pest organisms cause losses of more than 40% of crop yields globally [1] and their control accounts for approximately one third of the total expenditure of a farm. In the face of the current intensification of agriculture, it is becoming increasingly urgent to design and adopt more sustainable and efficient food production.Therefore, there is a strong need for proper management of phytosanitary treatments on crops, and for these to be carried out in a localized manner. Experimental studies on cereal crops in Germany [2], Spain [3] and the Czech Republic [4] showed savings of over 70%, 74% and 86%, respectively, in the applied dosis phytosanitary when it performed in a localized manner. This significant reduction of the amount of phytosanitary would allow the use of small treatment vehicles carrying small tanks of liquid instead of big ones. On the other hand, the ISO 11783 (commonly designated as ISOBUS) protocol is a communication standard using in agriculture, for connecting tractors with implements. Although this standard has been widely adopted in precision agriculture technologies [5], there is a shortage of research studies on its use for communicating agricultural robots with their implements.

Objectives

The main objective of this work was to develop and validate a platform based on a small commercial robot capable of controlling valves individually using the ISOBUS protocol for spraying phytosanitary on weeds. The opening of the valves is determined by the information of a weed treatment map previously created. Acting in this manner, a considerable amount of this liquid is saved, as this is only applied in the areas of the field that they really needed, instead of over the entire field.

Materials and methods

A small commercial robot (Robotnik RB-VOGUI) was equipped with a storage tank for phytosanitary liquid, an electric diaphragm pump, and a one-metre spray bar (Figure 1a). Three electric valves (Lechler ESV) capable of single nozzle control by ISOBUS were placed on the bar (Figure 1b). Furthermore, a RTK-GNSS receiver (Septentrio mosaic-H) was placed on-board the robot.

An algorithm was developed for generating treatment maps of patch weeds in fields (Figure 1c). Thus, once measured the geographical position of the weeds, a grid map of the field was obtained, where each cell was marked with a binary value that represents whether there is weed or not. Regarding the actuation system, a method that encoded the control signals to ISOBUS data frame format for the valves was implemented.

Thus, the operation of the entire system was that the platform moved forward over the field, it read its geographical position from its RTK-GNSS receiver, located the position of its valves on the treatment map, and, in the case that weed was present, it opened one, two or the three valves to spray phytosanitary over the weeds.

Results

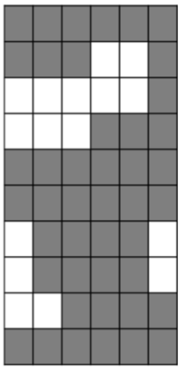
Several experiments were carried out to test the complete system on the field, showing a proper functioning. The treatment maps were correctly generated from the geographical position of the weeds. The robot went around the field, and the valves only opened in the regions where the treatment map indicated that weeds were present.

Discussion and conclusions

The developed platform allowed the localized weed treatment. Thus, the phytosanitary was applied only in the regions of the crop where weed was present, instead of in the entire fied. Therefore, it is possible to substantially reduce production costs and achieve more environmentally friendly farm management.

Figure 1. (a) Developed platform based on a small robot; (b) Electric valves placed on the bar on-board the robot; and (c) Example of weed treatment map.

(b)



(a) **(c)**

Acknowledgements

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P10 – Autonomous coordination between UAVs and UGVs for weed detection and removal

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Introduction

Unmanned Aerial Vehicles (UAVs) can acquire high-resolution aerial imagery for precision farming. Unmanned ground vehicles (UGVs), on the other hand, can be used for care of crops, weed removal, application of chemicals, and harvesting. Autonomous coordination between the two can further help minimize the use of chemicals, reduce cost, and reduce dependencies in human labour [1]. For example, UAVs can provide necessary information about the crops such as diseased plants/weeds and their locations to the UGVs, which can use the information provided by the UAVs to autonomously navigate to the area for application of chemicals (herbicides/pesticides) and removal of weeds. Collaboration between UAVs and large farming robots such as Bosch BoniRob has been investigated [2]. However, large ground vehicles cannot effectively be used for all types of row crops such as strawberry and lettuce. Moreover, using large vehicles results in soil compaction. Using small UGVs instead of large UGVs is more beneficial for precision farming [3].

Objectives

The purpose of this study is to investigate the autonomous coordination between small UAVs and UGVs for weed detection and removal. Experiment design, data collection and processing, development of machine learning models for weed detection, and real-time processing of the developed models are discussed. Also discussed is the progress on the collaboration between UAVs and UGVs for motion coordination and communication network for data sharing.

Materials and methods

An experimental strawberry plot has been designed and developed for the study. The test plot has a total of three replicate rows. It is a strip-plot design with four nitrogen treatments forming the main plots and five irrigation treatments forming subplots. Strawberry is a suitable crop for this research as it attracts a lot of weeds.

Two UAVs have been used for the project. One of the UAVs used is a DJI P4 multispectral equipped with a high-performance RTK capable GPS, an RGB camera, and 5-band multispectral sensor [4]. The second UAV used is a IF750 UAV and is equipped with a camera and a Gimbal. The UAV has been integrated with a Jetson Nano processor for processing the developed machine learning models. Jetson is a small and powerful computer suitable for UAV-based object detection and real-time applications.

The UGV used is a Husky UGV from Clearpath Robotics. It is a medium sized UGV and is equipped with cameras, LIDAR, GPS, robotic manipulator, and an adaptive robotic hand gripper. The robotic manipulator can extend up to 0.85 m and carry a payload of up to 5 kg. The adaptive robotic gripper picks up any object of any shape, and adapts to objects' shape for solid grip.

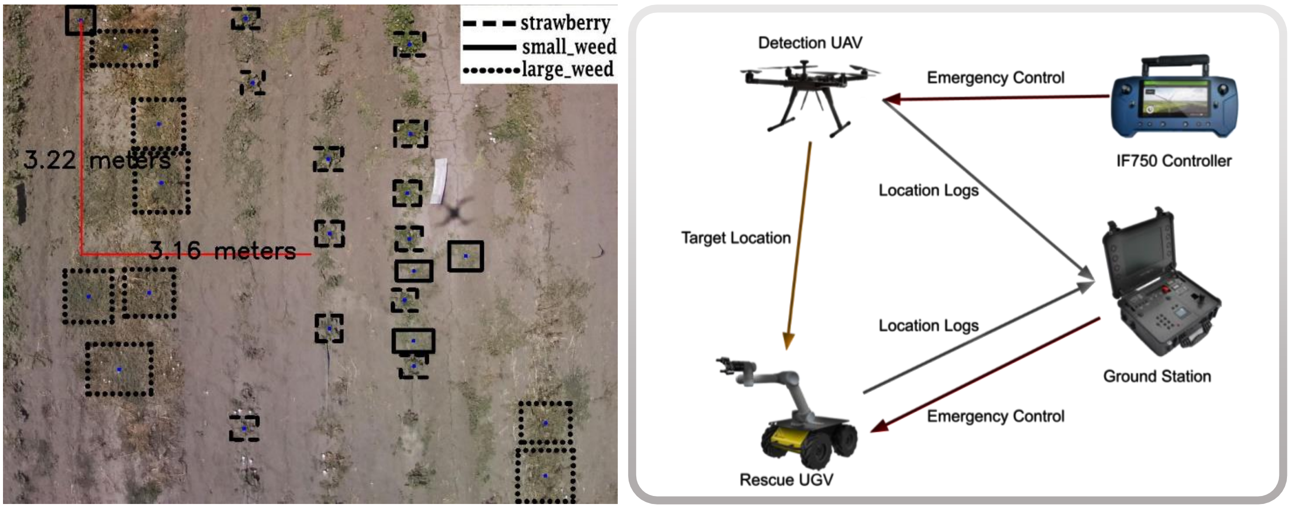
Images of the strawberry plot were collected for machine-learning model training form a DJI P4 multispectral UAV. Over one thousand RGB images were taken for testing over a period of two months while over 200 images were labeled for training. The model was trained on 96 labeled images with over 1000 annotations labeled within. These images were taken from the UAV flying 10 meter above the strawberry plot and were annotated with the labels: "strawberry", "large_weed", and "small_weed" [4]. The models were trained Tensor Flow Lite model Maker [5].

An architecture for the autonomous collaboration between UAVs and UGVs has been developed and tested. XBee radio modules are used to share the data between different nodes [6]. The UAV is capable of collecting the data while flying and processing the developed models. The location of the weed will be determined and sent to the UGV, which will then autonomously navigate to the weed location.

Results

The trained models were used to detect the weeds in the strawberry plot. Figure 1 on the left shows the detected weeds and strawberries using the images collected from the UAV. The center of each box is marked with a dot as the location of the weed or strawberry plant. Using the ground sample distance and starting from the center of the image, the location of each bounding box relative to the UAV in meters can be calculated [4].

Figure 1. Left: Detected strawberries (dashed bounding boxes), small weeds (solid bounding boxes), and large weeds (dotted bounding boxes). Right: Concept of operation for the autonomous coordination between UAVs and UGVs.



Source: [4, 6]

Each bounding box contains information on the coordinates (latitude and longitude) of the detected weed. This coordinate is shared with the UGV for autonomous navigation to the weed location. The UGV is has been successfully tested for autonomous navigation to the specified coordinates. Experimental testing for weed detection and removal using UAVs and UGVs is underway, and the results will be reported in future.

Discussion and conclusions

The developed machine learning models are able to isolate the weeds from strawberry plants and determine the location of weeds. An architecture for autonomous collaboration between UAVs and UGVs for information/data sharing has been successfully designed, implemented, and tested. The detection algorithms will be processed onboard the UAV and the information will be shared with the UGV in real-time for necessary action that includes autonomous navigation to the weed location.

The UAV has also been equipped with communication devices that can send the location of the detected weeds to the UGV. The UGV, equipped with a robotic manipulator and an adaptive robotic gripper, is able to receive the location data from the UAV in real-time.

Acknowledgements

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P11 - Allometric relationships for biomass estimation of persimmon trees using a field robot, LiDAR and photogrammetry

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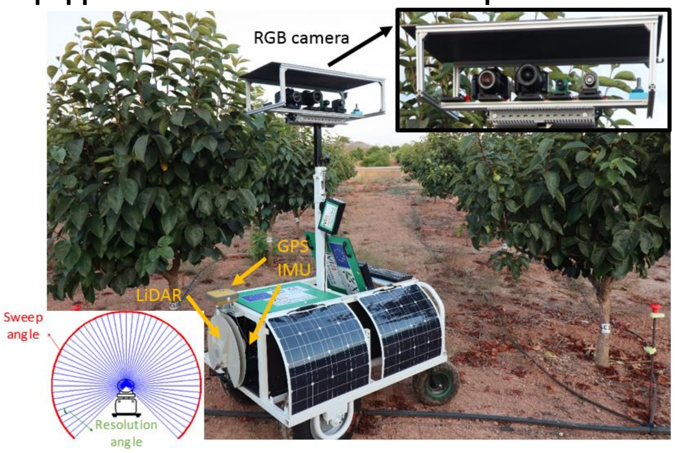
Introduction

Chemical analyses of plants for nutritional diagnoses are destructive, complex, and time-consuming. Fast and non-destructive alternatives based on optical sensors can perform the nutritional status of plants in the field [1]. While data captured by spectral sensors can be used to determine the nutritional status, the actual needs are influenced by other factors, such as the size of the plant or growth evolution. Allometric measurements, such as height, diameter, or canopy volume, along with the study of their temporal evolution, can provide valuable information. The use of 3D sensors can optimise this process, with one of the most widely used sensors being LiDAR [2]. Another technique is photogrammetry, which generates a 3D model from photographs [3]. The aim was to develop non-destructive tools for determining allometric measurements of a persimmon crop at various phenological stages using LiDAR and photogrammetry on a robotic platform [4].

Materials and methods

The equipment was a colour camera (EOS 600D, Canon Inc, Japan) that captured images for photogrammetry every 40 cm, synchronised with the advancement of the robot, a LiDAR (LMS111, Sick AG, Germany), a global navigation satellite system (GNSS) (Hyper SR, TOPCON Corp. Japan), accurate to ±1 cm, and an inertial measurement unit (IMU) (MTi-610, Xsens North America Inc. USA). The GNSS and IMU were used to geolocate and correct the scanned data, synchronised using a timestamp with a resolution of 1 ms. The sensors were mounted on a scouting robot developed at IVIA [5], remotely controlled (Figure 1). The measurements were conducted in a persimmon orchard located at IVIA in Moncada (Valencia), Spain, in 3 phenological stages from April to October 2022. Seven trees of an entire row were selected, geolocated and labelled. Automatic measurements were taken with the sensors using the scouting robot. After the third survey, manual measurements of the trees were obtained for reference, including the trunk height and diameter, and canopy height, volume and two diameters in parallel and perpendicular to the robot's movement.

Figure 1. Scouting robot equipped with sensors used in the experiments.



The scouting robot moved along the selected row at a speed of 1 m/s. After the row scan, the LiDAR points were converted from polar to Cartesian coordinates, filtered by distance and corrected using Euler angles. Using the GNSS, data were transformed into UTM coordinates. Images were captured from both sides of the row with the camera. The tree point cloud from the images was obtained using Metashape (V1.7, Agisoft LLC), working in local coordinates, using specific marks for size references. 3D voxel structures were created for each tree using the point clouds from LiDAR and photogrammetry. The point clouds were sliced every 5 cm from the bottom to the top of the tree, and each slice was divided horizontally into a 5x5 cm grid to create a voxel structure of a 5x5x5 cm^3 resolution. The voxels were set to 'on' if any point cloud was found inside that voxel. This resulted in a 3D binary model to calculate measurements, where voxels set to 'on' were part of the tree.

Results

Fig. 2 shows the evolution of the growth of the seven trees studied during the three stages using LiDAR and photogrammetry. A comparison between manual and scanned data was carried out. Table 1 shows the correlations obtained for the 3rd growth stage. Results for trunk parameters were slightly higher, probably due to the greater subjectivity of manual measurements from the canopy.

Figure 2. Evolution of the canopy parameters of the seven trees along the three growth stages for photogrammetry (top row) and LiDAR (bottom row). Units expressed in m but for volume (dm^3)

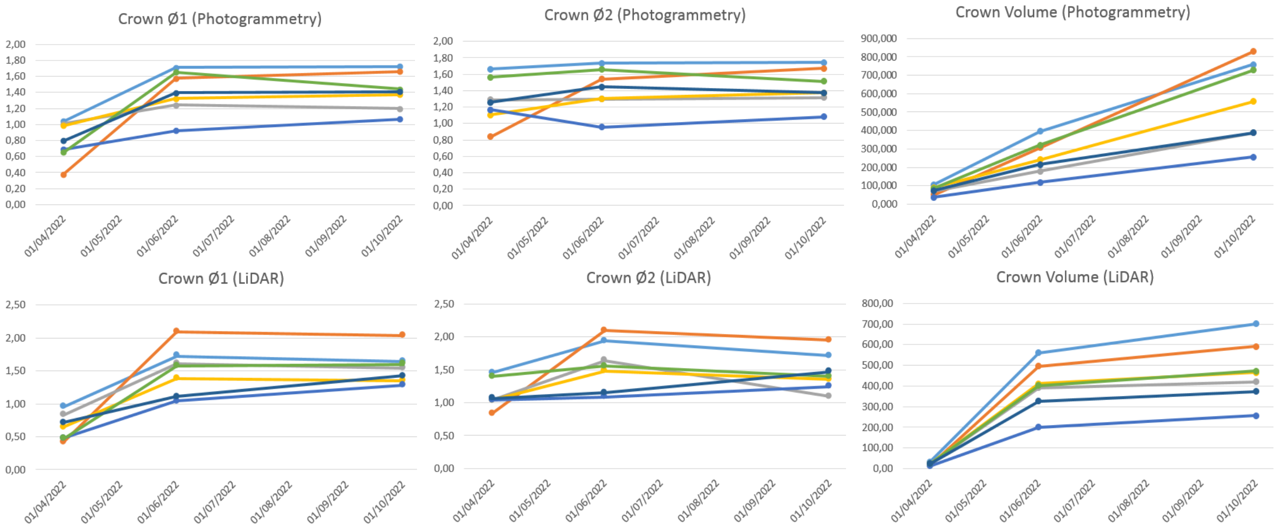


Table 1. Correlations between manual and automatic results in the 3rd growth stage ($p<0.0001$)

	Trunk height	Trunk Ø	Crown height	Crown Ø1	Crown Ø2	Crown Volume
Manual vs LiDAR	1.00	0.97	0.9804	0.959	0.9079	0.8820
Manual vs Photogram	0.99	0.98	0.9693	0.8155	0.9169	0.8889
LiDAR vs Photogram	0.99	0.92	0.9804	0.8773	0.8328	0.9899

Overall, the two technologies worked similarly, showing the development of allometric parameters. Photogrammetry demonstrated higher correlations with manual measurements for the trunk, and LiDAR performed better for the canopy. LiDAR was more effective in measuring canopy diameters parallel to the robot's advance, whereas photogrammetry performed better for those perpendiculars to it, probably because the LiDAR used a single beam scanning perpendicular to the advance, while the images captured a certain angle. It is important to note that manual measurements are imprecise and subjective, while sensor measurements are objective and repeatable. The results revealed that both technologies can operate at the plant/leaf scale with good accuracy and resolution.

Acknowledgements

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P12 – Evaluation of a low-cost drone sensor to discriminate water stress levels in ornamental plants

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Introduction

Nursery plants either for breeding or production require evaluation of traits. Usually those traits, such as tolerance to (a)biotic stresses or height, are manually measured or visually scored. In the U.S., ornamental nursery plants are grown in containers that are frequenlty irrigated via overhead irrigation. Containerized soilless-based media often has low water holding capacity, thus plants are often prone to rapid physiological changes [1]. Therefore, a critical (labor intensive) trait that requires frequent monitoring (i.e. hourly to daily) is plant water status. The adoption of technological tools such as aerial imagery could, in part, facilitate this task and provide insights into irrigation system uniformity. The use of sensors carried by drones are not common in this sector mostly due to smaller production areas and crop and cultivation systems diversity [2]. Development of an aerial water monitoring method could result in faster data collection, limit human bias, and reduce of labor costs.

Objectives

In this work we explored the potential of G-R-NIR images from a low-cost sensor to discriminate water stress levels in four species of ornamental plants: *Spiraea nipponica*, Floribunda Rose, *Itea virginica* and *Weigela florida*. Spectral information, as single spectral bands and vegetation indices (related with canopy water and crop health [3,4]), were evaluated as possible indicators of water stress. Minimize excess water use in contaner-grown plants would reduce production costs and achieve sustainable water management and use.

Materials and methods

This research was conducted at the Hampton Roads Agricultural Research and Extension Center (Hampton Roads AREC-Virginia Tech), located in Virginia Beach, VA, USA (36.8919N, 76.1787W). Four species of container-grown ornamental plants were studied (Table 1). Each plant group was divided into three or four levels of water stress plus a set of control plants (non-water stressed plants). Water stress was administered by removing plants from irrigation and withholding water for up to 7 days. There were no easily detectable visual symptoms of water stress in any of the treatment plants. After data collection on 28 August 2018, all water-stressed plants were returned to normal irrigation where they fully recovered and continued to grow. This strategy was part of a broader research program with the aim of studying the adaptation of ornamental species to stress conditions.

Table 1. Species and number of plants

Scientific Name	Common name	Height + SD (cm)	Width + SD (cm)	N Plants considered
Spiraea nipponica	Wedding Cake®	27.0 ± 2.7	49.9 ± 3.8	49
Rosa x 'Wekvossutono	Julia Child™ Floribunda Rose	38.0 ± 4.7	63.7 ± 5.7	40
Itea virginica	Scentlandia®	67.8 ± 4.3	75.8 ± 8.4	40
Weigela florida	Czechmark Trilogy™	30.9 ± 2.8	55.1 ± 4.1	40

Near-infrared images were collected with a quadcopter drone (DJI Inspire 2, DJI Science and Technology Co. Ltd., China) equipped with a MAPIR Survey3 (MAPIR, Peau Productions InC, USA) sensor at an altitude of 30 meters covering the entire experimental area in a single image. The images were processed in the software MAPIR Camera Control (MCC) to calibrate for reflectance, based on an image of the reflectance calibration panel, obtaining a percent reflectance value per pixel. In addition, an RGB image was also captured only for the purpose to automatically delineate plant boundaries.

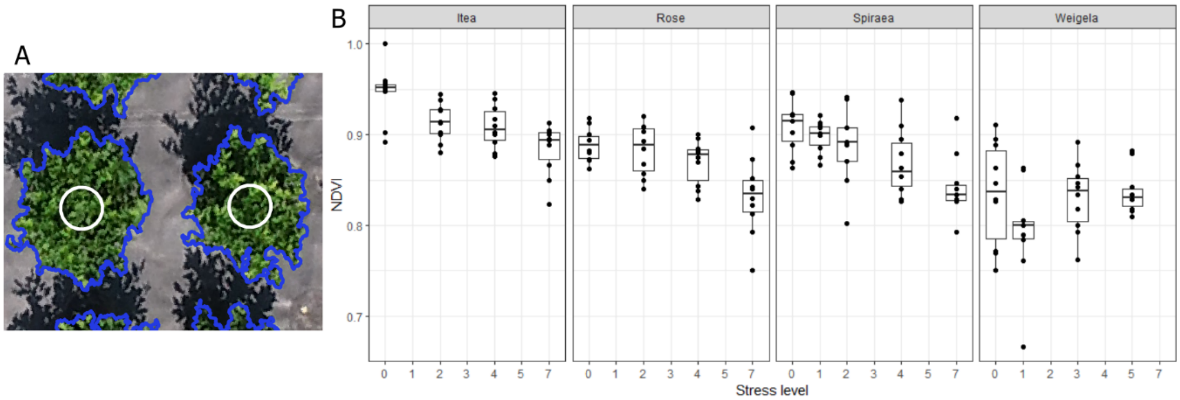
Single bands and vegetation indices values were extracted from the central area (0.031m^2, Figure 1A) of each individual plant using QGIS 3.30.1 (QGIS Geographic Information System. QGIS

Association. http://www.qgis.org) and data analysis, one-way ANOVA to check for significant differences, was perfomed in R version 4.2.2 using RStudio 2022.12.0 (R Core Team (2022). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Austria. https://www.R-project.org/).

Results

Between the indices selected, NDVI was the indicator with the highest number of observed significant difference. Single spectral bands provide a poor indicator of water stress, with no significant differences being obtained. Results presented herein are only for NDVI; one of the most widely used indexes. NDVI presented a decrease in its median values with increasing water stress for three of the four ornamental taxa (Figure 1B), but not all differences were significant (p-value <0.05). The case between control and the highest water stress level (0-7) was significant in all cases for itea, rose, and spirea, however, intermediate water stress that can result in stomatal closure and reduction in carbon assimilation and subsequent growth was not significant across taxa. In the case of *Itea virginica*, significant differences were obtained between 0-2, 0-4 and 0-7; other stress levels combinations were not significant. For rose, significant differences were between 0-7, 2-7 and 4-7. For spirea the significant differences were in the cases 0-7, 1-7, 2-7. For the fourth species considered, weigela, none of the differences in water status were significant. This could have been possibly due to the high numbers of flowers throughout that canopy interfering with spectral data.

Figure 1. A) Close-up of two itea plants (blue border) and central area considered (in white); B) NDVI values per species and stress level



Discussion and conclusions

The extreme case, control – highest water stress level, is the easiest to identify using spectral data. The container-grown plants after some days without water start to be affected. Due to the presence of flowers, spectral values are influenced and alter the monitoring of water stress. For further analysis, it is recommended to not consider those pixels. Thus, vegetation indices are based in the Green and NIR spectral bands, linked to the presence of pigments in the leaves, can provide insights into water stress across economically significant taxa.

Acknowledgements

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P13 - The aerial application of pesticides by drones: challenges and regulatory issues

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Introduction

Unmanned aircraft systems (UAS), commonly known as drones, have great potential in precision agriculture. The literature has acknowledged the benefits of their use, ranging from remote sensing applications to the delivery of material (pesticides, biological control agents, etc.) [1-3]. However, at the same time, it has also underlined a series of risks (in terms of safety, security, human health and environmental protection, crop residues, data protection, etc.) stemming from the use of the drone itself or the activity carried out (e.g. crop spraying), different from those associated with established methods of application [4]. These risks may increase depending on the drone's size, the operation's complexity, and location.

Therefore, policymakers must balance the will to promote their positive potential while preventing the risks of their use. This is a challenging task, as shown by the aerial application of pesticides which is, among the possible agronomic applications of drones, the one currently attracting the most attention from a legal point of view.

Objectives

Our study aimed to analyse the regulatory issues concerning the aerial application of pesticides by drones, considering the EU legal framework on pesticides (specifically on plant protection products, PPPs), some relevant national regulatory experiences, and private standards for unmanned aerial spraying systems.

Results

In the EU, there are notable legal challenges related to drone pesticide spraying. According to Art. 9, par. 1 of Directive 2009/128/EC on sustainable use of pesticides, also known as SUD, applying pesticides by aircraft (including drones) is generally prohibited. Although the SUD clarifies that "aircraft" means planes and helicopters, it must be interpreted as encompassing drones since they are equated to other air vehicles [5].

However, according to Art. 9 par. 2 of the SUD, Member States may grant derogations for applying pesticides by aircraft: exemptions are possible if clear benefits for human health or the environment can be demonstrated and when other viable alternatives are not available. Against this background, drone interest has prompted some Member States to launch specific initiatives.

Spanish Minister of Agriculture has adopted specific requirements for aerial spraying of pesticides by drones, in the case it is possible to grant a derogation according to art. 9 of the SUD.

In France, in 2018, drones were allowed to be used for a 3-year experimental period to spray pesticides to assess risks and benefits. Indeed, thanks to the approval of deregulation established by article 82 of Law n. 2018-938 to the Code Rural et de la pêche maritime (article L. 253-8), drones were allowed to spray PPPs which can be used in organic farming or in the context of a certified high environmental value farm. These operations could be carried out only in agricultural areas with a slope greater than or equal to 30%. This time frame served to collect data and decide whether to confirm unmanned aircraft use and extend it to other crops and contexts. Since October 2021, the end date of the trial period, aerial spraying of PPPs with drones has been prohibited again in France.

In 2022, the French Agency for Food, Environmental and Occupational Health & Safety (ANSES) published a note describing the experimentation results. According to the preliminary results (which must be interpreted with caution given the limited dataset), the ANSES concluded that, even though the performance of drones for spraying purposes seems to be lower than conventional sprayers, the use of UASs appears to reduce the operator exposure to the PPPs, especially during the application phase, and to lower the level of aerial drift. It is interesting to notice that, in light of the ANSES note and the results of the experimentation, in January 2023, a bill to the

Assemblée Nationale was presented to allow the aerial spraying of PPPs authorised in organic farming in areas that are difficult to access, by UASs equipped with anti-drift nozzles.

The experimental use of aerial crop spraying is also under consideration in Italy. The draft of the new National Action Plan (NAP) for the sustainable use of PPPs, which is being developed, explicitly refers to the experimentation of using drones for application purposes in the context of sustainable use of pesticides. Specifically, point A.4 of the NAP draft states that, even though aerial spraying is forbidden, a derogation may be granted when aerial spraying has evident benefits regarding the reduced impact on human health and the environment.

Moreover, on 8 January 2021, a bill to the Chamber was presented for introducing a 3-year authorisation for spraying PPPs with drones if the applicants demonstrate that these techniques have clear advantages in reducing the impact on human health and the environment.

At the international level, drone interest has resulted in the drafting of a specific ISO standard for aerial spraying, which is under development. The standard ISO 23117 consists of two parts, under the general title Agricultural and forestry machinery — Unmanned Aerial Spraying Systems: Part 1: Environmental requirements; Part 2: Test methods to assess the horizontal transverse spray deposition. When finally published, the ISO standard will be a pivotal reference also for EU operators.

Discussion and conclusions

The potential benefits and risks of using UASs for pesticide spraying in the EU results in significant legal challenges.

Nowadays, the aerial application of pesticides is generally prohibited by EU Member States, according to Art. 9.1 of the SUD. The initiatives launched by Member States, along with the bills presented, highlight the importance of adequately regulating the specific use of drones in precision agriculture for aerial spraying purposes, avoiding general prohibitions that can be detrimental to innovation and the achievement of some ambitious sustainability goals.

In this context, it must be underlined that legislative reforms are on the horizon. In 2020, the EU Commission launched a revision of the SUD for achieving the Farm to Fork Strategy (F2F) targets on pesticides, specifically the reduction by 50% of the use and risks of chemical pesticides and more hazardous chemicals pesticides by 2030. On 22 June 2022, the Commission presented a proposal for a new Regulation replacing the SUD, which will have binding legal force and be uniformly applicable to all EU Member States. The new Regulation aims at establishing rules to reduce the EU's environmental footprint in line with the F2F Strategy, for example, by defining legally binding targets. The proposal also sets criteria for exempting certain UASs from the prohibition of aerial application, considering that UASs are likely to help reduce the use of PPPs due to targeted application, lowering the risks to human health and the environment.

However, the Commission considers it appropriate to "defer the application of this exemption for three years given the current state of scientific uncertainty", therefore postponing the possibility for EU operators to use drones for spraying purposes unless Member States decide to permit aerial applications by way of derogation.

Acknowledgements

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P14 - Uncertainty analysis of a LiDAR-based MTLS point clouds using a high-resolution ground-truth

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Introduction

The plant properties and its interactions with the environment are related to plant geometry and structure [1,2]. Therefore, the study of plant geometry is crucial to design specific management by providing the optimal quantities of nutrients [3], fertilizers and pesticides [4], irrigation rates and reducing economic and environmental costs [5,6]. Before the advent of the first 3D characterization systems, it was tedious and costly to obtain accurate commercial scale 3D crop data. Nowadays, there are sensing systems which allow 3D canopy characterization to be performed in a relatively simple and fast way. LiDAR (light detection and ranging) sensors have been widely used in agriculture [7]. When 3D scanning techniques are used, it is essential to be aware of the total measurement error. One of the limitations when using real data is the difficulty to have a proper ground-truth to validate the obtained measurements [8]. In a previous research, [9] validated a high-resolution 3D point cloud on an actual defoliated tree obtained from RGB images and stereo-photogrammetry techniques based on structure-from-motion (SfM) and multi-view stereo-photogrammetry (MVS). This accurate 3D point cloud can be used as digital ground-truth (DGT) to validate 3D LiDAR point clouds. The accuracy of the scanning system includes the errors committed by the sensor, the positioning system (GNSS), the inertial measuring unit (IMU) if present, the data acquisition system, the point cloud generation algorithms [10] and the georeferentiation of the DGT.

Objectives

The purpose of this study is to develop a methodology to measure the total scanning error of LiDAR-based systems using a high-resolution ground-truth obtained with photogrammetry techniques. This methodology was applied to evaluate the uncertainty of the 3D point clouds resulting from scanning with a mobile terrestrial laser scanner (MTLS)at 0.5 km/h and 2 km/h.

Materials and methods

A defoliated apple tree (*Malus domenstica* Bork.) was used as actual ground-truth (GT). SfM-MVS photogrammetry techniques were applied [9] to obtain a high-resolution digital ground-truth (DGT) with a bias of the model of -0.0015 m and 0.0005 m for diameters and lengths, respectively. The GT was georeferenced with a topography total station and the DGT was georeferenced with the same coordinates.

To determine the error committed by the MTLS based on VLP-16 LiDAR sensor (Velodyne LIDAR Inc., San José, CA, USA) an experiment was designed consisting in scanning the GT at speed of 0.5 km/h and 2 km/h. The MTLS comprised a multi-beam LiDAR sensor on a gimbal and a real-time kinematics global navigation satellite system (GNSS-RTK). The obtained point clouds had the coordinates assigned point cloud creation algorithm.

In order to compare the point clouds, 30 points were scored on the DGT. The DGT was registered on the LiDAR-derived point cloud using the iterative closest point algorithm. The error distances were then measured between the homonymous points of the DGT located in the original coordinates and the DGT located in the coordinates resulting from fitting it on the LiDAR point cloud.

Results

Figure 1 shows the obtained point clouds when scanning at 0.5 km/h and scanning at 2 km/h. The scan performed at 0.5 km/h had a mean total error of 0.054 m, with a maximum error of 0.066 m and a minimum error of 0.047 m. The scan performed at 2 km/h had a mean total error of 0.050 m, with a maximum error of 0.052 m and a minimum error of 0.048 m.

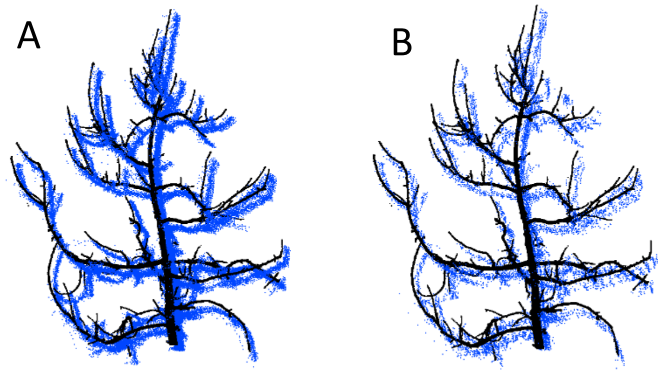

Figure 1. View of on side of the LiDAR 3D point clouds (blue) scaned at 0.5 km/h (A) and scanned at 2 km/h (B) and the digital ground-truth (DGT) (black).

Discussion and conclusions

A 3D point cloud was created using an MTLS system that represented reality with a mean total error of 0.054 m and 0.050 m when scanned at 0.5 km/h and 2 km/h, respectively. Several authors [11–13] have analyzed 3D point clouds and determined that error values between 0.10 m and 0.25 m give optimal performance to estimate biophysical and structural parameters of the fruit trees. In the same sense that [4], no significant error differences were found between scanning at different speeds.

Acknowledgements

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P15 – Performance of a Smart Autonomous Vehicle in vineyard pesticide application

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Introduction

Unmanned Ground Vehicles (UGVs), have been used in an expanding number of indoor and outdoor applications, and nowadays they have widespread attention in the agricultural sector [1,2]. A crucial step in the process of industrializing the UGVs for use in agriculture is the optimization of the design.

Objectives

The aim of the study performed was to assess the performance of the UGV prototyped by the University of Bologna (UNIBO) [3,4] in vineyard. The robotic platform was mounted with a commercial sprayer designed to localize the spray jet to evaluate the uniformity of pesticide distribution on the canopy and the off-target spray on the ground. Contemporarily field trials were conducted to evaluate the autonomous driving capabilities of the UGV.

Materials and methods

Field trials were conducted using an autonomous mobile ground platform developed within the University of Bologna. The vehicle was equipped with a commercially derived sprayer (Oktopus model from Nobili S.p.A.), adapted to the autonomous vehicle linkage system.

The vineyard selected for the tests was located in Cadriano (BO) on the experimental UNIBO farm and the vine variety considered was "Pignoletto". For the tests, 4 rows were considered: 3 rows were subject to the treatments and 1 row, adequately spaced, was maintained untreated in order to verify the biological effectiveness of the treatments.

The trial focused on the distribution of fungicides during the 2021 growing season. In reason of the weather conditions 6 treatments from May to June were performed. The uniformity of the liquid distribution on the canopy and the losses on the ground were assessed 3 times with water-sensitive papers, 3 replications per assessment were conducted.

The water-sensitive papers were collected immediately after the spray application and were analysed with ImageJ software to determine the percentage of area covered by the spray.

Finally, at the time of harvesting, to verify the effectiveness of the treatment, a biological assessment was carried out both on the grapes and on the leaves of the treated rows in comparison with the untreated row.

Results

The results of the three field trials were influenced by the vineyard LAI, the liquid application rate, the type of nozzles and the operating pressures.

In all the three tests, the results showed an uneven distribution on the canopy (Table 1) as denoted by the quite high standard deviation values.

Table 1. Percentage of the liquid coverage on the canopy at different heights

	First test		Second test		Third test	
Heights (m)	Averaged % coverage	St. Dev.	Averaged % coverage	St. Dev.	Averaged % coverage	St. Dev.
2.25	-	-	0.0	0.0	2.7	1.7
2.00	-	-	0.5	0.3	29.8	17.9
1.75	0.1	0.1	20.7	11.7	76.5	8.3
1.50	0.4	0.3	84.1	7.6	65.0	8.4
1.25	9.8	12.1	74.2	12.6	80.3	3.3
1.00	34.8	18.6	83.4	11.7	83.6	18.3
0.75	75.7	10.4	76.3	15.6	49.6	7.8
0.50	55.9	12.8	4.4	0.6	12.8	4.3
0.25	6.6	5.0	2.4	0.8	2.5	2.0

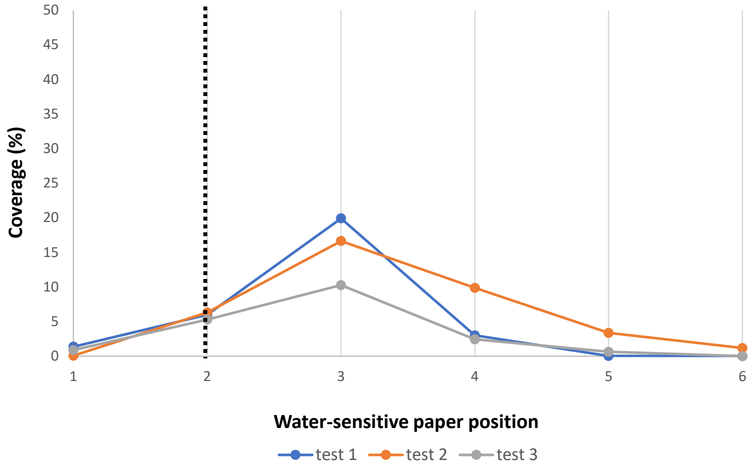
However, the results of the biological control of the fungal diseases obtained comparing the treated rows to the untreated one (Table 2) demonstrated the efficacy of the spraying treatments.

Table 2. Biological control analysis on the leaves and on the bunches

	Affected leaves (%)	Affected bunches (%)
Untreated row	73	87
Treated row	20	7

The off-target spray on the ground was quite low and concentrated mainly in the inter-row adjacent to the treated row (Figure 1).

Figure 1. Off-target spray on the ground



The robotic platform was remote-controlled during the field tests. However, the uneven soil and shape of the vineyard did not allow the correct performance of the sensors mounted on the UGV for the autonomous navigation.

Discussion and conclusions

The spraying operations proved to be effective from a biological perspective, despite some variability in the coverage, mainly because the implement used was not fully adjustable to match with the canopy and some methodological issues related to the water-sensitive papers management.

The robotic platform showed some critical lacks in the autonomous navigation; consequently, basing on the experience in the the testing activity, the system has been improved and redesigned.

Acknowledgements

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P16 - Is it possible to use current auto steering system in viticulture?

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Introduction

In viticulture, the reduction of chemical weeding for environmental reasons is leading to the use of more mechanical weeding over the row and inter-row (grassing management, tillage). This change results in a higher number of tractor passes, thus a higher consumption of fossil fuel and an increased workload [1]. Moreover, inter-vine mechanical weeding (on the row underneath the vines) requires considerable attention and dexterity from the driver to avoid damaging the vines. In this context, retro-fitting precise (RTK-GNSS) auto-steering (AS) to the tractor is an interesting solution to improve the quality of the weeding, to relieve the driver of the tedious job of concentrating on a task that requires a lot of mental attention while being adaptable to current farm equipments [2]. The commercial AS systems were originally designed for arable crops and to our knowledge, experiences with precise AS in viticulture have been little reported [3].

Objectives

The originality of this poster is to propose a systemic approach to evaluate the potential of commercial AS. Mechanical weeding on the row is certainly the operation for which SA is most interesting in viticulture. However, on a row crop such as vines, many other operations can be considered with AS (topping, trimming, leaf removal, etc.). Commercial AS will be evaluated on two aspects: i) the observed spatial accuracy with regard to each possible mechanised operations in the vineyards and ii) the user interface functionalities regarding specific context and operations in viticulture.

Materials and methods

Two precise (RTK) AS from Topcon (X25/AGS2 with AES-35, Topcon Positioning France) and Trimble (Trimble SAM-200 for GFX-750 and Trimble NAV-900, Trimble, USA) were installed and used in two different tractors in different vineyard estate (similar in terms of training system) during the 2022 growing season (April to October). Tests on reference routes (along vine rows) were carried out to assess the accuracy of each AS and its adequacy with requirements of different mechanised operations in viticulture. During the experiment, each pass was marked physically on the ground with a tracer (paint) positioned at the centre of the tractor (on the drawbar). The paint marker was used to measure manually, every 5 m (leading to eight measurements per pass of 50m), the difference between the real position of the centre of the tractor and the reference position it should have followed. Three working conditions corresponding to standard working speeds were tested (2.5 km/h, 4 km/h and 6 km/h) with two repetitions each. The reference route was recorded at 4 km/h.

At the end of the season, these tests were combined with semi-directive interviews that were performed with the two drivers to assess how relevant AS was for different viticulture operations. During these interviews, the drivers were asked to answer the following two questions for each vineyard operation: Is AS technically compatible with this operation? Is the use of AS relevant (in terms of penibility relief or comfort) for this operation? Finally, the drivers were asked whether the commercial AS features were suitable for viticulture.

Results

This study showed that the observed accuracy from 3 to 6 cm (Table 1) makes it possible to consider many common operations in viticulture as spraying, fertilisation, and inter-row weeding. However, the results show a significant variability (CI 95% can reach almost 10 cm) which is limiting for operations that require a lot of precision, for example when there is a risk of damage to the plant or to the fruits. As a result, observed accuracy may be limiting for like mechanical weeding on the row, thinning, leaf removal, etc.

Table 1: Average distance (mean spatial accuracy) and confidence interval at 95 % (CI 95%) of the theoretical route along the row (reference path) and observed path of the tractor with autosteering (AS). Three modalities: Mod1 with the same speed as the one used for the reference line, i.e. 4 km/h, one slower run (Mod2) at 2.5 km/h, one faster run at 6 km/h (Mod3)

Run	Mod1: 4 km/h	Mod2: 2.5 km/h	Mod3: 6 km/h
Mean Spatial accuracy	4.6	6.1	5.7
CI 95%	[3 - 6.1]	[3.6 – 8.6]	[2.6 – 9.3]

Source: author’s data

The interviews performed with the drivers show that they were in agreement about the potential of AS in viticulture. Drivers' evaluation and expectations vary with the considered operations. For example, they both consider that AS may not be relevant, either for accuracy or for gain in comfort reason, for grape harvesting of inter-vine tillage. However, they both consider that AS could be highly relevant for to support the driver in complex operations such as combining inter-row with inter-vine tillage, not however that the observed spatial accuracy may not be sufficient in this case.

Table 2. Technical compatibility and relevance perceived by tractor drivers after one season for some vineyard interventions.

Vineyard intervention	Spraying	Inter-row mowing	Mechanised harvesting	Inter-vine tillage	Inter-row tillage	Combination: inter-row and inter-vine tillage
Perceived technical compatibility	Yes	Yes	Maybe	Maybe	Yes	Yes
Perceived relevance	Low to moderate	Low	Moderate	Moderate	High	High

Source: author’s data from interview with tractor drivers were AS was deployed. Possible choices: Perceived technical compatibility: Yes - Maybe - No; Perceived relevance: Low - Moderate – High

Finally, tractor drivers have pointed out that the user interfaces, originally designed for arable crops, do not fit well with the requirements of viticulture (perennial crops in rows).

Discussion and conclusions

The first results of the study show a high expectation of the wine industry towards AS technology. However, while this technology has been developed for field crops, AS still needs to be characterised for use in a row crop context with different constraints especially in terms of expected accuracy. This study is a first attempt to provide some answers on the opportunity of current commercial AS for viticulture. It shows that many operations in viticulture could benefit from AS and that therefore, like arable crops, viticulture could be an important market for AS in the next year. However, for the most relevant operations, i.e. those for which the dexterity and attention of the driver is most important, AS might not be relevant because a lack of accuracy and the risk of plants/fruits injuries. Future experiments will test other guidance options (e.g. pre-registered lines) as well as the impact of factors related to vineyard planting accuracy to better understand the conditions for which AS (with high accuracy) could be recommended in viticulture, including for the most demanding operations in terms of accuracy

Acknowledgements

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P17 - An AI-empowered, Autonomous Weed Removal Robotic Platform for Precision Agriculture

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Introduction

In farming, one of the crucial issues is the presence of weeds; they compete with crops for water, light, and nutrients, so it is fundamental to eradicate them or control their growth. Manual weeding is still the most precise way to eradicate weeds as it allows them to be removed one by one without affecting the surrounding environment. Chemical methods are also effective; however, they might be not efficient and may be dangerous for humans and may also pollute soil and groundwater. Alternatives can be found in mechanical methods, which still cannot address the intra-row removal. In recent years, there has been an increased interest in moving from passive machinery attached to tractors to semi- and fully autonomous machines able to handle different tasks with minimal human supervision [1, 2, 3]. Nevertheless, there are some unresolved challenges in the development of such robotic systems.

Objectives

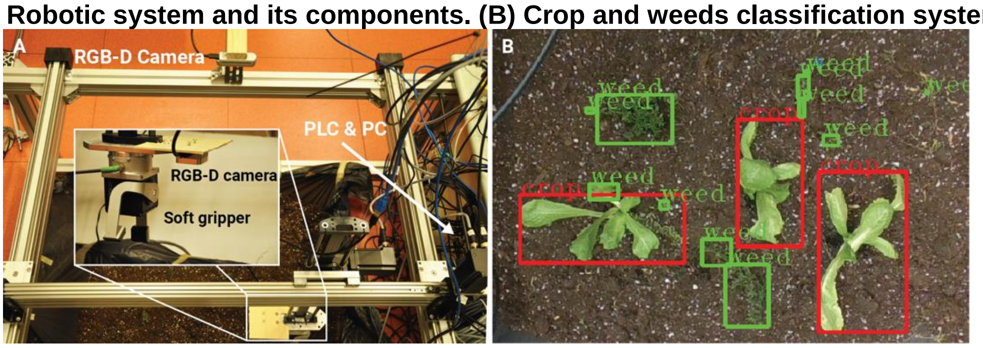
This paper presents the integration of an autonomous, robotic, weeding system designed to identify and remove weeds. Plants are identified using a common image processing approach which is enriched with the use of three-dimensional information and the integration of a state-of-the-art-level Deep Learning Network.

Materials and methods

The system (Figure 2A) is based on an XYZ gantry robot (drylin E 3 axes, Igus inc., USA) characterized by a maximum speed of 0.5 m/s. The z-axis is perpendicular to the ground and at the end, pointing towards the ground, a claw gripper (qb Soft Claw, by qb robotics, Italy). The picking force of the gripper can be adapted to avoid breaking the stem of the weed. The robotic system has a workspace of 800 mm × 800 mm × 500 mm which allows the use of the robotic system both in greenhouses and in the open field. Figure1A shows a schematic representation of the system.

Plant (*Lactuca sativa*) and weed (*Satureja*) identification is carried out in two stages by dedicated RGB-D cameras positioned, respectively, at 1 m above the ground level (Intel RealSense D345i, Intel, USA), and at the same height of the gripper, fixed on its flange (Intel RealSense 405, Intel, USA). The classification (Figure 2B) of crops and weeds, instead, is performed using a pre-trained, Convolutional Deep Neural Network. The system is controlled by a computer running ROS 2 which acquires and processes data from the cameras, controls the motion of the gantry robot, and operates the claw gripper.

Figure 2. (A) Robotic system and its components. (B) Crop and weeds classification system



Source: author's data

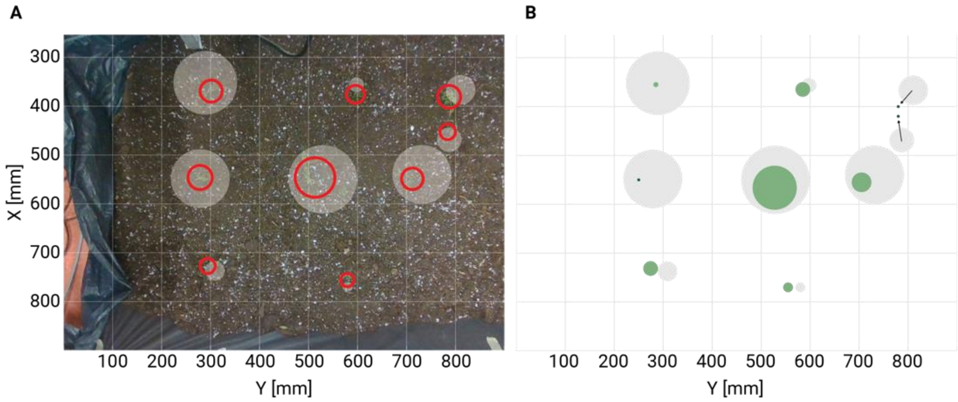
Results

Nine different targets were placed in the soil at known locations within the workspace. The position of each plant was obtained using the proposed identification method, then the results were compared with the ground truth value. The system was able to correctly identify the weed with an accuracy of 97.8%. As shown in Figure 3A, the system was also able to extract the weed locations. In the figure, red circles identify the real location of the plant; shaded, grey areas identify the space where the centroids of the computed bounding boxes lay.

After the initial estimation and correct classification of the target plants, the robot moves towards the target, and, once over it, optimizes its position by performing a second classification of the underlaid plant using the second camera. Doing so, the search area for the weed can be reduced on average by 57% (which corresponds to a movement of 30 mm) and up to 100% for cases where the plant was small and compact (Figure 3B).

With the updated picking height, the accuracy in weed removal is slightly higher than 92%. Failed removal occurred with plants that had a high bending of the stem (due to a wrong approach angle) and for plants with a total height lower than 50 mm (due to limitation on the z-axis).

Figure 3. Autonomous localization of weeds. (A) Initial guess (shaded area) with ground truth (red circles). (B) Refinements (green) performed by the camera attached to the gripper.



Source: author's data

Discussion and conclusions

Crop identification and weed classification is a well know issue in the field of precision agriculture; however, most of the proposed solutions are crop-dependent and cannot easily generalize to different infestation and crops. By way of example, in [4] Gai et al achieved a segmentation success rate of 92.4% on lettuce. Similarly, in [5] the obtained weed mortality was 92.8% in a maize field and 84.1% in pigeon pea crops. Differently from previous methods, the novelty of the proposed approach lies in the possibility of rapidly switching between different crops with no need for crop-specific training of the network, thus enhancing flexibility and efficiency, and simplifying its use in various cultivations. This, in combination with the integrated vision system, allowed to achieve more than 92% of correct weed identification and removal.

Acknowledgements

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P18 - An IoT electronic fence for agri-robots

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Introduction

Agriculture, as every other human activity, requires technology, consumes a large amount of resources and introduces risks. Robots can contribute to significantlyreduce the labor in fields addressing the Hand Free Precision Agriculture (HFPA) and Human Robot Collaboration (HRC) objectives. However at the same timer robots introduce new risks for the environment and humans. Together with known hazards (1), the gradual merging to the Internet of Things (IoT, 2), introduce new risks associated to the possibility malevolent hacking of systems.

According to the current regulatory approach for agro-robots, manufacturers are primarily responsible for ensuring product safety; therefore, they must comply with all the mandatory safety requirements set out in the applicable legislation, as implemented by European and national standards (e.g. EN ISO 18497:2018 for highly automated agricultural machines- HAAM) (3). This approach mainly considers the machine-induced risk to the environment, goods, animals, and health and focuses on machine characteristics (4). Users must follow manufacturers' instructions. However, the regulatory system is unsuited for addressing all robot risks, and international standards have shown several limitations (5). Indeed, the most relevant legislation is undergoing a revision , which will introduce specific requirements for autonomous mobile machinery, strengthening the need for their supervision

It is hereafter proposed and detailed a new system, named EFENCE, aimed at balancing the techno-agro-eco-system frequented by robots, with an independent survey system, featured to monitor the rover activity, adding a level of surveillance (intrusions by animals, humans) in the rover working area, together with the possibility to operate a continuous monitoring of the surface (crop status) and provide a mesh for connecting other IoT devices (weather station, precision irrigation, etc).

Description of the EFENCE

In EFENCE development the following requirements have been identified:

- Provide a solution that can reduce the limitations of the current regulation on robots and will favour compliance with future new legislation.
- Increase easier access to smart-farming technologies.

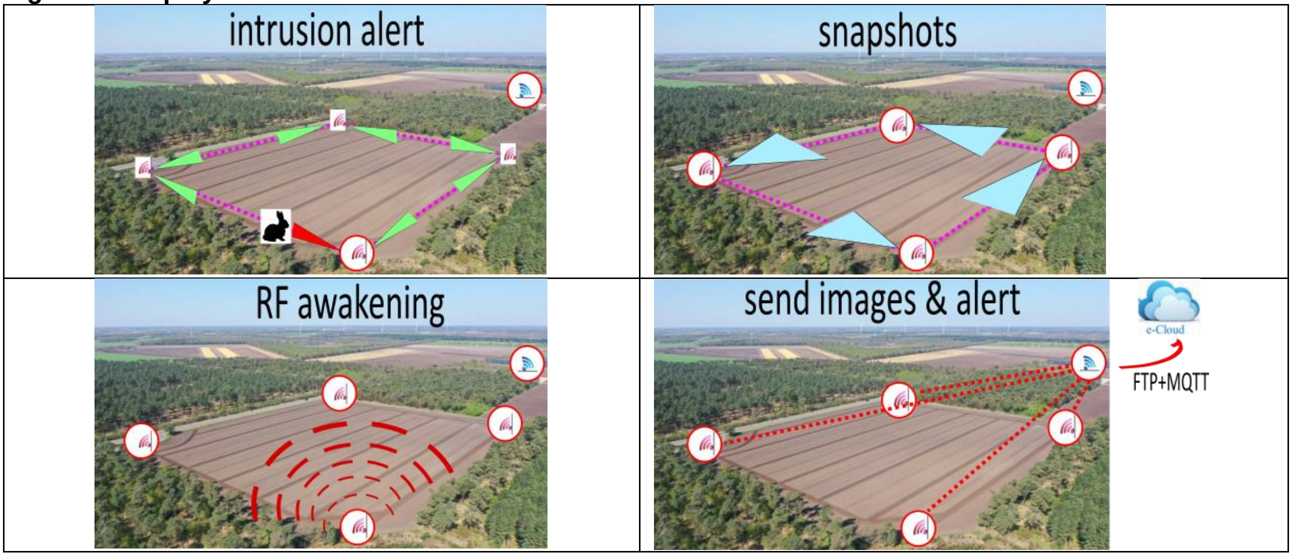
To do so the following characteristics have been identified: compliance with Low-Power IoT, Low costs, Robustness, and Scalability.

To combine such functions and constraints, the system should integrate multiple technologies including cameras, a long-time accumulator, an energy harvesting system, a reliable low consumption controller and a RF system. The system is also designed to communicate with network infrastructure together with the robots.

The solution consists of a set of devices (nodes) with three functions: Surveillance of an area by presence sensors, extension a WiFi coverage, and environmental monitoring. Each node is an autonomous device, powered by a low size photovoltaic solar pane (PV), and is characterized by the presence of two circuits, one of a very-low power (VLP) one, and the other, mainly composed of a controller (ESP32) and a camera, which is activate from the first one. The VLP circuit consists of a presence sensor system, aimed at detecting the presence or motion of animals or other entities with a relevant size, and a low power transceiver (RTX) used to send/receive alerts from other nodes, alerts generated from second circuit (the controller). The mesh includes a 'bridge', a node without the camera, which can connect to the local WAN or mobile phone network.

The system works with the following logics: when the presence sensor is alerted, it wakes-up its controller, which makes digital camera taking the pictures and wakes up all the other nodes that do the same. At the same time the bridge builds the mesh, receives the pictures and resends them back via SFTP to the cloud, together with an MQTTS message that is used to notify subscribed clients (see Figure 1).

Figure 1. Display of the main functions of e-fence



System evaluation

The EFENCE preliminary version is made up of 8 nodes, and has been used too delimit a 30 x 80m surface. Although the strenght of TRX RF signal strength was able to reach a far higher distance, the most sensitive component was identified to be the presence sensor (a PIR). Several models and optics have been tested, along with the possibility of using other sensing approaches, although the popular integration with the camera-based motion detection seemed the best option.
The image validation logics, based on a diversified image resolution, together with the bulit-in functions of the system, make it a feasible solution also for a larger field size as well. The EFENCE shown to be competitive with respect to other existing systems (e.g., Hunting Cameras) in terms of costs, scalability, maintenance, reliability and robustness, customization, elasticity.

Acknowledgements

This research was performed in the framework of the 'WeLASER - Eco-Innovative weeding with laser' H2020 project Grant Agreement N. 101000256. https://cordis.europa.eu/project/id/101000256.

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P19 – Laser safety during laser-based weed control with autonomous vehicles

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Introduction

Non-chemical weed control is becoming increasingly crucial in agriculture due to the growing incidence of resistance to previously applied weed-control agents and also because an increasing amount of chemical agents is banned due to health hazards. A promising method, which has recently been intensively investigated and can be applied selectively in combination with automated detection techniques based on artificial intelligence, uses high-power laser radiation: a laser beam is precisely directed to the plant's growth centre or stem base for a defined time interval in the millisecond range by a galvanometer scanner to deposit a lethal energy dose [1]. Lately, a thulium fibre laser with a wavelength of ~ 2 µm and an average power of 250 W was selected for the application. Apart from a robust laser-system design for outdoor use, it must be guaranteed that persons staying in the vicinity of the laser working area such as operators, passers-by, or onlookers are not endangered. Thus, any uncontrolled propagation of direct or stray laser radiation which could lead to irradiance levels above the existing exposure limit value for the eye according to Directive 2006/25/EC must be prevented. This is needed in addition to the realisation of the principles and requirements for the design of highly automated agricultural machinery described in EN ISO 18497 and summarised in [2].

Objectives

Laser safety requires an appropriate design of the enclosure of the laser-weeding implement to serve as a shield against the laser radiation, as well as of the laser-safety control system, which immediately switches off the laser radiation in foreseeable fault cases detected with special sensors. This is even more important as the laser-based weed control is to be combined with an autonomous vehicle, where an operator trained in laser safety is not present. This work presents results on the design of the required laser-safe enclosure, based on irradiation experiments of selected materials, and on the design of a laser-safety control suitable for application on the field.

Laser-safe enclosure of the laser-weeding implement

The basis for evaluating the suitability of a potential shielding material is the determination of the foreseeable exposure limit (*FEL*) at the inside of the laser implement's enclosure (see Figure 1). This *FEL* must be compared with the protective exposure limit (*PEL*) given by the manufacturer of the shielding material as material characteristic according to EN 60825-4. As no adequate data were available for the materials under consideration, the material's durability had to be determined by means of irradiation experiments, simulating the conditions of the real laser-weeding application.

The enclosure of the laser implement was made from 2 mm thick aluminium sheets as main components. These sheets were attached to aluminium profiles giving the housing's framework. The system construction led to a minimum laser-spot diameter on the inside of the housing of ~ 8.9 mm under worst-case irradiation conditions. Corresponding irradiation experiments using a continuous-wave laser power of ~ 185 W showed reproducibly that within more than 120 s, the aluminium sheet could not be damaged seriously. Only the anodised layer was affected visibly.

Figure 1. Autonomous mobile robot platform with adapted laser-irradiation unit for laser-based weed control (light grey) with laser-protective curtain strips (dark grey) attached to the lower edge [3].

The laser-implement's enclosure needs to be open to the bottom in order to fulfil its function of irradiating weeds. To minimise the risk of laser radiation escaping from the housing, curtain strips were arranged at the lower edges in two overlapping rows, moving across the ground at a small distance. Different curtain materials were evaluated with respect to their durability under the same laser irradiation conditions as described above. For most of these materials, the time up to hole formation and laser radiation-transmission exceeded 4 s. As the laser-based weeding is to be done with laser pulses in the range of ~ 100 ms, the time up to hole formation will not be reached during normal operation. However, a system error could lead to increased irradiation times. To effectively counter such errors, the emission time of the laser-beam source is to be limited to 1 s electronically.

Laser-safety control design

Laser-safety control systems of laser material processing machines must meet the requirements of EN ISO 13849-1 and -2. According to EN ISO 11553-1, performance level $PL_r = d$ must be achieved at least. The design of the laser-safety control implemented as part of this work was based on the requirements of the aforementioned standards. The hardware setup is shown in Figure 2.

Apart from a safety-door switch and an emergency-stop button, the laser-safety system comprises four ultrasonic distance sensors and an inclination sensor. These sensors shall help to detect situations in which the gap between housing and ground increases unexpectedly: if the pre-set sensor thresholds are exceeded, the laser safety control will immediately turn off the laser emission. This further minimizes the risk of laser radiation escaping from the housing. If future investigations require it, the safety system can be easily extended and supplemented with additional functions.

Figure 2. Laser-safety control of the weeding implement, based on a Beckhoff Industrial PC solution.

Conclusions

It was shown that a proper system design according to existing standards, comprising a laser-safe housing as well as a laser-safety control connected with electronic sensors which provide redundancy and diversity, can ensure the laser safety for persons staying in the vicinity of a laser-based weeding device installed on an autonomous vehicle. The correct functionality of the realised laser-safety control has to be demonstrated in future experiments. To finally guarantee that any risk due to propagating or stray laser radiation is avoided, the laser-safety control can be coupled to the LIDAR system of the autonomous robot: if the LIDAR recognises any person entering a pre-defined safety area, this information is forwarded to the laser-safety control for immediate laser shutdown.

Acknowledgements

Major parts of the work presented here were carried out in the course of the Horizon 2020 project WeLASER (https://www.welaser-project.eu, grant agreement no. 101000256), which is gratefully acknowledged. The authors thank their project partners for the good cooperation.

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P20 - Farmers Friendly Digital Portable Soil Testing Device

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Introduction

Worldwide many developed countries invented new technological solutions for precision agriculture. The adoption of digital technologies in agriculture is important for smallholder farmers [1]. Digital technology like Microfluidic Soil Nutrient Detection Systems using Electrical Conductivity Detection [2], IoT-based soil moisture monitoring on the Losant platform [3], drone technology for farm monitoring & pesticide spraying [4], and many more technology made a revolutionary change in the farming industry. The vast majority of the population of Bangladesh depends on agriculture, directly and indirectly. Most of them are smallholder farmers. The smallholder farmers don't know how to manage their field smartly due to lack of access to technology, tools, training, and financing. Most of the farmers lives in rural area. In this modern world, many technologies came in the agriculture sector but rural people don't get benefit of those technologies. For this reason, they follow the traditional way of farming. By considering this issue, an attempt was done to develop a farmer's friendly portable soil testing device which can measurement soil pH and moisture. Normally sending the soil sample to the labs and getting the report back takes a long time. But this portable device is reducing soil testing time to know their soil condition and to get the proper guideline to plant their crops.

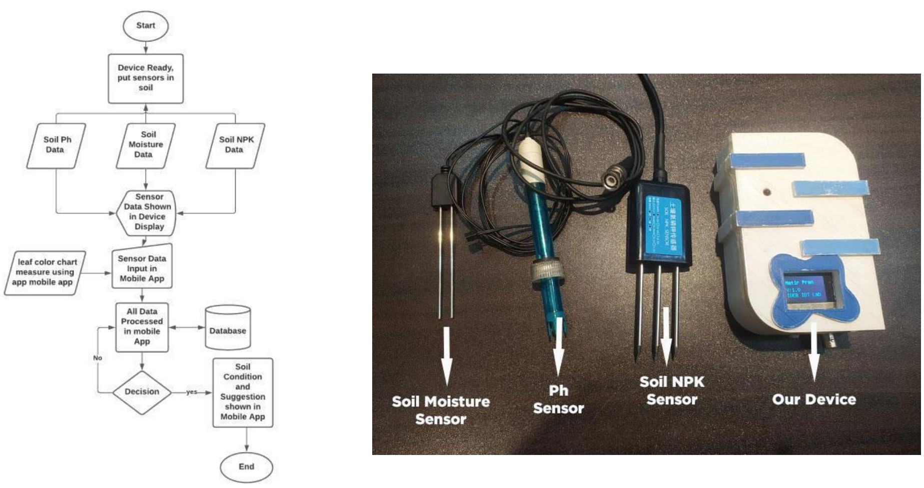
Objectives

The objective of the research was to make a smart device for soil testing, measuring pH, NPK and moisture, and collecting data from three sensors, providing an easy and user-friendly digital system that can suggest type of fertilizer with aplication rate to grow different types of crops in the field.

Materials and methods

This proposed system is devided into two side: one is device side and another is mobile app side. The device has three sensor soil pH, moisture and NPK. After getting sensor data from the device, using the mobile application farmers can analyze soil condition and got fertilizer suggestion. We showed whole process of the farmer's friendly portable soil testing device and apps (Figure 1). At first user prepare the device and puts all sensors in the soil. The sensors are the soil pH sensor, soil moisture sensor, and soil NPK sensor. After that, all data was processed and shown on the device display. User can collect all sensors data and put it in the developed mobile apps. In the app, there is a leaf color chart. By inputing all soil data, users can get results and suggestions from the database for their crops and soil.

Figure 1. Flowchart of the system



Results

When the features were prepared and a test run was done with the sensors and the apps. The system was tested several times for different pH, moisture and NPK value. The input and output for the results are showed in Table 1. Output data of the sensors were inserted in the databases and found satisfactory suggestions from the apps.

Table 1. Test case of the system

Test Case	Test	Expected	Obtained	Result
pH check	Tested on Various – 4.5 5.0 6.0 6.5 7.0	To see user field condition and crops planting list	Showed the actual output	Passed
Moisture check	Tested on Various – 30% 26% 10% 7%	To see user field condition and crops planting list	Showed the actual output	Passed
NPK check	Tested On Various N- 154 mg/kg P- 136 mg/kg K- 98 mg/kg	To see user field condition and crops planting list	Showed the actual output	Passed

Source: Our testing result

Discussion and conclusions

This project (smart device with application) system provides the capability to minimize the gap between rural area agriculture and technology. It will help to both rural farmer and agriculture officer to reduce time. Sometimes we face difficulties like in developing Use Case the first technical challenge we encountered was that the selection of technical indicators and the Regression model.

Acknowledgements

The authors would like to thank ICT Division Bangladesh & Bangladesh Agricultural Research Institute for providing funding & technical support for this system development. The authors are also grateful to IDEB Research & Technological Institute to give us lab facility in this work.

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P21 - Multichannel LiDAR supported Simultaneous Localization and Mapping In Complex Natural Environment

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Introduction

One of the fundamental algorithms of modern autonomous robots are Simultaneous Localization and Mapping (SLAM) algorithms, designed to build maps and localize robots in unknown environments. They work well in artificial environments but may face challenges when dealing with semi-changing conditions, such as those found in natural environments, due to their underlying assumption of environment staticity [1]. This necessitates further research into dynamic SLAM algorithms maybe by leveraging 3D sensors or machine learning techniques.

The paper investigates the potential of using multichannel LiDAR (e.g., Velodyne VLP-16) readings to enhance the performance of SLAM algorithms in complex natural environments like orchards and vineyards. The proposed approach builds upon the existing 2D SLAM algorithm, called FieldSLAM, which employs image registration techniques. The study aims to enhance the algorithm's robustness and accuracy by incorporating 3D point cloud data from a LiDAR sensor. By exploiting the unique features of the Velodyne VLP-16 sensor, the enhanced algorithm can provide more precise and reliable mapping and localization in natural environments.

To validate the enhanced version of the FieldSLAM algorithm, a 3D model of the environment is generated using the algorithm and evaluated in terms of accuracy and efficiency. The resulting model is compared with one generated using basic photogrammetry with RGB recordings from a multispectral camera Micasense Altum and Agisoft Metashape stand-alone software product.

Objectives

The objective of this article is to compare and evaluate the effectiveness of a 3D model of the environment generated from data acquired from multiple LiDAR planes utilizing frequency domain and correlation techniques for motion estimation in complex natural environments, against a basic photogrammetry model using RGB images from the Micasense Altum multispectral camera. The article presents an analysis of the results obtained in the study, along with an evaluation of the methodologies used. Based on these findings, the article offers practical recommendations for further research in this field of agriculture.

Materials and methods

In order to evaluate the approach a measurement system including a multichannel LiDAR (VLP-16), IMU system (Xsens MTi 600), and a multispectral camera Micasense Altum was constructed. The system also consists of other elements (sensors and peripheral devices) that will be used in further research. It is depicted on Fig. 1 (a).

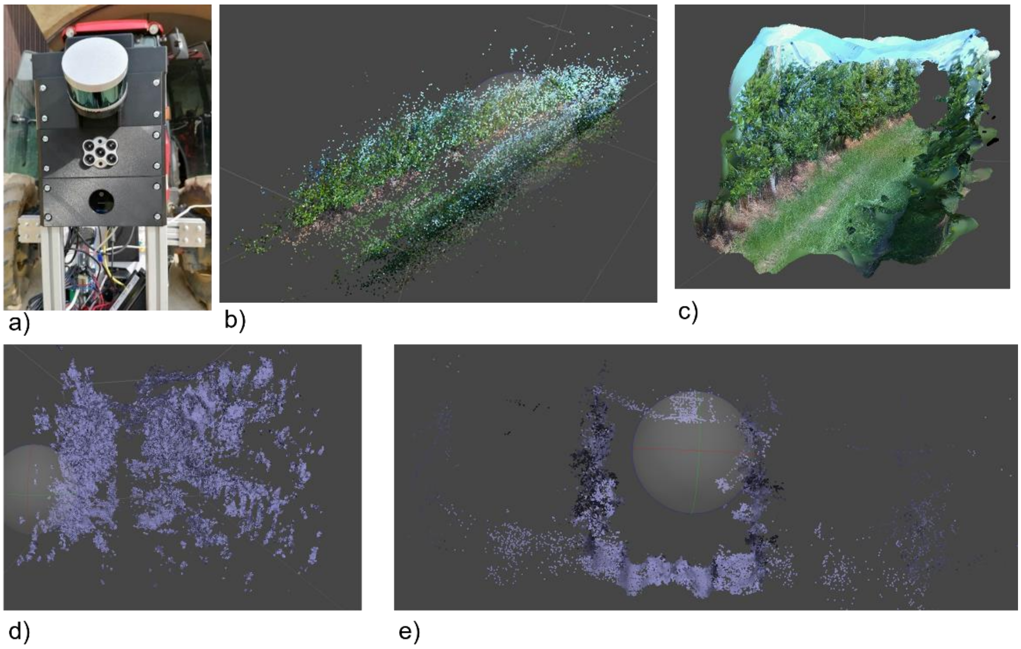
The system provides a simple and a stable data collection since the sensors are fixed. It is based on the meta operating system ROS [2], which records the input data from sensors and stores them in bag files that can be replayed and analyzed with different tools. Based on the captured data point clouds can be constructed with the help of IMU data and the RGB images captured by the multispectral camera. The approach does not require real time processing, since we are analyzing the accuracy of data gathered by the multichannel LIDAR sensor versus data gathered from the multispectral camera.

To make a comparison with the SLAM and LiDAR data constructed point cloud a 3D reconstruction of the scene is made using the Agisoft Metashape software. This is a tool that can perform photogrammetric processing using various sources of input data [3]. In this approach it is used for 3D reconstruction based on the data captured by the multispectral camera.

Results

A decent 3D reconstruction (Figure 3 b and c) of the orchards is made based on the use of RGB images from the multispectral camera and Agisoft Metashape software. This is compared with the reconstruction of the scene produced by the FieldSLAM algorithm [4] and the readings of a multichannel LiDAR sensor.

Figure 1. A multisensor based capturing system (a), process of developing 3D reconstruction using RGB images from the multispectral camera (b, c), point cloud out of RGB images from the multispectral camera d) and a point cloud based on SLAM and LiDAR meassurments (e)



By comparing both point clouds (parts d and e in Fig. 1), it can be concluded that on both the tree lines are clearly visible, along with some parts of tree trunks and other objects and plants. Due to the nature of the approaches, the photogrammetry seems more informative due to the precise color information (part c in Fig. 1). However, looking at the shapes, the photogrammetry is not perfect and more accurate structure is visible in SLAM based reconstruction.

Discussion and conclusions

The research has shown that it is possible to achieve similar data collection using either a camera sensor or a multichannel LIDAR sensor. Yet for real time processing and maximum accuracy, the multichannel LIDAR is still a better choice. In conclusion, if we would need to do a 3D reconstruction of an environment, a camera sensor can suffice to gather decent data. Further research using photogrammetry could be done using several camera sensors, tilted differently to gather as much input data as possible. Combining that data with the multichannel LIDAR sensor could provide the user with great precision and additional info that can be gathered by using camera sensors with various wavelength filters [6].

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P22 - Multispectral camera system performing real-time VRA applications toward sustainable wheat production

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Introduction

A major challenge for modern agriculture is to balance sustainable productivity with increased food safety (Sharma et al., 2018). A pillar of sustainable agriculture is the optimised input requirements that will minimise the environmental impact and realise sufficient economic benefits to the farmers (Spiertz et al., 2009). Precision Agriculture can positively contribute to the sustainable management of crop production inputs by addressing the actual needs of specific field regions rather than average needs of whole fields (Bongiovanni et al., 2004). Variable Rate Applications are defined as the targeted use of input in appropriate zones throughout the field in accordance with the natural variability to maximise profit, create efficiencies in input application and ensure sustainability (Grisso et al., 2011). The scope of this study is to determine the impact of Precision Agriculture and in particular on Variable Rate Applications in sustainable productivity of wheat utilising a multispectral camera system that can perform real-time VRA. The multispectral camera system, which is mounted on top of a tractor or a self-propelled sprayer, utilises data gathered in the red-InfraRed region in order to calculate an NDVI based Vegetation Index and generate in real-time a vegetation Index map upon which the application is performed concurrently.

Objectives

Trials trials were performed in different fields in the USA, Australia and Greece during 2020-21 cultivation period. Wheat was selected as a model crop given its importance in the rural economy and in-season Nitrogen fertiliser was considered as a major input in wheat for sensor–based VRA. The value proposition of the trials regarding a Variable Rate Application is that by delivering the optimal amount at the right place on the field, Precision agriculture will produce savings of inputs and thus enhance income, reduce environmental impact, and improve the living and working conditions of the farmer. A proximal sensing, passive, multispectral camera system (Augmenta Mantis ™) mounted on top of a tractor was utilised to perform Variable Rate Application (VRA) of Nitrogen in real-time. The proprietary algorithms utilised by the multispectral camera system are of a dynamic nature and designed to realise savings of inputs whenever possible.

Materials and methods

A split application pilot has been set up in selected winter wheat fields in the Prefecture of Thessaly (Greece). Based on historic data regarding the productivity potential each field was split into two equivalent parts. All standard cultivating techniques were performed in both parts of the field to ensure the unimpeded completion of the crop's life cycle and productivity. In one-half of the fields, in-season Nitrogen application was applied as a Fixed Rate application of a predetermined fixed rate as a control treatment. On the other half, at harvest, the two halves of the field were harvested and weighed independently to determine the impact of the VRA treatment on productivity.

In the USA (Colby, Western Kansas) and Australia (Ballarat, Western Victoria) the field trials took place in several winter wheat fields. Four different wheat cultivars were tested in 28 and 12 different fields, respectively. For each cultivar, comparable fields were selected and in some of them, VRA treatments were performed while in the rest Fixed Rate applications were performed for the selected input (Nitrogen) as control treatments

In all cases, the recommended dose of Nitrogen fertilizer suggested by the collaborating local agronomist was used.

During each session, the amount of Nitrogen fertiliser input added was calculated along with the savings achieved. For the evaluation of the impact of the VRA treatments, data gathered during the VRA operations (Vegetation Index maps, Application maps, etc) have been compared to yield data gathered at the end of the growing season and were correlated with respective yield maps whenever possible.

In order to match the operational data of Nitrogen VRA with the yield data, geographic coordinates were converted into Cartesian coordinates (3D). Fertiliser dosages and yield data were set as reference and secondary paths respectively. Final matched data sets are extracted and 2D-line statistical plots are generated through Excel software of the Office 365 application platform in order to evaluate the performance of VRA operation.

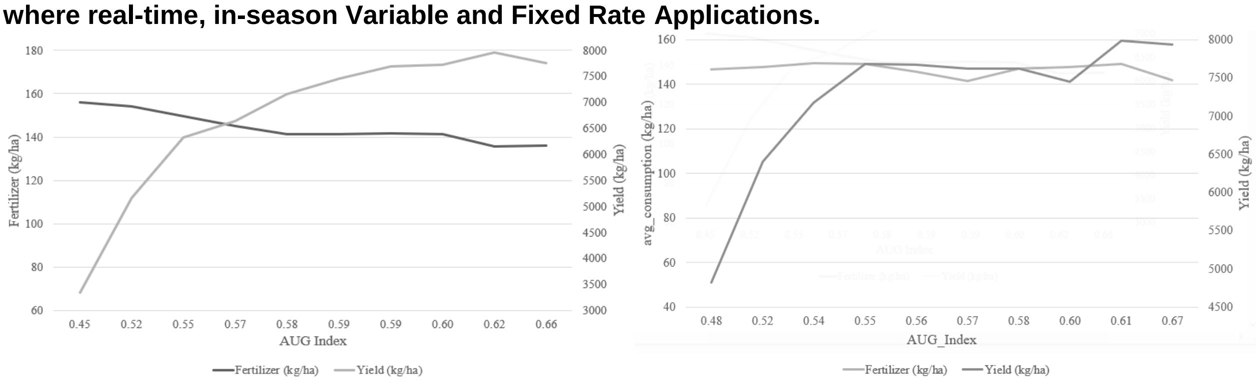
Results

During field trials in Greece savings of 4.9% were realised in the VRA-treated parts of the fields, while the average yield increase was 9.9%. During the large-scale pilots were set up in the USA and Australia, an average of 16.5% and 7.8% of fertiliser savings were achieved in the treated with VRA, while the average yield increase was 10.2 and 11.2%, respectively.

Table 1. . Statistics regarding the in-season real-time Variable Rate (N-VRA) N Fertiliser applications based on data gathered during operations utilising close-range remote sensing (Augmenta Mantis TM) in 3 different geographies, 2020-21

Description	#N of fields	Fixed Rate Area (ha)	VRA Area (ha)	Nitrogen Savings (%)	Yield Increase (%)
- USA Pilots	29	990	313.5	16.5	10.2
- Austalia Pilots	12	227.7	184.5	7.8	11.2
- Greece Pilot	6	16.7	13	4.9	9.9
Totals	47	1234.4	511	13.1	10.6

Figure 1. Correlation between fertiliser added, yield and AUG-Index of a wheat field in Australia where real-time, in-season Variable and Fixed Rate Applications.



Correlation of the Vegetation Index, Application, and Yield Map showed that the fertiliser savings occur mostly due to the slight reduction of added fertiliser in the areas of the field which have already reached their potential. However, as evident in Figure 1, there are yield increases in the respective areas, despite the reduction of added fertiliser, or even because of it.

Conclusions

This study presents the impact of Variable rate treatments utilising an integrated multispectral camera system performing real-time applications, in three different regions around the globe, that in comparison with the Fixed Rate operations, achieved to reduce inputs while increasing yield in winter wheat fields. The average fertiliser savings was 13.1%, while the average yield increase was 10.6%. The proprietary algorithms utilised due to their dynamic nature consistently realised savings the magnitude of which is highly dependent on the variability encountered in each field. The correlation between VRA and yielding shows that there is a tendency for increased yielding in the fields treated with VRA. However, given the multitude of parameters included in the pilots that might affect the results such as different cultivars, different soil profiles, different growth stages, etc extensive analysis of yield data throughout the years is essential to better understand and possibly model the variability of the results detected.

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P23 - Soil prospection and aerial imagery in management zone delineation in a hazelnut grove in Italy

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Introduction

The development of homogeneous field zones requires verification by integrating multiple layers of datasets such as soil parameters, remote and proximal sensed data, and canopy parameters [1]. Potentially different management zones (MZs) can be useful for strategic planning of crop practices at sub-field level. This work addresses apparent soil electrical conductivity (ECa), UAV-based aerial images, proximal sensing and field scouting for delineating MZs in a five-year old, 3 ha hazelnut (*Corylus avellana*) grove in Italy.

Objectives

The objectives of this study were: (1) to characterize the spatial variability of soil ECa and set homogeneous zones potentially suited for differential management (2) to use aerial RGB imagery, field scouting and the MECS-VINE® derived Canopy Index (CI) to validate the established MZs.

Materials and methods

Soil data: on March 26, 2022, an ECa survey was conducted with the proximal ECa sensor Top Soil Mapper at four depths (0-0.25 m, 0-0.4 m, 0-0.6 m, 0-0.8 m). Two MZs were identified with the k-Means Clustering method (Córdoba *et al*., 2016). A composite soil sample was taken in each MZ to describe average soil properties (texture, pH, organic carbon, total nitrogen, and C:N ratio).

Remote sensing: on July 14, 2022, ultra-high resolution RGB imagery (0.01 m) was collected by an unmanned aerial vehicle (UAV). Two vegetation indices (VIs) were calculated: visible atmospherically resistant index (VARI), Eq. 1, and normalized green-red difference index (NGRDI) Eq. 2. In both cases, data were normalised in the 0-1 range [2,3].

$$VARI = \frac{R_{GREEN} - R_{RED}}{R_{GREEN} + R_{RED} - R_{BLUE}} \qquad \text{(Eq. 1)}$$

$$NGRDI = \frac{R_{GREEN} - R_{RED}}{R_{GREEN} + R_{RED}} \qquad \text{(Eq. 2)}$$

Figure 1. MECS-VINE multi-sensor mounted behind the tractor prospecting the hazelnut grove

Proximal sensing: on November 10, 2022, the Micro Environment and Canopy Sensor MECS-VINE® (TEAM Group, Piacenza, Italy) was used to characterize the canopy of the hazelnut based on the Canopyct index which combines the RGB bands provided by two RGB optical matrix imaging sensors positioned at the right and left of the device.-[4,5].

Field scouting: on November 11, 2022, field data was collected on 84 randomly selected plants across the grove. The following traits were assessed: plant height, two orthogonal crown diameters, average stump diameter, and the diameter of the three most vigorous shoots.

Data analysis: field polygon layer was subjected to QGIS zonal statistics module to extract mean, min and max data of the two VIs and 16 MECS-VINE® raster layers (1 m grid size), to match each tree with its values. All data in the two MZs were statistically compared (T-test).

Results

Clustering sub-divided the field area into two MZs: MZ1 (1.65 ha) and MZ2 (1.31 ha) at lower/higher ECa values, respectively (Figure 2). The soil traits within the two MZs exhibited compositional differences reflecting the different ECa values (Table 1): MZ1 vs. MZ2 had coarser texture (sandy loam vs sandy clay loam), neutral vs. slightly acidic pH, lower organic C and total N contents, and similar C to N ratio. Overall, MZ2 featured a more fertile soil.

Figure 2. Field subdivision into two MZs: MZ1 (black) and MZ2 (white)

Table 1. Principal soil parameters in the two MZs

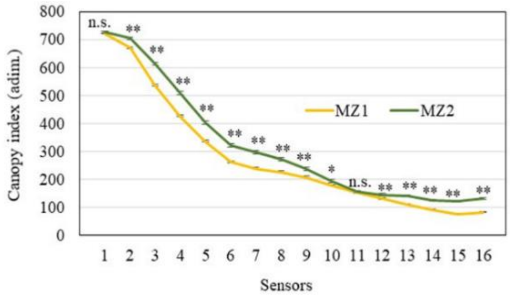
MZs	Sand/Silt /Clay (%)	Soil texture	pH	Org. C (mg g^{-1})	Total N (mg g^{-1})	C:N
MZ1	78/13/9	Sandy loam	7.0	5.97	0.59	10.2
MZ2	54/25/21	Sandy clay loam	6.3	8.76	0.93	9.4

Both VIs and field scouting data indicated more vigorous growth in MZ2 than MZ1 (Table 2). More specifically, crown size (i.e., area and diameter) was most sensitive to different soil fertility. Since crown size directly influences crop canopy and light interception, it may be noted that MZ differences in soil fertility reflected in the plant organ that is the main driver for productivity.

Table 2. VARI and NGRDI and various hazelnut growth traits in the two MZs

MZs	VARI (adim.)	NGRDI (adim.)	Tree height (m)	Crown area (m^2)	Crown diameter (m)	Stump diameter (mm)	Most vigorous shoots diameter (mm)
MZ1	0.457	0.418	1.84	1.28	1.58	289	20.4
MZ2	0.463	0.454	2.32	2.86	2.12	355	25.0
T-test	**	**	**	**	**	**	**

Figure 3. The CIs shown by the two MZs described a slope from base to top sectors.



Results obtained by MECS-VINE on hazelnut were consistent with those of Gatti et al. [4], who observed a declining CI from bottom to top sectors of vineyard canopy.

Discussion and conclusions

This work contributes to the discussion on hazelnut precise management by demonstrating that hazelnut trees, despite specific growth habit and general suitability for varying ambient conditions, respond to different soil characteristics which, in turn, may be evinced by a rapid prospection as that offered by apparent electrical conductivity. It is evinced that more fertile soil conditions in one of the two management zones of the surveyed grove reflected in a larger crown size, which is the premise for accrued light interception and final yield. Future studies should address the issue whether higher external inputs (fertilizers, irrigation, etc.) in the less fertile zone could bridge the gap with the more fertile zone.

Acknowledgements

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P24 – Utilizing functional soil maps for precision management for Smallholder Farmers

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Introduction

Since the early digital soil mapping (DSM) definition, the applications of DSM have expanded rapidly not only in the research community, but also in the communities of users and practitioners at large. The processes used in digital soil mapping are many and not standardized. The has been an increase in the use of methods which utilize knowledge combined with point data to generate soil property maps and group properties into functional units or functional zones which allow for precision management. The major goal of the Water Smart Agriculture (WSA) project was to address the existing large gap on soil information in Central America from farm to country level with soil information products for short-,mid- and long-term decisions on soil and water management, soil restoration and drought management in the Dry Corridor of Central America (Schmidt and Burpee, 2014; CRS, 2019, Water-Smart Agriculture Program for Mesoamerica).The purpose of this project was to build local capacity in generating ready-to-use digital soil maps related to water in rainfed agriculture systems in the hillsides of Central America that are easy to interpret and incorporate into decision making at multiple scales. Managing soils to manage waterwas the major focus as it is very important for sustainable agriculture production by smallholders in this drought-prone region in the time of climate change, as detailed by Schmidt et al. (2012).

Objectives

This paper highlights some of the implementation challenges encountered during the use of DSM in Central America as part of the Water Smart Agriculture (WSA) project. Specifically, we focus on issues such as (i) assessing training needs based on existing skills and capacities in the country teams and available data; and (ii) developing a DSM framework appropriate for the data available.

Materials and methods

The DSM pilot study was conducted in Zapotitán, a sub-basin of the Sucio River that encompasses three administrative departments of El Salvador and has a total area of 375 km2. This area was selected for its agricultural importance as the main productive area for vegetables and grain crops in El Salvador. The team in El Salvador consisted of eleven members representing the following institutions: CRS, Ministerio de Medio Ambiente y Recursos Naturales (MARN, Ministry of Environment and Natural Resources), Centro Nacional de Tecnología Agropecuaria y Forestal (CENTA, National Center of Agriculture, Livestock and Forestry Technology), Universidad de El Salvador (UES, University of El Salvador), Ministerio de Agricultura y Ganadería (Ministry of Agriculture and Livestock) and Caritas Internationalis.

A set of 390 soil point observations for the study site were shared by CENTA. These observations consisted of surface samples from the top 15 cm with measurements of soil pH. The set of soil point observations was split into training and validation sets (315 and 65, respectively). A DEM with a spatial resolution of 10 m was shared by MARN. The DEM was used to derive an initial set of terrain attributes and the final set of terrain attributes was selected for use in the DSM process. The following terrain attributes were selected: multiresolution valley bottom flatness index, normalized height, profile curvature and SAGA wetness index. In addition to the DEM, MARN shared raster layers of mean annual temperature (°C) and total precipitation (mm), both with 10 m of spatial resolution. A parent material layer was derived from a 1:50,000 scale soil series map from1996 which contained parent material attributes. This map was shared by the collaborating institutions and it was credited to a past national collective effort to produce soil spatial information. Lastly, soil pH was modeled following the DSM approach.

Results

A map of soil pH at 15 cm depth was generated for Zapotitán at 10m of spatial resolution. Statistical validation of the soil pH map resulted in a large RMSE value (1.37), which denoted a poor performance of the soil pH inference model. A versioning process was established as a component of the DSM framework with the objective of generating a new soil pH map with improved statistical performance. The first stage of the versioning process was to implement quality control methods for the model inputs. Subsequent analysis of the shared database revealed two issues with the soil pH observations. The first issue was that standardization across laboratory methods for soil pH measurements had not been performed. When the soil pH observations were shared, the associated metadata was not appended, and so it was difficult to trace the data to its source and determine the inconsistencies related to the laboratory methods. Once the metadata was appended, it was discovered that the soil samples for soil pH had been collected through different sampling campaigns and had been analyzed through different laboratory methods. Previous studies have shown the importance of measurement methods on the accuracy of soil pH predictions (Libohova et al., 2019; Seybold et al., 2019) and suggested different pedotransfer function for harmonizing the measurements (Libohova et al., 2014; GlobalSoilMap, 2015). A collective effort was undertaken to standardize the soil pH measurements given the newly acquired metadata. The second issue was the existence of spatial overlap among the soil pH observations resulting from duplicate records. To address this issue, spatial analysis was performed to identify all observations with the same geographic location, that is, a set with duplicate X and Y coordinates. For observation with the same coordinates and the same soil pH value, the duplicated record(s) was removed from the dataset. For observations with the same coordinates but different soil pH values, expert knowledge was used to determine which soil pH value to retain for that observation. Data quality standards were established, and quality control management was integrated into the DSM framework, including the construction of metadata and a spatial analysis protocol for data cleaning. The standardized and spatially curated soil database was used as a model input for a new version of the soil pH map. Validation of the resulting version 2.0 map demonstrated an improved statistical accuracy. The RMSE of the version 2.0 map was 0.49. Table 5 shows the RMSE and MAE for the final map of soil pH. Following the process outlined in Section 3.1, upper and lower confidence interval maps at the 90% confidence level were produced to represent the uncertainty in the modeling of soil pH.

Discussion and conclusions

This paper highlights some of the experiences fromthe implementation of the WSA project that aims to produce soil functional maps. The participatory group process helped overcome some of the data sharing issues, leading to increasing numbers of point data available for the property predictions and validation of the maps. These maps will support decisions at multiple levels and build local capacity for expanding the pilot project to the national levels.Digital soil mapping is used as the platformto achieve these objectives. Such a platform is key to providing access to the correct type of information at the appropriate scale for decision makers at multiple levels.

Acknowledgements

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P25 – Evaluating management, environment and spectrometer type impacts on soil texture prediction via gamma spectrometry

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Introduction

Mobile proximal gamma spectrometry (GS) has become an acknowledged technology to predict topsoil texture for precision agriculture. It relies on the emission of gamma quants of the entity of nuclides in soil (Total Counts, TC) and, more specific, of K-40, Th-232, and U-238. Soil maps based on mobile GS are already commercially available. Yet, studies on the relevance of environmental factors for spectra recording have hardly been published. Further, different instruments with varying crystal materials (CsI, NaI) are in use, and their impact on texture prediction has seldom been compared. Yet, service providers and researchers mostly rely on their own, individual models to derive soil texture from gamma surveys. However, variable conditions in field surveys potentially impede the comparability and universal interpretability of gamma spectra for soil texture prediction.

Objectives

The objective of this study was to elucidate if and to which extent potentially disturbing factors influence or not gamma spectra taken in the field. Therefore, some detailed investigations were conducted on the influence of (i) soil moisture and frost, (ii) tillage status (TS) and bulk density (BD), (iii) potassium (K) fertilisation, and (iv) spectrometer type.

Materials and methods

Soil moisture, frost, TS and BD were investigated through repeated stationary measurements at different dates with variation of the factors under study. For this purpose, grids of 13 fixed points each were established on two arable fields with loess-dominated Ap horizons close to Bonn (Western Germany). Spectra were recorded with a tractor-mounted RSI spectrometer (two 4.2 L NaI crystals) [1]. Tillage was performed as in common agricultural practice. Spectra were recorded in five different situations: in November at high soil moisture, (i) directly after sugar beet harvest (compacted soil), (ii) after subsequent ploughing and (iii) after seedbed preparation for winter wheat. In August on dry soil, spectra were taken (iv) on the wheat stubble and (v) after superficial grubbing.

The possible influence of K fertilisation was studied on 55 plots of the Rengen Grassland Experiment (RGE), running since 1941 and comprising plots with and without K fertilisation [2,3]. Texture variability between the 55 plots is limited; (clay+fine silt) proved best as texture parameter.

At the RGE, spectra were recorded with the RSI spectrometer [1] and additionally with a Medusa device with a 2 L CsI crystal [2]. Measuring time and geometry were equal for the two surveys [1]. In view of the rather small texture variability in the RGE, the two spectrometer types were additionally compared on two agricultural fields revealing a large in-field variation of clay content and TC.

As gamma quants emit predominantly from topsoil, all soil samples were taken from that depth.

Results

The influence of variable moisture was comparatively small during repeated measurements and is therefore not shown here. The common IAEA factor for moisture correction, i.e. 1% signal attenuation per % soil moisture, was generally confirmed at least as an approximate. Though, the correction factor merits some refinements which should consider soil texture. The TC recorded at 61 grid points on the same day, early in the morning when soil was superficially frozen and later in the day after thawing were almost identical (R^2=0.99, correlation slope 1.02, not shown).

In contrast, TS and BD had a stronger influence (Figure 1). The relationship between those two parameters and TC was obvious; at large bulk density, the gamma signal was attenuated. Ploughing led to a clear increase of TC at the grid points. After wheat harvest, i.e., at small soil moisture content, the relationship was principally the same, but less clearly expressed (not shown).

After 80 years with and without fertilisation in the RGE, the ratio of K-40 to total K was not affected [2]. Accordingly, the relationship between the K-40 counts and soil texture showed no differences which could be related to the K fertilisation regime (Figure 2a). Both spectrometer types yielded the same result for the RGE (not shown). Comparing the two instruments on two fields with large texture heterogeneity (141 measuring points) showed that the TC were very close to each other (Figure 2b). However, the reason for the small offset between the two sites could not yet be identified.

Figure 1. Raw data for bulk density (a) and total gamma counts (b) after sugar beet (SB) harvest and subsequent tillage for winter wheat (WW) and scatterplot for the moisture-corrected data (c).

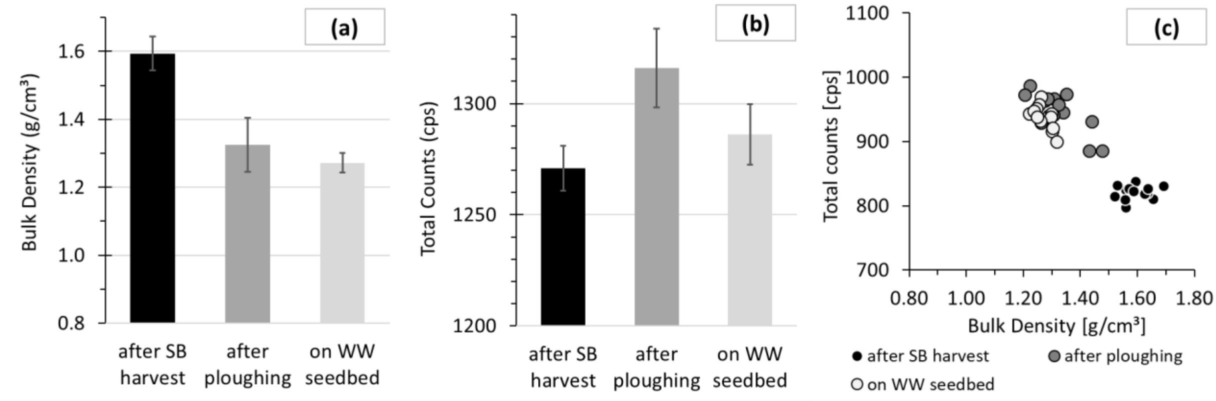
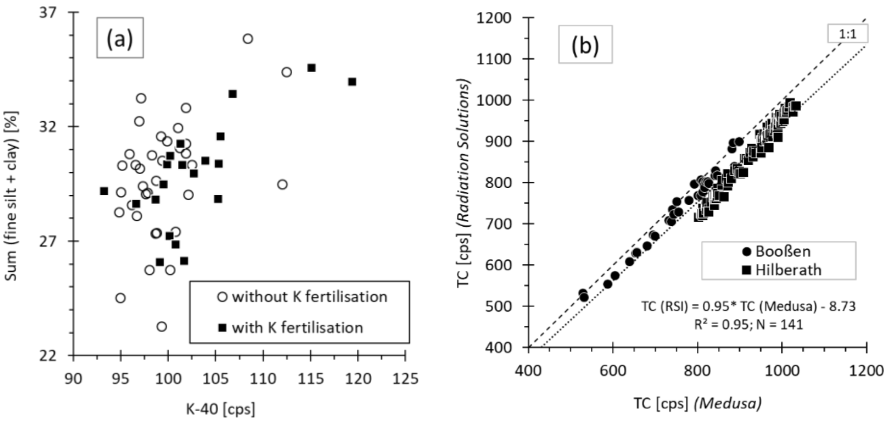


Figure 2. Influence of K fertilisation and spectrometer type on gamma features. (a) Relationship between soil texture and K-40 counts in the Rengen Grassland Experiment (RSI spectrometer). (b) Total counts on two study fields with two different spectrometer types.



Discussion and conclusions

Among the factors studied, the strongest influence on TC was observed for TS and BD. The spectra were recorded at fixed grid points, i.e. at constant soil texture. Nevertheless, the TC ranged from 800-1000 cps, even after moisture correction. Note that the clay content at these grid points varied only between 17 and 19%. In consequence, BD must not be neglected when taking gamma spectra. Otherwise, transforming gamma features to soil texture via any existing model decreases prediction quality considerably. On the contrary, the K fertilisation regime can be neglected. In view of the common K fertiliser production process, this result was expected [2]. Although the results need further confirmation, it is assumed that TC recorded with different instruments are most probably equivalent. For a broader introduction of gamma spectrometry in precision agriculture, a universally valid texture prediction model is recommended, ideally on the basis of a large database. Spectra recording conditions should therefore be standardised, in particular with respect to soil tillage.

Acknowledgements

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P26 – Multilayer data and artificial intelligence for the delineation of corn management zones

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Introduction

The primary sector of agriculture is vital to the economy and rural development. Enhancing agricultural efficiency and sustainability requires the advancement of digital technologies, including artificial intelligence (AI) [1], cloud computing services [2], remote sensing [3], blockchain, drones, and the Internet of Things (IoT). Similarly, crucial techniques involve the implementation of sensors, automatization, or the delineation of management zones (MZs).

Objectives

The research aims to develop a methodology for automatically delineating MZs in corn based on the combination of AI models, cloud programming platforms, satellite imagery, and crop yield data.

Materials and methods

The study was conducted during the 2022 maize cultivation season across ten agricultural plots in the Spanish provinces of Huesca, León, Salamanca, and Zamora. Eight plots were used for the training dataset, while the remaining two were designated for the test dataset.

Throughout the season, which spanned from late April to mid-December, yield data were collected from each plot using a Class Lexion 750 combined equipped with a yield sensor. These data underwent both numerical and geospatial analysis conducted via the QGIS platform. The yield data from the test plots served as the ground truth. Furthermore, using the Google Earth Engine (GEE) platform [4], 54 images were obtained for the agricultural campaign period, enabling the calculation of 10 vegetation indices, as represented in Tables 1 and 2.

The GEE platform also facilitated the implementation of four supervised ML algorithms: Classification And Regression Tree (CART) [5], Random Forest (RF) [6], Gradient Boosting Trees (GBT) [7], and Support Vector Machine (SVM) [8], as well as one unsupervised algorithm, k-means [9]. Additionally, a training-validation dataset based on yield and vegetation index values was applied for these algorithms.

Results

It is crucial to assess classification accuracy to generate maps using ML models. To do so, the overall accuracy [10] (Table 1) and the Kappa coefficient [11] (Table 2) were used for each of the proposed indices.

Table 1. Overall Accuracy of supervised ML models in classifying training data for map generation

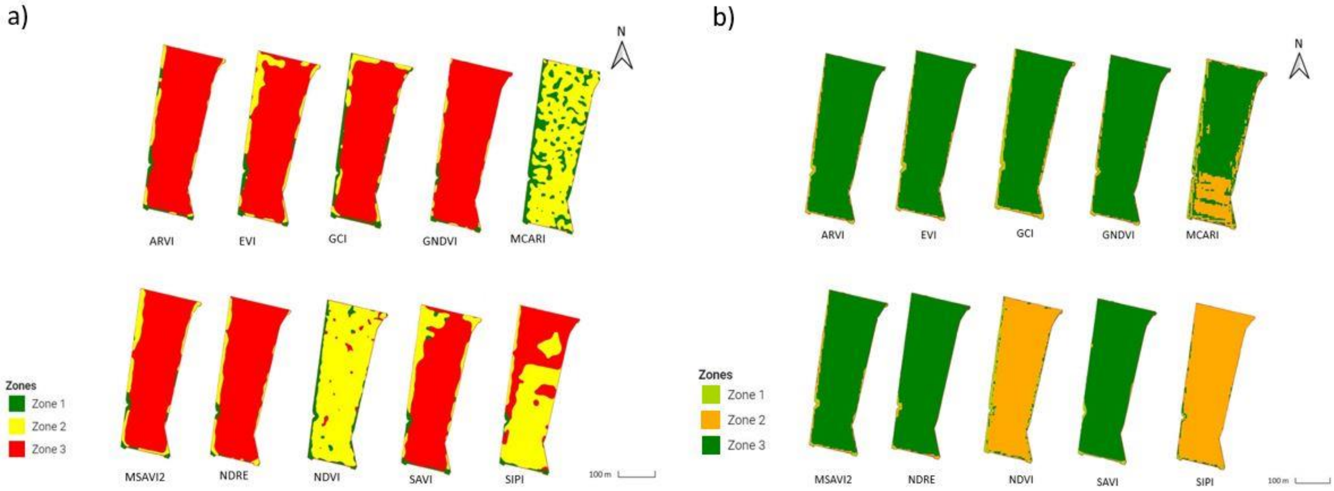
		Accuracy									
Plots	Model	ARVI	EVI	GCI	GNDVI	MCARI	MSAVI2	NDRE	NDVI	SAVI	SIPI
Training-validation	RF	0.9501	0.9538	0.9520	0.9492	0.9547	0.9507	0.9493	0.9502	0.9510	0.9505
	GBT	0.7848	0.7848	0.7747	0.7811	0.7254	0.7807	0.7772	0.7628	0.7794	0.7807
	CART	0.9931	0.9935	0.9937	0.9937	0.9936	0.9933	0.9935	0.9929	0.9929	0.9930
	SVM	0.6779	0.6675	0.6831	0.6926	0.4638	0.6662	0.7771	0.6556	0.6628	0.6897

Table 2. Kappa Coefficient of supervised ML models in classifying training data for map generation

		Kappa Coefficient									
Plots	Model	ARVI	EVI	GCI	GNDVI	MCARI	MSAVI2	NDRE	NDVI	SAVI	SIPI
Training-validation	RF	0.9227	0.9169	0.9189	0.9232	0.9229	0.9149	0.9162	0.9242	0.9206	0.9194
	GBT	0.6330	0.6280	0.6270	0.5360	0.6361	0.6352	0.5789	0.6369	0.6314	0.6331
	CART	0.9891	0.9882	0.9889	0.9884	0.9891	0.9882	0.9887	0.9880	0.9891	0.9894
	SVM	0.4144	0.4445	0.4319	0.1894	0.4452	0.4608	0.3960	0.4361	0.4281	0.4466

The two tables exhibit a higher overall accuracy and Kappa coefficient for the CART method. Consequently, zone maps were generated from one of the test plots utilizing this method as a function of different vegetation indices (Figure 1a). The zone maps obtained with the k-means method are also represented in Figure 1b.

Figure 1. Class maps of the test plot for the ten vegetation indices used originating from the CART supervised ML model (a) and class maps of the test plot for the ten vegetation indices used creating from the k-means unsupervised ML model (b).



Discussion and conclusions

Unlike studies such as [12,13] in which it is necessary to download images, the use of GEE allows the analysis of large amounts of data and images in the cloud without the need to download and in an updated way.

Likewise, image segmentation and classification processes based on calculating vegetation indices using ML techniques such as CART, RF, or K-means, among others, allow the identification of patterns in the data and understanding of the spatial and temporal variability of the plot.

In conclusion, using the GEE platform, machine learning models, and yield data from field yield monitor combined with high-resolution Sentinel-2 satellite imagery to create MZs maps has excellent potential to improve precision agriculture, reduce production costs and minimize environmental impact.

Acknowledgments

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P27 - Satellite Remote Sensing Detects the Legacy Effects of Crop Rotation on Subsequent Crops

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Introduction

Crop rotation is a widely adopted practice by farmers globally [1], but the impact of different crop rotation patterns is often overlooked. Short-term crop rotations or monocultures may result in reduced yields and soil degradation, increasing the need to understand the long-term effects of crop rotation to ensure sustainable cropping systems [2].

Traditional crop rotation analysis is often biased and limited to experimental sites. However, with the increasing availability of remote sensing technology, the potential for studying crop rotation patterns beyond annual major crops and their legacy effects has emerged, providing valuable insights for sustainable crop management practices [3].

Objectives

In this study, we used multi-temporal satellite imagery and machine learning to obtain the time-series information of the crop rotation in multiple experiment fields of the Technical University of Munich, Germany, from 2014 to 2018. The resulting data were used to estimate the legacy effects of crop rotation patterns on yield of the subsequent winter wheat crop. This can not only provide support for farmers' planting practices, but also provide a reference for the sustainable management of crop agriculture.

Materials and methods

The research station in Viehhausen is an organic cash crop farm run by TUM, which focuses on organic farming, ecological crop rotation, and long-term trials with organic fertilization . The study area cultivates winter wheat (WW), winter barley (WB), summer barley (SB), rapeseed (WR), maize (SM), and other crops. We used Landsat 8 and Sentinel-2 data from 2013-2018 with less than 20% cloud cover to generate remote sensing image sequences. We used Google Earth Engine with the python API to identify crop types by calculating various features (Vegetation Index and texture features) from April to September, and then tested several classification algorithms, including Random Forest (RF), Artificial Neural Network (ANN), Support Vector Machine (SVM), XGBoosting, and K-Nearest Neighbor (KNN). The optimal method was chosen based on accuracy evaluation and F-score index. The final crop type map was classified using the best algorithm, and the researchers evaluated the crop characteristics across years using random sampling points in the sample plot. The amount of fertilizer applied to each crop is fixed. Finally, according to the crop rotation mode information obtained, the statistical method was used to analyze the impact of crop rotation mode on wheat yield.

Results

Table 1 summarizes the accuracies of different methods which we used to identify crop rotations. From it, we can see that the overall classification accuracy of various methods is higher than 77%, but the random forest method has the highest accuracy, reaching 82.93%. Therefore, we used random forest as the main method to obtain the crop rotation time series map in the study area.

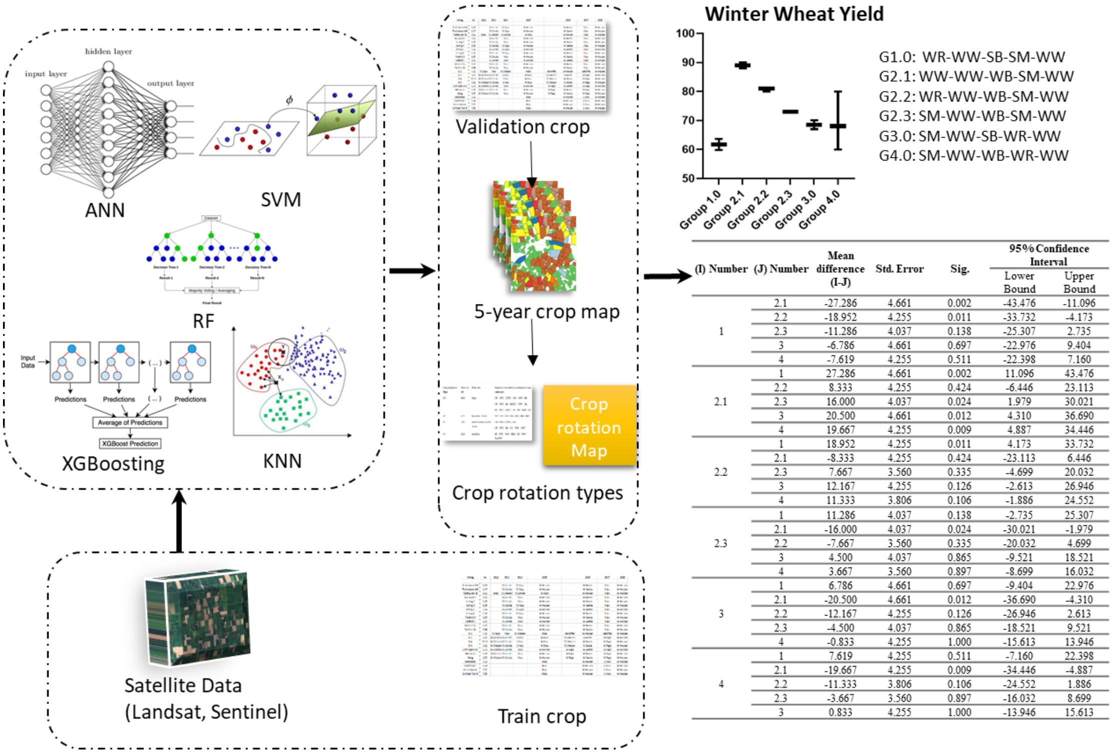
Table 1. Comparison of Different Classification Methods

Model	Precision	Recall	F1-score	Accuracy
RF	0.83	0.83	0.81	82.93%
KNN	0.77	0.77	0.76	77.40%
ANN	0.84	0.82	0.82	82.21%
SVM	0.76	0.80	0.76	80.29%

According to the random forest crop classification results, we got 6 crop rotation patterns (Figure 1). The crop rotation pattern from 2014-2017 has a significant effect on the yield of winter wheat in 2018. Among the six selected groups, group 2.1, with the rotation pattern of Winter Wheat - Winter Barley - Maize - Winter Wheat, had the highest yield, while group 1.0, with the rotation pattern of Winter Oilseed Rape - Winter Wheat - Summer Barley - Maize, had the lowest yield. Groups with

Winter Oilseed Rape in 2014 had higher yields compared to groups with Maize in 2014. The same rotation pattern from 2015-2017 with different crops in 2014 also had a significant effect on the yield of winter wheat in 2018. Different crops in 2014 under the same rotation pattern from 2015-2017 had a significant impact on the yield of winter wheat in 2018, with group 2.1, 2.2, and 2.3 having significantly different yields. Overall, the findings suggest that careful selection and planning of crop rotations can have a significant impact on the yield of winter wheat.

Figure 1. Frame diagram of the study and the impact of crop rotation patterns on yield



(I) Number	(J) Number	Mean difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
1	2.1	-27.286	4.661	0.002	-43.476	-11.096
	2.2	-18.952	4.255	0.011	-33.732	-4.173
	2.3	-11.286	4.037	0.138	-25.307	2.735
	3	-6.786	4.661	0.697	-22.976	9.404
	4	-7.619	4.255	0.511	-22.398	7.160
2.1	1	27.286	4.661	0.002	11.096	43.476
	2.2	8.333	4.255	0.424	-6.446	23.113
	2.3	16.000	4.037	0.024	1.979	30.021
	3	20.500	4.661	0.012	4.310	36.690
	4	19.667	4.255	0.009	4.887	34.446
2.2	1	18.952	4.255	0.011	4.173	33.732
	2.1	-8.333	4.255	0.424	-23.113	6.446
	2.3	7.667	3.560	0.335	-4.699	20.032
	3	12.167	4.255	0.126	-2.613	26.946
	4	11.333	3.806	0.106	-1.886	24.552
2.3	1	11.286	4.037	0.138	-2.735	25.307
	2.1	-16.000	4.037	0.024	-30.021	-1.979
	2.2	-7.667	3.560	0.335	-20.032	4.699
	3	4.500	4.037	0.865	-9.521	18.521
	4	3.667	3.560	0.897	-8.699	16.032
3	1	6.786	4.661	0.697	-9.404	22.976
	2.1	-20.500	4.661	0.012	-36.690	-4.310
	2.2	-12.167	4.255	0.126	-26.946	2.613
	2.3	-4.500	4.037	0.865	-18.521	9.521
	4	-0.833	4.255	1.000	-15.613	13.946
4	1	7.619	4.255	0.511	-7.160	22.398
	2.1	-19.667	4.255	0.009	-34.446	-4.887
	2.2	-11.333	3.806	0.106	-24.552	1.886
	2.3	-3.667	3.560	0.897	-16.032	8.699
	3	0.833	4.255	1.000	-13.946	15.613

Discussion and conclusions

The study investigated the impact of previous crop rotation patterns on the yield of winter wheat in 2018. It was found that previous crop patterns may have legacy effects on the yield, but it was not possible to identify the specific crop that may still affect the yield. More years of data and field investigations are needed for further confirmation. The study was limited by the number of plots available, which may have affected the accuracy of the results. Future studies should consider using remote sensing data to improve the accuracy of predicting crop rotation patterns. Additionally, the study only considered the impact on the yield of winter wheat, and future experiments should explore other economic benefits, such as fertilization efficiency and soil health. The study also highlighted the limitation of optical data measurements, which can be affected by weather conditions, and suggested that combining other satellite sources and classification methods may improve classification accuracy.

Acknowledgements

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P28 - Comparing machine learning approaches for the prediction of clay content via proximal gamma spectrometry under varying geopedological conditions

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Introduction

In the context of precision agriculture and viticulture, high resolution information on soil properties is needed to establish site-specific and sustainable management. Soil clay content affects important soil services such as water retention, nutrient availability or organic matter storage and is therefore crucial for decision making (e.g. lime requirement) in agriculture. However, upon today conventional methods are laborious, costly and fail to provide the necessary spatial resolution. Here, mobile Gamma spectrometry (GS) is becoming a recognizable technology for proximal soil sensing applications. Machine learning methods can be superior to linear regression approaches for the calibration of GS because these methods are able to determine complex and non-linear relationships, which is the case for GS measurements under varying geopedological conditions (Heggemann et al. 2017). Various algorithms exist but only few have been tested in the context of GS calibrations. To now, no optimal approach was identified for the calibration of GS and in consequence, various ML methods need to be tested for the calibration of site-independent texture prediction models using GS. Four state of the art ML algorithms for the calibration of site-independent GS and soil clay content were evaluated in this study, namely: Support Vector Machines (SVM), Random Forest (RF), *k*-Nearest Neighbors (KNN) and Bayesian Neuronal Networks (BNN).

Objectives

The aims of this study were (i) to show that proximal GS can predict soil clay content, (II) to compare four state of the art ML calibrations for a dataset of eight vineyards with varying geopedological settings, (III) to evaluate the calibrations on the field-scale, and (IV) to produce soil clay maps via mobile GS measurements and ML calibrations.

Materials and methods

Random Forest was compared to KNN, BNN, and SVM for a dataset of eight vineyards in Germany with a broad range of soil parent materials and large variation of clay content (62-647 g kg^{-1}; n = 245). Measurements were conducted with a tractor-mounted spectrometer comprising two 4.2 L sodium iodide crystals and evaluated with the regions of interest for 40K, 232Th, the ratio of 232Th/40K as well as the Total Counts.

Results

All ML methods revealed satisfactory model robustness for the calibration dataset with $RPIQ_{cv}$ ranges from 3.78 (KNN) to 8.65 (RF). The RF approach additionally revealed lowest $RMSE_{CV}$ (36.8 g kg^{-1}) and best R^2_{CV} (0.96).

Table 1.: Cross-Validation and testset-Validation results for the prediction of soil clay content via Support-Vector-Machines (SVM), K-Nearest-Neighbors (KNN), Bayesian Neuronal Networks (BNN) and Random Forest (RF) for 245 soil samples from eight vineyards.

Model	CV			TSV		
	RMSE	R^2	RPIQ	RMSE	R^2	RPIQ
SVM	62.3	0.87	4.77	80.8	0.80	4.02
KNN	78.5	0.79	3.78	91.7	0.75	3.54
BNN	72.2	0.83	4.11	93.2	0.74	3.48
RF	36.8	0.96	8.65	57.6	0.87	4.64

For TSV, the excellent model performance of the RF method was maintained with best $RPIQ_{pr}$ (4.64), prediction error ($RMSE_{Pr}$ = 56.7 g kg^{-1}) and highest accuracy with R^2_{pr} = 0.87, while clay prediction of the other ML methods was less accurate (Tab. 1).

The final goal of a site-independent model should be valid texture prediction at a given site to capture its in-field soil heterogeneity. Therefore, the RF calibrations where evaluated for each individual vineyard. Here, the site-independent model performed better for vineyards with larger heterogeneity of measured soil clay content.

The RF model was then used to evaluate on-the-go GS measurements for four exemplary fields (n = 7617) with variable degree of heterogeneity and prediction quality. For those vineyards with good prediction results and sufficient in-field heterogeneity (welche/Wieviele?), clay maps derived from on-the-go GS measurements revealed precise and accurate predictions.

Discussion and conclusions

Compared to more straight forward approaches such as KNN, more complex ML methods (BNN, SVM or RF) have a high number of parameters to fit. To fit them correctly, a sufficient dataset size is an important factor (Jordan & Mitchell, 2015). These findings were obviously not valid for this study, with its rather small dataset, as KNN revealed the worst prediction results of all tested methods. Yet, there is no clear rule on the required dataset size because it always depends on the complexity of the underlying problem (Padarian et al., 2020). While Heggemann et al. (2017) had success in calibrating site-independent prediction models for 10 arable fields and a rather small dataset (n=291 for calibration), SVM calibrations were outperformed by RF in this study. Accordingly, (Heung et al., 2016 and ; Zhang et al., 2020) found that RF calibrations yielded the most reliable results similar results when comparing ML methods for texture prediction. Though, these studies did not use GS as basis for calibration but a number of environmental covariables (including remote sensing data). In this study, the RF approach coped best for the limited information provided by the rather small number of calibration samples for GS model calibration. This clearly demonstrates the suitability of RF regression for site-independent GS calibration on soil clay content with a limited amount of reference samples. Yet, when the overarching RF model was evaluated at field-scale it became evident that only some vineyards were predicted with precision. This was presumably due to different sample numbers and varying degrees of in-field heterogeneity. For those vineyards, where the calibrated model performed well, on-the-go GS measurements were useful to predict the spatial distribution of clay content, even for heterogeneous geopedological settings in individual vineyards. It is therefore concluded that a larger calibration dataset with appropriate heterogeneity and ML model building will allow to produce precise clay maps in the future.

Acknowledgements

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P29 - Inoculation with biostimulants for improved plant performance under stress conditions

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Introduction

Biostimulants as a group of beneficial microorganisms and active natural compounds, which by modes of action as phytohormonal activities and mobilization of sparingly available nutrients can have positive effects on plant performance. Especially under stress conditions, plant performance and their nutritional status can be promoted [1, 2, 3]. The application of biostimulants in targeted combination with mineral fertilizers could thus contribute to an optimized agricultural management and soil fertility.

Objectives

In this study, treatments with different BE preparations were tested in a pot experiment for their beneficial effects in maize exposed to a phase of cold stress during critical early growth stages.

The main objective of this study was to elucidate the modes of action of different microbial and non-microbial biostimulants having plant-growth promoting properties in more details, especially under biotic and abiotic stress conditions [3].

Materials and methods

In this study, beneficial effects of biostimulants was tested in maize pot experiment exposed to cold stress. Preparations tested: SuperFifty® (Ascophyllum nodosum; BioAtlantis, Tralee, Ireland), AvytZn/Mn®, Algafect®, Proradix® (Pseudomonas sp. DSMZ 13134; Sourcon Padena, Tübingen, Germany), RhizoVital® FZB42 + R41 (Bacillus amyloliquefaciens, Bacillus simplex R41; ABiTEP, Berlin, Germany). Maize (Colisee–KWS) was cultivated in 2kg pots (silty-loam) from field-station Ihinger Hof, Germany. The soil substrate was fertilized with 100 N, 50 P, 150 K, 50 Mg, 50 Mg mg/kg dry matter. The pots were installed in a cooling system to control root zone temperature. After an initial warm phase (ca. 22 °C), the cold stress phase (14 °C) began at 14 days after sowing [3].

Results

The effects referring to improved plant growth and especially on improved root development at low root-zone temperatures were detected exclusively for algae extracts containing high Zn and Mn contents. Similar growth promotion effects were induced by Zn and Mn application in comparable amounts. This finding suggests that the selected algae extracts were mainly acting via improved Zn and Mn supply to tested maize plants. The beneficial effect of Zn/Mn treatments and algae extracts was associated with increased superoxide dismutase activity in the root and leaf tissue, with key functions in antioxidative stress defense, depending on Zn, Mn, Cu, and Fe as co-factors of important enzymes in the antioxidative stress defense mechanisms. Accordingly, measured properties such as leaf damage, shoot and root growth observed inhibition in cold-stressed plants were associated with a rather low Zn-nutritional status in plants, mitigated by the application of the algae-based non-microbial biostimulants [3].

Discussion and conclusions

A beneficial effect on plant performance was observed in response to the treatment with AvytZn/Mn. It was observed that in contrast to other treatments and the control, there were no symptoms of P deficiency. This finding indicates that AvytZn/Mn effectively improved the tolerance of maize plants to cold stress conditions [3]. Further investigations are necessary to elucidate the functional mechanism behind this phenomenon. This phenomenon is currently examined under field conditions.

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P30 - Quantifying within-field spatial variability in Canola Flowering for Yield Estimation

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Introduction

Precision agriculture concepts heavily rely on identifying within-field spatial variability of crop growth. Within-field yield variability is driven by soil, climate, topographic, biotic factors and their interactions which are not fully understood yet. Climate driven temporal variability further compounds the difficulty in identifying and estimating the variability of a heterogeneous farm land. With the advances made in remote sensing technology, data driven machine learning algorithms have made prominent advances in identifying the spatial variability of crops. However, despite knowledge of data availability, most are inaccessible to the general public. Hence, due to such restrictions, there is a disconnect between scientific findings and user adaptation.

Objectives

The objective of this study is to compare the performance of two machine learning-based approaches developed to identify and predict the within-field spatial variability in Canola seed yield.

The first approach uses datasets and software which are limited to the general public. The second approach uses open-source datasets and software.

Materials and methods

Under first approach (Model-1), satellite imagery from PlanetScope were used to extract Canola flower canopy information for a time series analysis, and were processed within ArcGIS Pro. The second approach (Model-2) used open-source imagery from Landsat-8 and Sentinel-2 through Google-Earth-Engine to map the temporal variability in flowering intensity of canola to develop a similar model to that of approach one.

The flowering phenology of canola were quantified using five yellowness indices (YI): Normalized Difference Yellowness Index (NDYI), Canola Index (CI), Red Blue Normalizing Index (RBNI), Modified Yellowness Index (MYI), High-resolution Flowering Index (HrFI). The cumulative flowering intensity of each spectral profile was used as an proxy to the total yield potential, while the peak flowering intensity of each index during the flowering period was used as an indicator of the maximum yield potential. Use of indicators quantifying peak and cumulative yield potentail provides valuable information regarding flowering dynamics of the crop within the season. In addition, soil information (electrical conductivity, topography and elevation) acquired from a precision agriculture company were used as predictors of yield variability.

In both models, 70% of the data was used to train a 10-fold cross-validated random forest model. Two models were then tested on 30% of the data and were compared using coefficient of determination (R^2), Pearson's correlation coefficient (R) and Root Mean Squared Error (RMSE). Furthermore, most important features explaining the within-field yield variability for Model-1 and Model-2 were compared.

Results

Model-1 with PlanetScope-based phenology parameters explained 66% of yield variability with a validation correlation (R) of 0.68 and Root mean squared error (RMSE) of 730 between the actual and the predicted seed yield. Model-2, with haromonized landsat-8 and Sentinel-2 phenology metrics explained 67% of yield variability with a validation R and RMSE of 0.44 and 872 respectively.

Model-1 identified electrical conductivity of soil as the most important feature in explaining canola seed yield, while Model-2 identified peak NDYI date followed by electrical conductivity of soil.

Discussion and conclusions

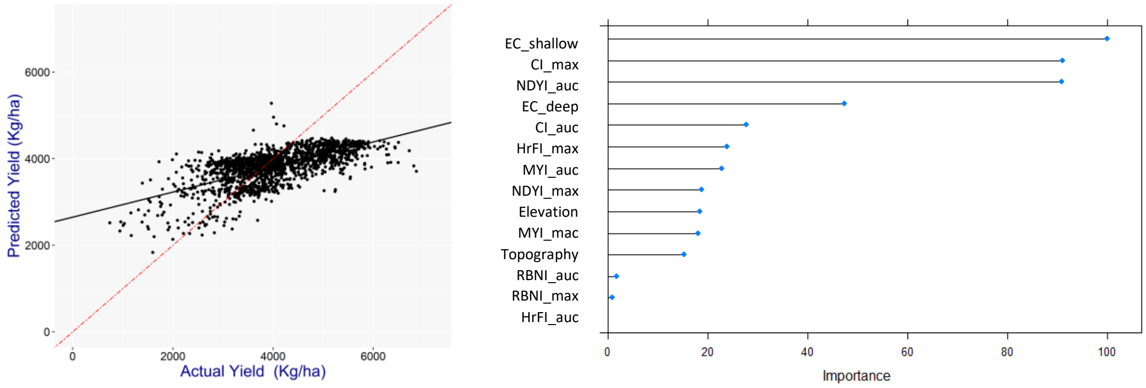
The results of the study suggest that while Model-2, which used open-source imagery and data, had a lower R value and higher RMSE value compared to Model-1, which used restricted data, the two models are still comparable. The difference in performance between the two models may be attributed to the lower temporal density of the open-source dataset used in Model-2. This is further corroborated by the variable importance plots, where cumulative flowering indicators were ranked lower in Model-2, compared to Model-1, which shows that phenology dynamics are inadequately captured by Landsat-8 and Sentinel-2 (Figure 1). The significance of soil variation on crop yield is emphasized by the fact that in both models, Electrical conductivity emerged as one of the top two factors that account for the differences in crop yield.

Additionally, the study found that both models exhibited a saturation effect, where the predictive power of the model plateaued after a 4000 kg ha^{-1}. This suggests that further improvement in model performance may require more diverse and larger datasets, especially at high yielding areas, as well as more advanced machine learning techniques.

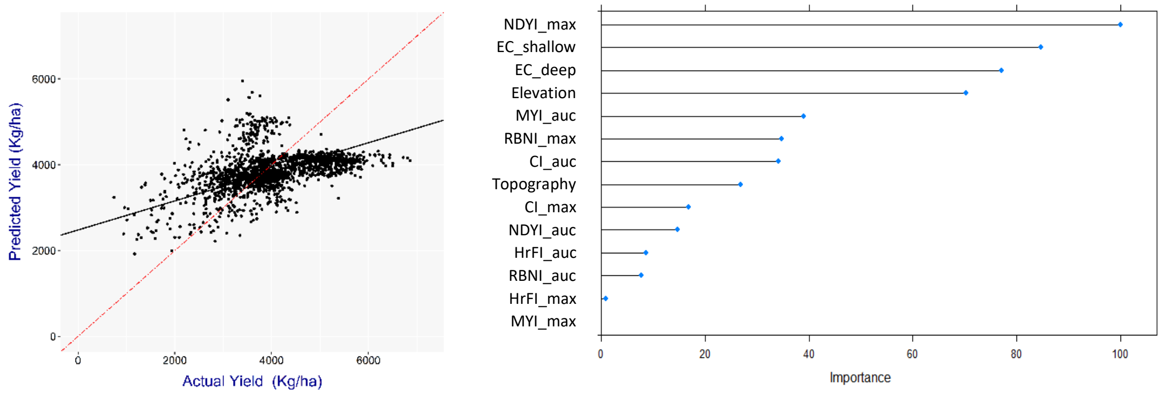
Despite these limitations, the results of this study highlight the potential of machine learning-based approaches in identifying within-field spatial variability in crop growth. By using remote sensing technology and data-driven algorithms, researchers and farmers can gain valuable insights into the dynamics of crop growth and make more informed decisions about crop management practices.

Overall, this study underscores the importance of open-access data in facilitating scientific advancements in precision agriculture. By making data more widely available, researchers and farmers can work together to improve crop yields and enhance food security on a global scale.

Figure 1. Comparison of validated Model-1 (R=0.68, RMSE=730) and Model-2 (R=0.44, RMSE=872) and the respective variable importance plots



Model-1



Model-2

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P31 - Assessment of high cadence remote sensing data for providing phenology of key crops in Germany

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Introduction and Objectives

Accurate definition of the timing of crop phenology is of vital importance for precision agriculture. Remote sensing data and derived products have been shown to measure changes in crop characteristics and weather conditions that indicate crop phenological stage. Advances in resolution mean these sources are now available daily, at a scale meaningful for field level study. These harmonized multimodal datasets have yet to be fully exploited for identification of key crop phenological phases and transitions. To this end, we have utilized a set of innovative remote sensing-based datasets with the aim of; (i) identifying the onset of key crop phenological phases such as elongation, flowering and senescence for a variety of key crops in Germany and (ii) determining the optimal combination of machine learning techniques and a variety of remotely sensed spectral, biophysical and meteorological products for identifying these key phenological phases via a systematic analysis of predictive impact and importance.

Study Area and Crop Data

The study was executed over three years, 2019 - 2021, to introduce interannual variability. A subset of four unique 24x24 km areas were selected across three regions in northern Germany. These study areas were selected by ranking a 24x24 km sample grid on the volume (number of individual fields) and variability (high number of multiple different crop types) of key crops planted within the region. Crop planting information and field boundary geometry for the three regions were sourced from publicly available user submitted datasets that form the basis of official EU reporting (Integrated Administration and Control System). The selected areas were longitudinally stratified, to ensure variability in climate, planting practices and environmental conditions [1].

Ground phenological observations for the study area were obtained from the German Meteorological service (Deutscher Wetterdienst, DWD Climate Data Centre). This publicly available database contains phenological observations collected for a specific field by surveyors two times a week [2]. The precise field coordinates are not available, but the sampled fields are located within 5 km of a DWD station, for which coordinates are available. For each crop, a set of phenological stages are recorded, linked to the BBCH scale [3]. A change to a new phenological stage is deemed to have occurred when more than fifty percent of the plants in the field exhibit its characteristics. We selected three crop types with distinct phenological development characteristics to focus on; Maize, Winter Wheat (Wheat), and Winter Rape (Rape).

Materials and methods

A high cadence multimodal dataset was constructed using the data products described in Table 1. All available values for the three years were extracted for each field boundary in the study area from each of the products for further analysis.

There are numerous approaches for identifying phenological stages from remotely sensed data. To ensure the detected phenological transitions were useful for crop management, we began analysis by exploring the relationships between phase transitions across a time series of data for all variables in the dataset. For example, increased temperature might coincide with early germination phases, SWC increases as the crop grows and biomass decreases during flowering and the timing of ripening is indicated by a fall in NDVI as the plants yellow but maintain biomass.

As the specific field where the phenological change dates were recorded is unknown, the dataset was first cleaned to eliminate fields with a significant dissimilarity in observed and recorded phenological stage timing. Data removal tolerance was determined based on systematic sampling and quantitative and visual inspection.

We intend to explore phase identification using processes like; (i) data transformations to extract or emphasize patterns, (ii) fitting time series from the current year to reference label data and (iii) machine learning techniques such as, random forests and multi output regression. Although the machine learning techniques must consider sample numbers and high potential for overfitting.

This will help us determine which phenological phases can be identified in the remotely sensed data. In order to study the impact of high cadence biophysical data this analysis will be performed on PF-SR data alone and then other biophysical and weather data sources will be systematically added. The accuracy of the different approaches will be computed based on metrics recording calculated and observed phenological stage change dates.

Table 1. Dataset remote sensing products and derived metrics.

Variable	Resolution	Frequency	Description	Ref
Surface Reflectance and Vegetation Index	3m	Daily	Gap filled and cloud free, level-3 harmonized, four band (visual and NIR) surface reflectance. Derived vegetation indices (NDVI, GNDVI, SAVI etc).	[4, 5]
Biomass Proxy	10m	Daily	Fusion of microwave and optical imagery, estimate relative crop biomass regardless of cloud cover.	[6]
Soil Water Content	100m	Near Daily	Satellite observed volumetric soil water content derived from L band microwave data	[7]
Land Surface Temperature	100m	Near Daily	Satellite observed land surface temperature using multi-frequency microwave data.	[7]
Leaf Area Index	3m	Daily	Leaf Area Index based on sensor fusion and Planet Fusion SR.	[8]

Discussion and conclusions

This study is expected to improve the timeliness and accuracy of crop phenological stage identification by exploiting the synergies of high resolution multi-modality remote sensing products. It will help define the limitations and opportunities of high spatial and temporal resolution multimodal data and provide a comparison of the power of surface reflectance, vegetation indices, and biophysical and climate data sources for the identification of phenological stages within Germany. This would also help inform phenological stage detection in near real time or 'online' methods for the current year.

Acknowledgements

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P32 - Ongoing Qualitative Observations and Field Scale Maize Yield Prediction

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Introduction

Newly published work [1] found that ongoing seasonal observations by local growers and extension personnel, aggregated at the USA state level, were of reasonable value in predicting statewide maize yields at the end of the season. These "crop condition ratings" are submitted weekly during the maize production season and have been made for nearly 40 years. Agronomists and other field scientists have made little use of these 'testimonial' observations and did not use them in their modeling work. A significant remaining question is whether the aggregated state level data are useful to individual growers, for any given farm or field with an adequate yield history – a question of scale. If the maize crop condition ratings are valuable early in the season, agonomic and economic management adjustments are plausible. That said, previous work [1] has not been validated for all USA corn production regions/states, including Kentucky and West Virginia.

Objective

The objective of this study was to determine if these statewide and aggregated seasonal observations wouild bring value to yield prediction at field scale, allowing a producer who did not have access to a sophisticated crop growth model to better predict maize yield for a field.

Materials and Methods

We first validated that crop condition ratings for Kentucky were well related to average annual state corn yield. In support of that effort, we downloaded [2] weekly maize crop condition ratings and average annual maize yields for 32 years (1986 to 2017). The weekly data consist of an aggregate assessment of the percentage of the maize crop area that is in "Excellent (E)", "Good (G)", "Fair (F)", "Poor (P)" or "Very Poor (VP)" condition. Each weekly set of condition data was combined into one Crop Condition Index (CCI) value [3] as follows:

$$\%E(1.0) + \%G(0.75) + \%F(0.50) + \%P(0.25) + \%VP(0.0)$$

Given that CCI values are both annual and numerically confined, we removed the long-term linear trend in Kentucky average annual maize yield and related the annual residual yield deviation over the 32-year time period to each group of weekly CCI values, optimizing using the resulting r^2 values.

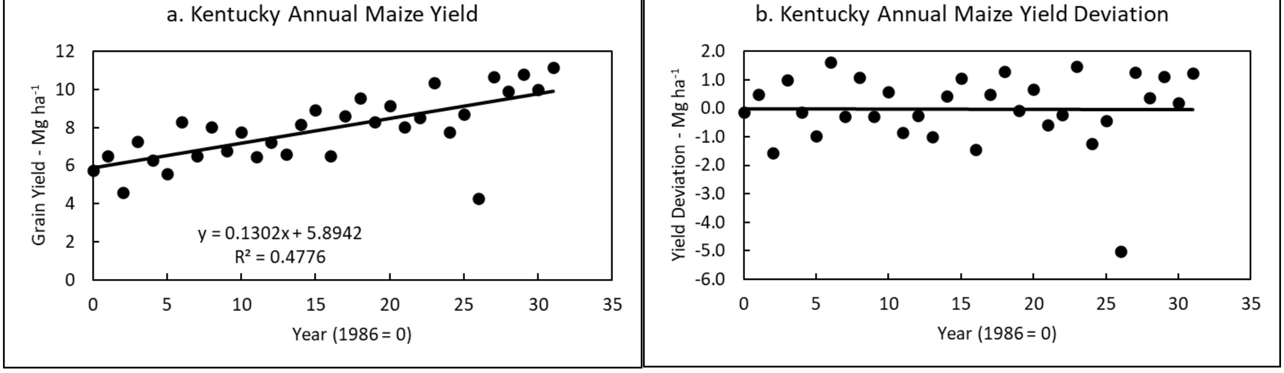
We then examined the question posed in the Objective by relating CCI values determined above with annual yield data from a single 50-year long continuous maize study located near Lexington, Kentucky. Nearby weather station data were gathered and also assessed as to their in-season value in maize yield prediction.

Results

The statewide maize yield data (32 yr) are shown in Figure 1a. A linear trend was evident. After that trend was removed, the annual yield deviation from the trend is illustrated in Figure 1b. The trend represents yield change to improved genetics and management. Deviations result from seasonal factors, of which air temperature and rainfall are important with rainfed maize production.

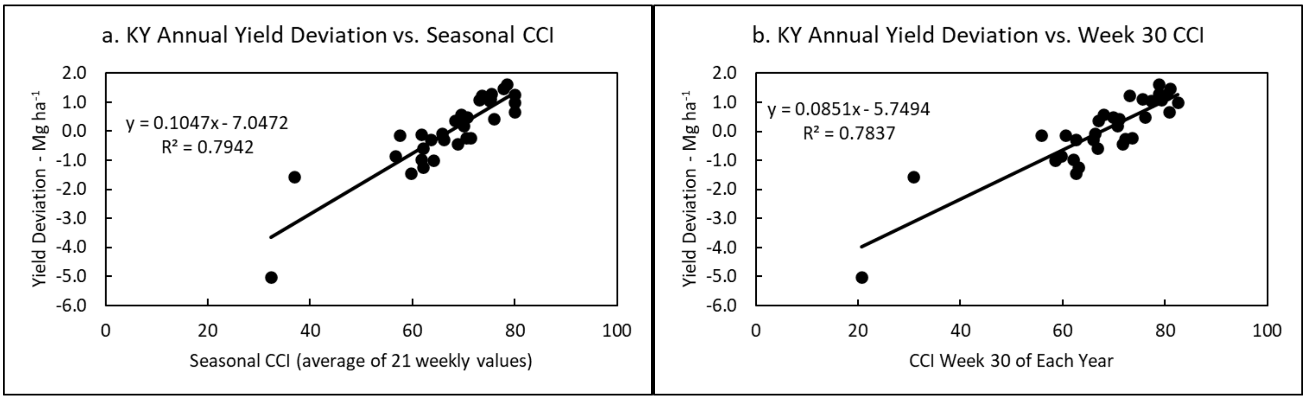
The annual yield deviation was significantly and positively related to the seasonal average CCI

Figure 1. a) Kentucky average annual maize yield; and b) annual maize yield deviation from the linear trend shown in a).



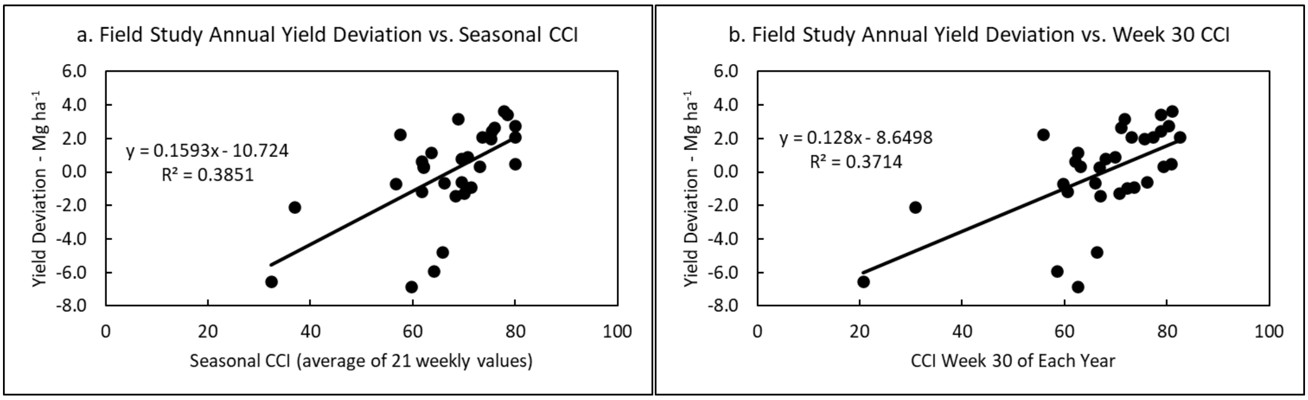
value (Fig. 2a). Looking at the yield deviation versus CCI relationship for individual weeks, the strength of the relationship, as measured by r^2, rose with time (data not shown) and reached a meaningfully high level at 28 to 30 weeks (mid to late July) into the year (Fig. 2b).This latter mid-season strength to the relationship can inform both maize growers and maize users.

Figure 2. a) Kentucky annual maize yield deviations (32 yr) as related to the average annual CCI; and b) as related to the annual week 30 (late July) CCI value.



With the field study, average annual yields exhibited greater variation in the observed linear growth trend, resulting in a greater range in annual maize yield deviation. This greater variation resulted in statistically significant, but more variable relationships between annual yield deviations and CCI (Fig. 3a, b).

3. a) Field study annual maize yield deviations (32 yr) as related to the average annual CCI; and b) as related to the annual week 30 (late July) CCI value.



Field study annual yield was negatively related to air temperature and potential evaporation, and positively related to precipitation during a time period beginning in late July and continuing through August (data now shown). These relationships, probably because of the spatial coincidence of the field study and the weather station, were stronger and than those involving the statewide CCI.

Discussion and Conclusions

Extrapolating the statewide maize yield versus CCI relationship to a single field/farm, even in the presence of considerable maize yield history, would possibly carry additional risk due to the greater variation in the observed field study maize yield versus time relationship. The work indicated that there is good value to the provision of weather information at a scale similar to that of the field/farm if the grower is intending to better predict maize yield during the production season. That said, there is considerable value to the testimonial CCI information as an in-season predictor of maize yield in the USA.

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P33 – New methods for rapidly measuring the effect of agronomic treatments on grass growth

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Introduction

Grass yield measurement is uncommon due to laborious methods or lack of access to yield-mapping forage harvesters, slowing the adoption of on-farm experimentation, learning and yield improvement compared to combinable crops. Remote sensing is an option for measuring grass growth but holds additional challenges to arable crops as the crop reaches full ground cover quickly during the season and undergoes multiple cutting or grazing events. A recent Innovate UK feasibility study [1] demonstrated that spectral reflectance of grass crops measured by satellite could be used to measure grass yield (kg dry matter/hectare) up to a yield of 4500 kg/ha, with an accuracy of +/- 200 kg/ha. Hence, the remote sensing approach should be applicable for measuring grass growth during the first few weeks of the growing season and after a silage cut or grazing.

To determine that an agronomic treatment effect is not due to underlying field variation, ADAS, an environmental and agricultural consultancy and research centre in the UK, developed a statistical, peer-reviewed approach for analysing spatially referenced data points from combine yield maps called 'Agronomics' [2, 3], which is carried out by around 200 farmers each year to test agronomic treatment effects on yield in various arable crops.

Objectives

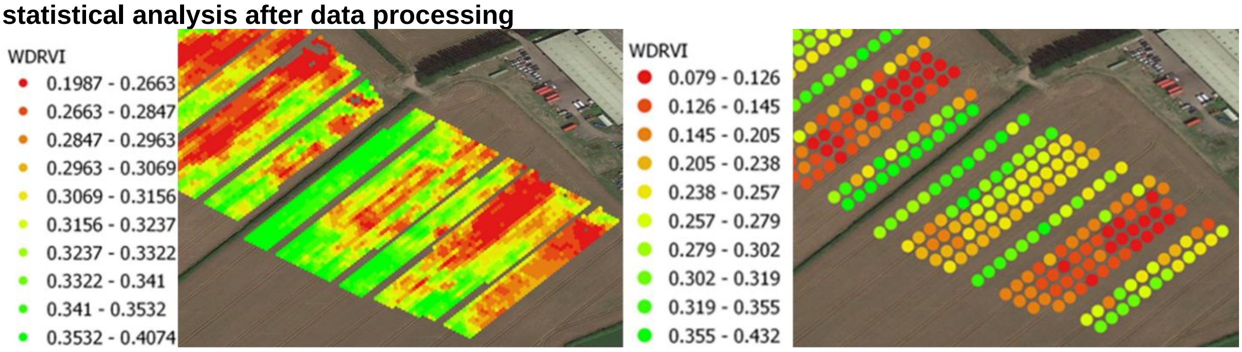
Develop a novel way of measuring the effects of agronomic treatments on grass yield using spectral reflectance data collected by satellite and drone by extending the 'Agronomics' approach currently used in arable crops.

Materials and methods

Five tramline trials were carried out with three grassland farmers on similar loam soil types in South Wales, UK, over a two-year period. Agronomic treatments included variety, sulphur, slurry or biostimulants. Rising plate meter (a tool to determine grass biomass [4]) measurements were taken weekly from June until the crops were cut for silage. RGB and multispectral imagery from drone data were captured on one date in each year, along with grass samples. Sentinel-2 satellite images were acquired captured from Environment Systems and the UK Joint Nature Conservation Committee (JNCC) at the closest possible date to the drone flight, from which vegetation indices were derived.

Eleven vegetation indices were calculated from the data for statistical analysis. Wide Dynamic Range Vegetation Index (WDRVI, formula = (0.1 * NIR - Red) / (0.1 * NIR + Red), using Red and NIR wavebands) was found to have the strongest relationship with grass biomass from rising plate meter measurements. Satellite and drone data were analysed through the Agronomics process [2, 3]. Data were processed to remove headlands, field boundaries and unreliable data points, and rows removed on either side of treatment boundaries to ensure no overlap of treatments (Figure 1). A model of underlying variation was applied to the data to account for spatial variation across and along rows, and the effect of the treatment. The statistical analysis returned treatment effects with standard errors (SE), allowing calculation of 95% confidence limits.

Figure 1. Example of drone (left) and satellite (right) WDRVI data retained in the Agronomics statistical analysis after data processing



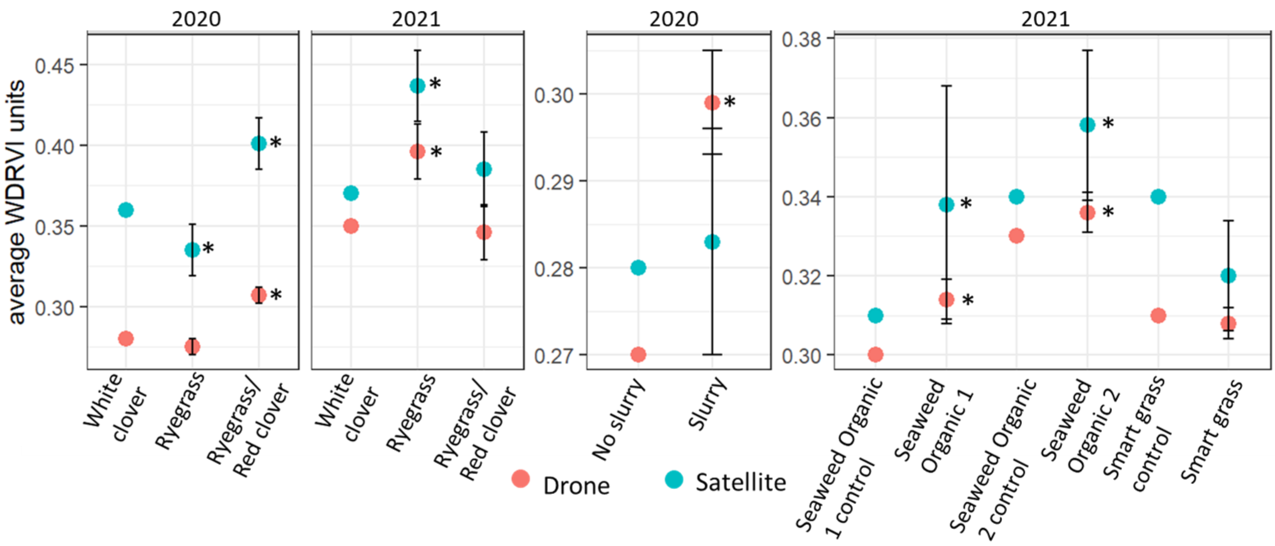
Results

Analysis of the drone data revealed statistically significant ($P<0.05$) differences in WDRVI in four of the five trials (Figure 2), which correlated best out of all vegetation indices analysed with the ground-truthed rising plate meter measurements across all trials in both years. The drone data was able to detect treatment effects on WDRVI of 0.006 to 0.046 units. Analysis of the rising plate meter and WDRVI data showed that an increase in the WDRVI of 0.1 units corresponded with an increase in dry forage biomass of 2400 kg/ha, meaning the drone data was able to detect treatment effects ranging from about 140 to 1100 kg/ha.

In the variety trials, the red clover/ryegrass mix had 650 and 775 kg/ha more dry biomass than the white clover and ryegrass treatments, respectively, in 2020, whilst in 2021, ryegrass had 1100 kg/ha more dry biomass than the white clover and red clover/ryegrass. The slurry trial identified that slurry increased dry biomass by 500 kg/ha in 2020. In the 2021 biostimulant trial, Seaweed Organic 1 increased dry biomass by 340 kg/ha and Seaweed Organic 2 increased dry biomass by 140 kg/ha on 30th May. No significant differences were seen in the sulphur trial in 2020.

Analysis of satellite data gave similar treatment effects to the drone data, but did not detect the smallest treatment differences detected by drone, as the standard error was typically two to three times greater. Analysis of plate meter readings was either unable to be performed, due to agronomy practicalities, or did not show any significant differences.

Figure 2. Main WDRVI results from the line trial experiments. Asterisks (*) next to points signifies a significant difference compared to its relative control treatment.



Discussion and conclusions

This study demonstrated that both drone and satellite data could be used by farmers to test the effect of agronomic treatments on grass biomass. This study has shown that drone data has the potential to detect small agronomic treatment differences equivalent to a dry biomass yield difference of as little as 120 kg/ha. Lower resolution satellite imagery had a detection limit that was about three to five times larger than the drone, preventing recognition of smaller treatment differences. Further work should test these approaches in a wider range of conditions and agronomic treatments.

Acknowledgements

This project was funded by European Innovation Partnership (EIP) Wales (Project no. 1021570-1 (00)). We would like to thank the farmers for their involvement in this project: David Jones, David Morgan and Russell Morgan.

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P34 - Efficient site-specific management approach using multispectral, soil, and rice based cropping data

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Introduction

Several research have been performed to identify the best method to delimit management zones (MZs); however, the decision about the selection of the best method to implement remains a big challenge (Reyes et al., 2019) especially when it comes to rotational cropping system**.** The number of zones is considered based on natural variability, the extension of the land and the ability to easily apply differential management within the system without increasing costs (Zhang et al., 2002). In Tolima region (Colombia), despite the importance of the rice-based cropping systems for the economic development of the region, there is a lack of literature about the delineation of MZs for site specific management. The efficiency of using remote sensing to map soil properties, in densely vegetated area, depends on indirect relations between vegetation and soil attributes.

Objectives

The aim of this study was to 1) Delineate and compare MZ in four datasets, i) MI: multispectral images, ii) ALL variables, iii) spatial principal components (sPC) and iv) Soil and crop variables; and to 2) Compare between three cluster algorithms, fuzzy c-means, K-means and Mcquitty.

Materials and methods

The study was conducted in a 5-hectare field in Colombia, which was cultivated with a mixed cropping system of rice-corn and cotton. The study area has a tropical climate with a mean annual temperature of 26°C and an annual average rainfall of 1522 mm [8]. Soil and plant data were collected from 72 sample points in the field, including physical and chemical soil properties, relative chlorophyll content, and crop yield data. Remotely sensed data used in this study included vegetation indices (VI) obtained in different phenological stages. The study employed kriging interpolation and spatial principal component analysis to delimit management zones (MZs) in the field, using fuzzy partition clustering algorithms and a hierarchical clustering algorithm. The yield variance reduction index (VRI) was used to compare the performance of the different techniques. The analyses were carried out using the R software.

Results

The study used three strategies to differentiate zones and compared MZs for rice-based cropping systems across four datasets. The sPC database had significant differences for all three crops and clustering methods, while ALL and SOIL only had significant differences for cotton. The MI database showed significant differences for rice and corn across all three clustering algorithms. Table 1 presents the comparison of MZ.

Table 1. Comparison between different data sets and clustering methods.

DB	Method	3 MZs rice		3 MZs corn		4 MZs cotton	
		F-value	p-value	F-value	p-value	F-value	p-value
SOIL	FCM	0.985	0.374	1.463	0.233	2.881	0.036
	KMS	0.272	0.762	1.600	0.203	2.881	0.036
	MQY	0.010	0.991	0.489	0.614	1.751	0.156
MI	FCM	10.968	0.000*	1.2199	0.2965	0.716	0.543
	KMS	11.565	0.000	7.4309	7e-04	1.110	0.345
	MQY	14.871	0.0001	0.3049	0.5812	0.317	0.728
ALL	FCM	0.985	0.374	1.4626	0.233	1.192	0.313
	KMS	0.272	0.762	1.6	0.2033	3.447	0.017
	MQY	1.500	0.225	1.3334	0.2649	4.874	0.003
sPC	FCM	8.989	0.0002	5.3517	0.0051	6.2705	0.0004

KMS	17.871	0.000	3.8524	0.0221	5.7925	0.0007
MQY	10.442	0.000	4.3	0.0143	3.0187	0.0299

** Bold values denote statistical significance at the p < 0.05 level.*

The final MZs for rice, corn and cotton are presented in the Figure 1.

a) **b)** **c)**

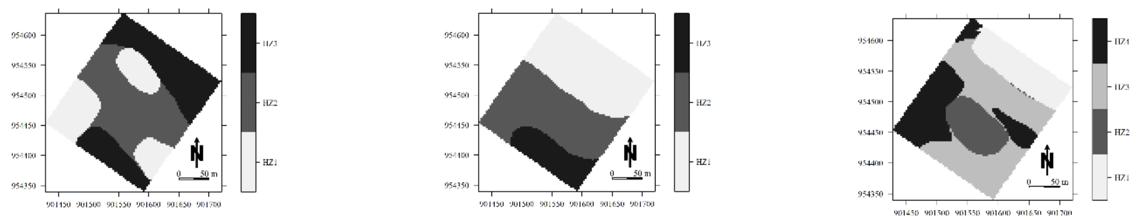

Figure 1. Management zones in the rice-based cropping system. a) sPC with KMS in Rice (VRI= 51%), b) MI with KMS in corn (VRI= 38.6%), c) sPC with KMS in cotton (VRI= 35.7%).

Discussion and conclusions

This study focused on delimiting management zones (MZs) for a rice-based cropping system in Colombia, using three strategies and comparing four datasets. The obtained MZs can be adapted to other study areas based on rotational cropping systems, agronomic practices, and climate variability [9]. The study found that using vegetation indices and the K-means algorithm was a reliable approach for delineating and validating MZs. The study also identified specific bands that were statistically significant in delimiting MZs. The results suggest that multivariate spatial analysis based on Moran's index technique was the most reliable among the evaluated datasets[10]. The study expands the possibilities of using Moran's index in delineating MZs for rice-based cropping systems.

Acknowledgements

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P35 - Eco-innovative weeding with laser. New oppportunities for improving sustainability in agriculture

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Introduction

Weed control is an essential process of crop production and currently depends heavily on the use of chemicals and mechanical treatment. In the project: Eco-innovative weeding with laser – acronym WeLASER a new solution is being developed to eliminate weeds based on autonomous platform, weed recognition and laser implement. It is essential to assess the invention in the perspective of its sustainability, with identification of key advantages and risks of its practical use, as well as barriers and bridges to its implementation. There are practical examples of assessment performed for agricultural sector. In the poster key points regarding sustainability of WeLASER weeding equipment are summarised and discussed as a prerequisite for its wide implementation in agricultural sector.

Objectives

To ensure sustainability of WeLASER invention a variety of aspects and perspectives of relevant actors have to be considered. In WeLASER project one of the objectives is to assess the invention in its testing phase as to specific social, economic and environmental aspects to get essential clues for its future commercialisation. The poster presents results of a qualitative assessment on base of which qualitative assessment was performed.

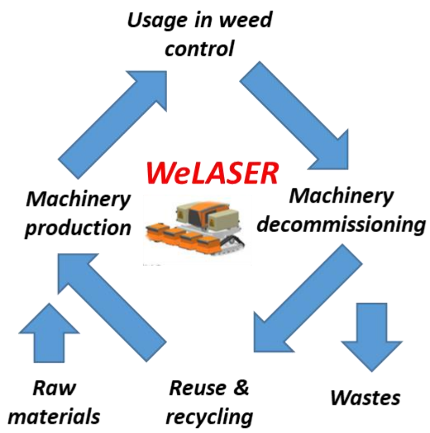
Materials and methods

The Life Cycle Perspective (Figure 1) was applied in expert evaluation of the environmental aspects of WeLASER application. The qualitative assessment was performed based on literature review regarding social, environmental and economic aspects of precision agriculture as well as results of Focus Groups Interview studies performed in the project. The identification of key aspects was done in three dimensions:

1. stakeholders perspectives: farmers, business, society
2. phases of the life cycle of WeLASER technology: production, use, post service life
3. sustainability aspects: environmental, societal, economic

The qualitative assessment is done in two aspects: potential drawbacks of implementation and potential for improvement of the weeding practices.

Figure 1. WeLASER Life Cycle Perspective



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Results

The assessment performed is in line with other studies [1, 2, 3, 4, 5] showing that WeLASER can provide a positive impact on sustainability of the agricultural sector in Europe although there are identified some risks and potential drawbacks that should be considered in future socio-economic development. The main aspects are presented in Table 1.

Table 1. Impact of WeLASER sustainabillty aspects in key stakeholders perspectives

Phase	Perspectives
Production	- *Society:* higher impact on critical resources - *Business:* advantages related to development of the innovative products and services - *Farmers:* requirements concerning reliability of the product functional design and support
Usage	- *Farmers:* energy efficiency, cost effectiveness, purchase and maintenance costs, raised responsibility for safety, positive influence related to agricultural workforce availability and occupational health issue - *Society:* positive influence on demographics and job market, benefits related to environmental performance improvement and safe food - *Business:* raised responsibilities related to safety issues, new opportunities for the development of innavative product and services
Post-service	- *Society:* more demanding system for disposal and recycling - *Business and farmers:* raised liabilities related to disposal ferrous and non ferrous metal recycling

Discussion and conclusions

The results show an essential potential for improving performance of agricultural practice but new invention had to fulfill many requirements. In principle WeLASER eliminates use of herbicides which are harmful substances to ecosystems, farmers and consumers. It might bring certain values meeting the interests of relevant actors and the society as a whole. WeLASER solution can bring ecological, social and economic added values to the agricultural sector. It concerns EU policies favouring new effective and innovative solutions to weed control. First of all the design must be functionaly efficient, socially acceptable by farmers, fitted into the farming practicies and environmentally friendly. The final design must ensure that the overall environmental and socio-economic impacts in the life cycle perspective are positive.

Acknowledgements

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P36 - Determining What Counts: Applying UAV imagery to estimate canola emergence

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Introduction

Canola (*Brassica napus*) is the #1 most produced crop in Saskatchewan, growing 11.3 million of the 20.7 million acres seeded in Canada in 2019 [1]. Measures of crop emergence are important as it affects crop yield, especially in canola as emergence is often variable and low. Current practices to estimate canola emergence consist of time-consuming manual plant population counts that are prone to human-based inconsistencies and are likely inadequate because of the small number of samples collected [2,3]. Unoccupied Aerial Vehicles (UAVs) have the potential to automatically sample emergence, but the sampling intensity required to capture spatial variability in canola emergence efficiently has not yet been determined [4]. UAV imagery can be an advantageous addition to commonly used agronomic practices as it is more time efficient and less physically invasive than traditional scouting methods. To thoroughly assess a high number of points over a large field is not practical on foot alone, which is why the use of Unmanned Aerial Vehicle (UAV) imagery could be the next practical step.

Objectives

The objective of this research is to determine the relationship between intensity of plant population subsampling and the accuracy of plant population count estimations.

Materials and methods

The experimental design consisted of four 0.4 ha research blocks within a canola field. There were two sites in 2021 and two sites in 2022 for a total of 16 research blocks on University of Saskatchewan land near Saskatoon, SK, Canada. No treatments were applied, and each site was managed as part of a whole comercial canola field. Elevation and surface topography within each field was the only differing factor between research blocks. UAV Imaging flights took place at canola seedling emergence (cotyledon to first-leaf stage) using point sample and orthomosaic data collection methods. The point sample data was collected using a DJI Mavic 2 Pro with a RGB sensor and Skippy Scout flight software by Drone Ag. Forty 1.5 m^2 high resolution subsamples were collected for each block at an altitude of 2 m. The research blocks were also imaged using a DJI Matrice 600, with a high-resolution 100-megapixel RGB sensor. Pix4D imaging flight software was used to fly the blocks and stitch the orthomosaic images. Plant population predictions were collected using the base model in the Canola Counter web interface (a specifically designed computer model for canola seedling counts) for point sample image sets and orthomosaics. All 40 point sample images from each research block were manually annotated. In the orthomosaics, areas of interest were created to precisely outline the 0.4 ha block. Annotations were done within 1-2 testing regions and 3-4 training regions of each image. Orthomosaics were trained using the base model to increase prediction accuracy of each image. The plant population prediction data was extracted from Canola Counter for statistical analysis. Bootstrap resampling was used on the point sample data with 100 iterations for each resampled survey size from 1 to 40, within R version 1.4.1717. Mean (plants/m^2) and standard error (SE) for each iteration were collected then analyzed by research block and location. An accuracy assessment was conducted using a single-class confusion matrix in Microsoft Excel.. This matrix used Precision and Recall to caluclate the F1 score [F1 = 2 * Precision * Recall / (Precision + Recall)]. Point sample surveying techniques were then applied at the field scale (65 ha) to collect plant population counts and ground cover values at emergence in 71 producer fields across 5 farms in central Saskatchewan. This was to understand and identify obstacles to applying point sample UAV imagery methodology and to provide suggestions for field applications moving forward.

Results

As the sample size increased, the range of the mean and SE both decreased consistently, with a range of mean less than 10 and a SE of less than 2.5 occuring in all research blocks by a reampled size of 20. The mean and SE values of all the research blocks followed a similar pattern. When examined by site year, a consistent 50th percentile between sample sizes (1-40) can be observed, while the full range of means at each sample size were more variable in comparison (Figure 1). The median value for most survey sizes is consistent with the average mean of the site-year, seen in blue. The confusion matrix calculated an F1 Score of 0.898. A large number of false negatives decreased the Recall value, therefore there was a skew towards the larger Precision value. The point sample count mean was compared to the orthomosaics predicted count of each research block with a difference of less than 5 plants/m^2 in all but one.

Figure 1. Annotated plant count (plants/m2) mean foe each resampled survey sizes (1-40) by site-year. Overall average mean for the site year is shown as a blue line. a) Kernen 2022, b) Goodale 2022.

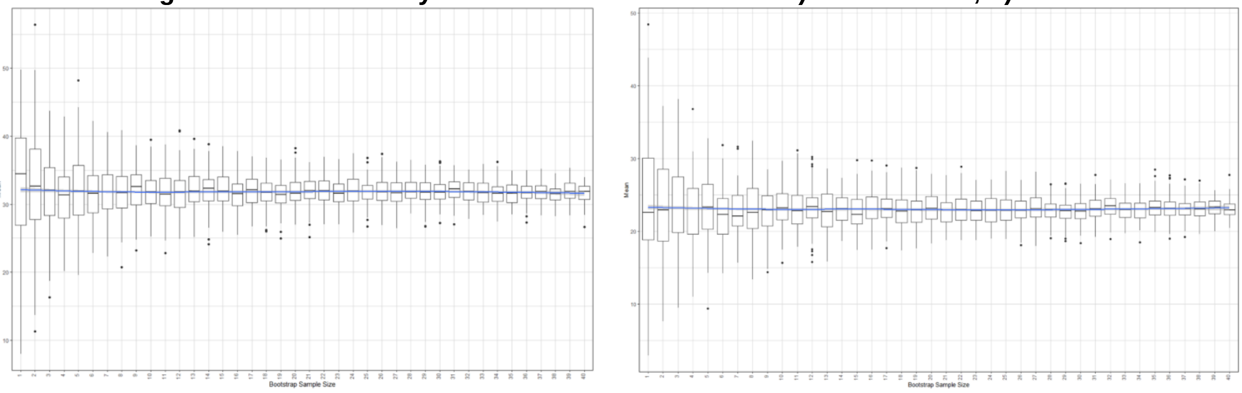
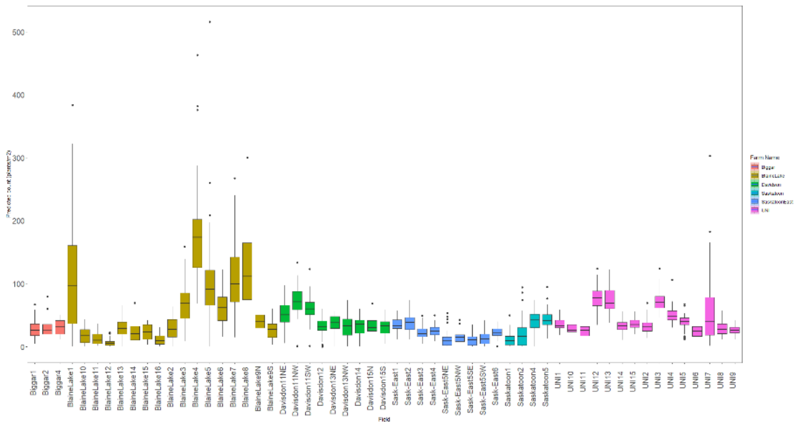


Figure 2. Field-scale Predicted plant populations (plants/m2) seperated by field and coloured by farm owner.



The field-scale data showed variability in plant prediction counts between fields and between locations. The 50th percentile contained plant predictions of 1 – 203 plants/m^2, but with outliners included this range increased to 0 – 515 plants/m^2 (Figure 2). Biggar and Sask-East were the most consistent farms, while BlaineLake held the most vaiability between fields.The confusion matrix calculated an F1 Score of 0.936.

Discussion and conclusions

As the resampled size increased the range of mean and SE decreased, although the noted sample size of 20 samples/ 0.4 ha is extremely dense for field scale applications considering current manual practices survey 25 subsamples for a 65 ha field which equates to 1 sample/ 2.6 ha. To gain a better understanding of the variability within the field, it would be important to focus on studying the amount of error associated with smaller sample sizes, rather than relying solely on extremely dense samples. Subsample imaging for plant population counts of canola seedlings that accuaratly represent the field are achieveable. Further statistica analysis into acceptable SE and suggested sample size are needed.

Acknowledgements

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P37 - Application of precision farming technologies in organic farming

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Introduction

Organic farming is seen as a promising way to address growing societal concerns about environmental pollution, animal welfare, and food quality. However, some shortcomings need to be improved in organic farming. Crop yields under organic management are, on average, 19 %–50 % lower than under conventional farming [1]. Yields in organic farming are often limited by nutrient supply.

Almost all digital technologies of precision farming have been developed and used in conventional farming. However, the transfer of digital technologies to organic farming is not trivial, because other yield potentials occur, and other fertilization and management strategies are required (e.g. N transfer in crop rotation, biological N fixation) [2].

Objectives

This study investigated the influence of spatially variable soil parameters [soil organic carbon (SOC), soil total nitrogen (TN), phosphorus (P), potassium (K), pH] on winter wheat and soybean yields in a heterogeneous cropland under the conditions of organic farming.

Spatially variable soil parameters will be related to digitally determined yields to investigate which relationships between soil and yield parameters occur in organic farming. It will also be clarified whether legumes and wheat depend on different soil parameters.

Materials and methods

Soil and plant parameters were determined on a heterogeneous arable field at the research station Viehhausen (30 km north of Munich; 48o40’15”N 11o63’99”E) in southern Germany. The research station has been managed under the conditions of organic farming (80 ha) for 25 years.

On study field “V5“ (size: 4.9 ha), the spatial variation of yield data from a combine harvester yield sensing system (volume flow sensor) was used in 2020 (soya) and 2021 (wheat). Additionally, satellite data were combined with a plant growth model (PROMET) [3] to calculate yields in a 10 m x 10 m raster in 2021.

The spatial variability of nutrient contents were determined by 32 georeferenced soil samples and laboratory analysis, and also soil sensor techniques (Veris® P4000 NIR-EC-force probe) have been applied [(diffuse reflectance spectroscopy, apparent electrical conductivity (ECa), penetration force]. Correlation analyses were carried out between the soil and plant parameters.

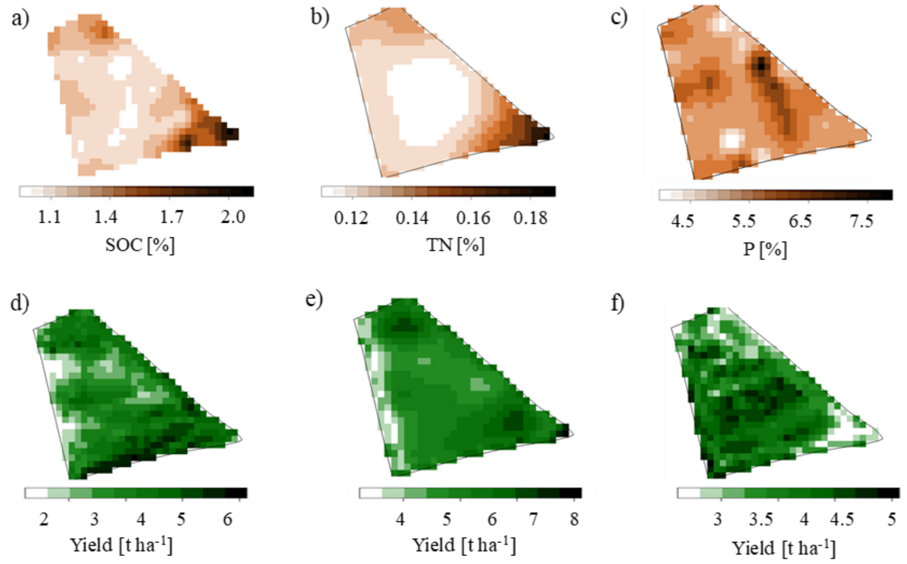
Results

The digital technologies identified high- and low-yielding zones (Figure 1). In 2021, the combine harvester yield sensing system determined average wheat yields of 4.3 (with minimum of 2.2 and maximum of 6.2) t ha^{-1}. Wheat yields ranged from 3.7 t ha^{-1} to 8.8 t ha^{-1} with a mean of 6.2 t ha^{-1} determined by satellite and model data. In 2020, the combine harvester yield sensing system determined soybean yields of 4.1 (2.9-5.2) t ha^{-1}. The SOC content varied from 1.2-2.5 %, the TN content from 0.12-0.20 %, the P content from 4.9-7.6 mg 100 g^{-1}, the K content from 6.2-25 mg 100 g^{-1} and the pH-value from 5.7-7.2.

The highest wheat yields were found in areas with high SOC and TN content (Figure 1). Very strong correlations between SOC and TN were found in the investigated field ($r = 0.94$). In the year 2020 soybean yield showed negative correlations to SOC and TN ($r = -0.60$), but positive correlations to P content ($r = 0.30$). P content showed no relationship to wheat yields. The correlation between wheat yield determined by satellite respectively model data and the combine harvester yield sensing system in 2021 was strong ($r = 0.71$).

The derivation of the estimated soil parameters and yield from the in-situ measurements with the Veris P 4000 multi-soil sensor showed the best results for the parameters SOC and TN ($r = 0.89$).

Figure 1. Kriged maps of the spatial distribution of SOC, TN, P, wheat yield, and soybean yield determined by digital technologies



a) Soil organic carbon content
b) Soil total nitrogen content
c) Plant available phosphorus
d) Wheat yield (by combine harvester yield sensing system)
e) Wheat yield (by satellite data and model data)
f) Soy yield (by combine harvester yield sensing system)

Source: author's data

Discussion and conclusions

P content showed a different distribution pattern than SOC content on the study field. Spatial wheat yields were positively correlated with SOC content and negatively correlated with P content, respectively soybean yields were negatively correlated with SOC content and positively correlated with P content.

The use of digital systems in soybeans (grain legumes) have been little studied. Soybeans are less dependent on soil N supply and humus content than cereals due to symbiotic N_2 fixation. However, they apparently respond to insufficient P supply on sub fields with yield losses. Thus, it can be concluded that different soil parameters have different impacts on soybean and wheat growth. Knowledge of the nutrient requirements of different crop types is enormously important, in particular the differences between legumes and cereals, especially since significantly more legumes are grown in organic farming. Digital technologies can help to close the yield gap between conventional and organic systems by identifying different yield zones and site-specific nutrient applications.

The results found in this work suggest a site-specific fertilization, for example, targeted humus supply and targeted P supply with positive effects on yield and yield stability. Organic fertilizers such as composts or manure - with high C and P contents can be used in organic farming to improve yield stability on sub fields. With the application of digital systems, such as Veris® P4000 for the determination of nutrient contents, the heterogeneity of arable land could be quickly and inexpensive determined in the future (without long waiting times for laboratory analyses) and fertilization measures (e.g. manure or compost) could be quickly adapted site-specifically.

Acknowledgements

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P38 - UAV multi-temporal thermal imaging to evaluate wheat drought resistance

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Introduction

Deficit irrigation is a commonly used water-saving measure in the case of insufficient water resources (Wen et al. 2017). However, crop will face the threat of drought stress in deficit conditions, which will lead to a decrease of yield (Tari 2016). Therefore, how to identify appropriate wheat varieties to maximize yield in different degrees of deficit irrigation, which is very important for drought or semi-arid.UAVs with thermal camera can obtain thermal imagery which have sub-meter spatial resolution , So, it makes a possible to accurately obtain canopy temperature even at high altitudes and in a short time . With these advantages, UAV thermal infrared images can quickly assess the spatial temperature situation of crops, and then estimate the water stress status of crops (Gerhards et al. 2018). Moreover, UAV thermal infrared images were used to evaluate and rank the physiological performance in different wheat genotypes under moderate and high salty treatments, successfully identifying the salt-tolerance of each genotypes (Das et al. 2021). Although UAV thermal infrared imagery have widely been used, especially in the field of stress monitoring and varieties identification. Whereas, little is known about the identification of the drought resistance of wheat varieties in different deficit-irrigation regimes.

Objectives

(1) To understand the relations of canopy temperature from UAV-thermal imaging with physiological traits and (2) to evaluate the drought resistance of ten wheat varieties by UAV-based canopy temperature, respectively.

Materials and methods

Three main irrigation treatments were set, namely, W0 treatment (no irrigation), W1 treatment (one irrigation at jointing) and W2 treatment (two irrigations at jointing and anthesis). There are 10 winter wheat varieties were test. Two replicates were set for each variety under each water treatment and making a total of 60 plots in this experiment. UAV thermal remote sensing system was developed with a Matrice M600 Pro (DJI Inc., China). The thermal infrared camera is Zenmuse XT2 (FLIR Systems Inc., USA). On May 5, May 11, May 20, May 25 and June 2. Handheld infrared analyzer for temperature correction.Net photosynthetic rate (Pn), transpiration rate (Tr) and stomatal conductance (Cn), Chlorophyll content (SPAD), and Leaf area index (LAI) measurements were taken.

Results

1. Under W0 and W1 treatments, CT-UAV was closely correlated with SPAD and LAI in W0 and W1 treatments (R2 values are 0.28 to 0.79 and 0.22 to 0.72, respectively). CT-UAV have the closely relationships with Pn (R2 = 0.35 to 0.68), Tr (R2 = 0.40 to 0.66) and Cn (R2 = 0.28 to 0.71). However, CT-UAV had no correlation with SPAD, LAI, Pn, Tr and Cn in almost all growth periods under W2 treatment.
2. The 10 wheat varieties were clustered for the first group (good: with lower CT), the second group (moderate: with moderate CT) and the third group (poor: with higher CT) based on CT-UAV in multiple periods. In addition, CT-UAV may have a large difference between different wheat varieties at the late growth stages.

Discussion and conclusions

Although drought can make crop physiological performance deteriorate, while for some wheat varieties with outstanding physiological traits in normal water supplement, like larger leaf area, higher chlorophyll content and photosynthetic rate (Barutcular et al. 2017), mild or moderate water deficit had no significant impact on them (Zhao et al. 2020). Therefore, suitable wheat varieties should be selected in accordance with the degree of water stress for efficient utilization of water resources as well as maximum yield.In addition, the differences of the canopy temperature between different drought-resistant groups had appeared significant level until May 20. This is mainly due to the fact that in deficit irrigation conditions, a large amount of soil moisture was lost by plant transpiration in the early stage, which resulted in short of soil water during the grain filling stage and further drought stress (Thapa et al. 2017). Consequently, it is recommended to capture UAV thermal infrared images during the grain filling stage or later, which can evaluate drought resistant performance of wheat varieties more efficiently.

We identified the drought resistance performance of 10 wheat varieties under three deficit irrigation regimes by obtaining UAV thermal infrared images and physiological traits at multiple growth stages. Moreover, the UAV thermal imagery of the grain-filling stage (May 20) and later may have a higher efficiency for drought resistance evaluation than the early stages, which should be further validated.

Acknowledgements

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P39 - High-throughput spectral phenotyping of drought response in spring wheat

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Introduction

Under the Mediterranean basin climatic conditions, terminal drought stress is the major constraint to wheat production. The Mediterranean cropping system is characterized by a short and highly fluctuating growing season, which is expected to accentuate due to climatic change when crops are exposed to relatively longer periods of extreme conditions such as drought and heat [1]. Currently characterization of drought-related traits is time- and labor-consuming which inhibited breeding programs. Remote sensing is a discipline highly adapted for evaluating rapidly and indestructibly physiological traits with great importance for wheat breeding under drought conditions [2]. Combining genomic information and high-throughput phenotyping data and analysis supports developing cultivars more suitable for future challenges. It will enable breeders to screen larger populations faster and with higher accuracy, assess complex traits and increase the genetic gain [3].

Objectives

The main goal of this study was to develop and test a combined approach between hyperspectral time series and genomic data for rapid and accurate screening of wheat genotypes under drought conditions.

Materials and methods

A diversity panel of 300 modern spring wheat (*Triticum aestivum*) genotypes were characterized for terminal drought stress responsiveness in an automated rainout shelter facility. The panel was genotyped using a 90K SNP markers array. Throughout the season hyperspectral and thermal UAV-mounted cameras were used to capture canopy level changes. LAI and total chlorophyl content (chlt) were acquired weekly from 120 plots to use as ground truth measurements for models' calibration. Spectral models were projected to the entire dataset (i.e., all plots and all dates) to examine the seasonal dynamic in well-water (WW) and terminal drought (TD) conditions based on the spectral signature (400-850 nm). The predicted values of these traits used as a phenotype for Genome Wide Association Study (GWAS) to detect genomic regions underlying these traits.

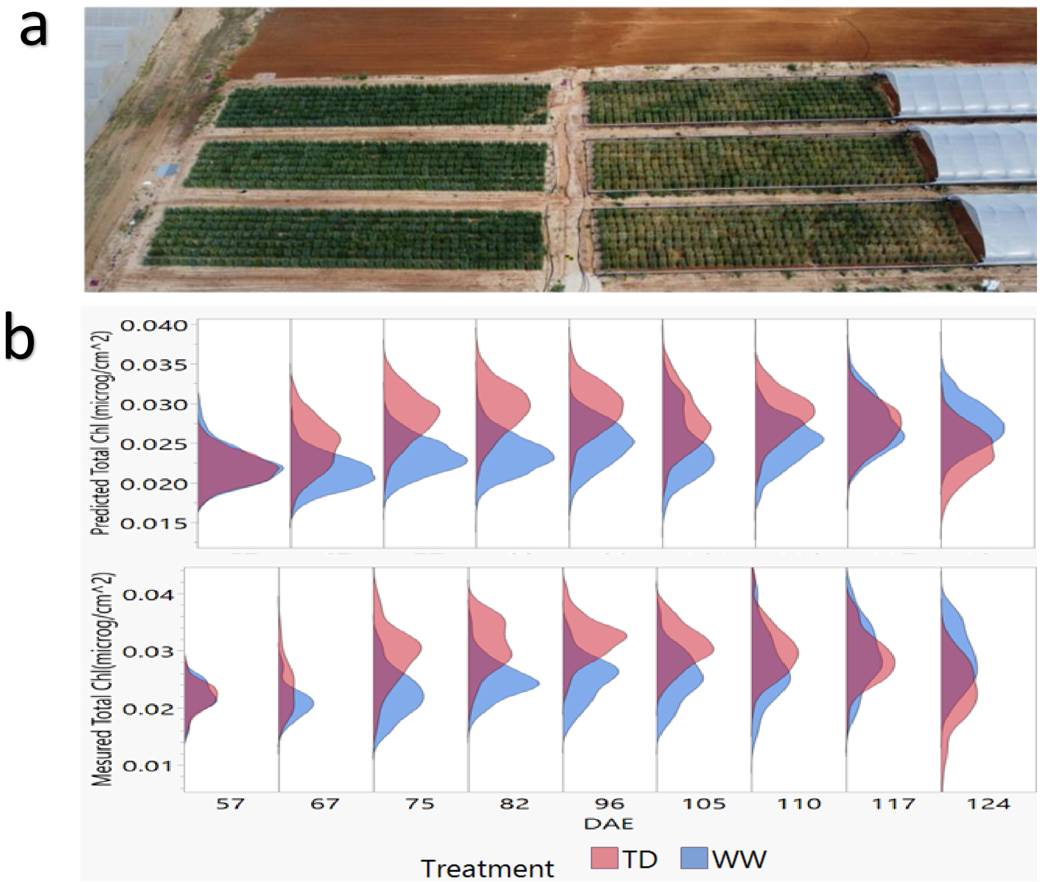
Results

For LAI assessment the partial least square regression (PLSR) model resulted in R^2 value of 0.56 and a root mean square error (RMSE) value of 0.63 for the independent validation data set. After projecting this model to all the plots in the experiment, the TD treatment showed higher LAI values than the WW but on the last measurement (i.e., a week after heading) both treatments showed similar LAI values. In the LAI GWAS analysis, no genomic region was found to be significantly associated to the trait under TD conditions, on the WW a genomic region on chromosome 4A was found to be significantly associated with LAI. Support Vector Machine (SVM) regression method was used to independently validate leaf chlt estimation to the same dataset as the PLSR model, resulting in R^2 and RMSE values of 0.68 and 0.0025 µg/cm^2, respectively. The chlt seasonal trend was similar to the LAI trend, on the first part of the season the chlt of the TD treatment was higher but during the grain filling period the WW showed higher chlt values. The early season advantage of the TD treatment might have been caused by heavy rain fall between mid-December to February (480 mm). The GWAS analysis did not detect any markers associated to chlt in most of the dates but on the last measuring data of the season (during senescence) two markers on chromosomes 7A and 1D were found significantly associated to chlt TD conditions. The WW canopy temperature was lower in 1-3°C then TD throughout the reproductive stage.

Discussion and conclusions

The assessment quality of both traits (i.e., LAI and chlt) was similar to previous studies using hyperspectral UAV-borne images by showing similar R^2 and RMSE [4-5]. By extracting data from UAV-borne imagery, it was possible to obtain meaningful data on a large number of small-scale plots. The ability to predict and investigate seasonal and spatial trends of physiological traits under terminal drought can assist breeders in a more accurate and time efficient selection of new cultivars more adapted to future climatic scenarios. Reliable phenotype large populations are also a key component in next generation breeding that use tools such as genetic mapping and genomic selection to increase the genetic gain in breeding programs.

Figure 1. (a) RGB image of the rainout shelter experiment and (b) seasonal dynamic *chl_t* measured (upper) and predicted by SVM model (lower)



Source: author's data

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P40 - Precision agricultural management of rice terraces using UAV in Japan

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Introduction

Rice terraces differ in elevation in different paddy fields, which can lead to variations in plant growth. Variation in plant growth reduces agricultural productivity; therefore, achieving maximum uniformity is desirable. To achieve uniform plant growth, it is necessary to determine the optimal fertilizer management for each paddy field. Specifically, a technology that makes it possible to measure plant growth conditions over a wide area is required. Recently, in Japan, an agricultural work support system was developed to predict plant growth and diagnosis of pests and diseases using an unmanned aerial vehicle (UAV) [1,2]. This has improved agricultural productivity; however, in this case, to achieve sustainable rice production on rice terraces, developing a more advanced agricultural work support system that advises farmers on the optimal management practices in real-time is desirable.

Objectives

In this study, we verified whether it is possible to diagnose plant information of paddy rice on rice terraces using a UAV, and whether it is possible to determine the plant growth stage by acquiring plant information over time. If understanding the changes in plant growth in real-time is possible, then farmers will be able to manage their cultivations more precisely.

Materials and methods

Rice terraces in Kanagawa, Japan were used as test fields. The paddy rice cultivar 'Kinuhikari' was planted on June 17, 2021. Plant state was measured using a UAV (Mavic Pro, DJI) during the growing period. The flight conditions were set at an altitude of approximately 30 m aboveground. Two types of cameras were mounted on the UAV: visible and multispectral cameras. Image data were used to create a 3D model of the plants and a normalized difference vegetation index (NDVI) map. 3D models were created using the Structure-from-Motion (SfM) method [3]. After acquiring plant images, the plant height, moisture content of paddy rice ears, protein content of paddy rice, and nitrogen content of brown rice were measured. Each plant parameter was compared with the 3D models and NDVI [4] value to verify the possibility of plant growth diagnosis. All plant parameters were calculated using Pix4D mapper software (Pix4D).

Results

The correlation between measured and predicted plant height calculated using the 3D models was $R^2 = 0.98$ (Figure 1), indicating a highly positive correlation.

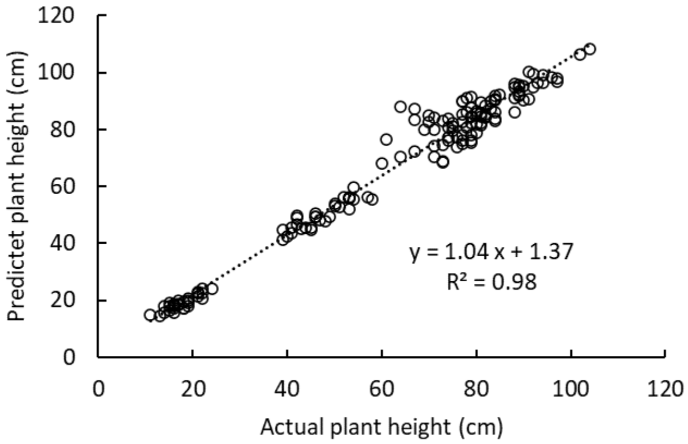

Figure 1 Comparison of the actual and predicted plant height of paddy rice (n=150)*.
*The predicted values were calculated using the generated 3D model.

Based on our findings, plant height of paddy rice can be measured with high accuracy using a UAV. The results indicate that the 3D reconstruction method can be used to estimate plant growth rate.

Next, the correlation between the measured plant height and NDVI value was highly positive (R^2 = 0.89). However, there was little correlation between the NDVI value and moisture, protein, or nitrogen contents in brown rice (Figure 2). These results suggest that the spectroscopy method can be used to predict plant growth rates and stages. However, estimating plant quality and balance of the plant growth in this study was difficult.

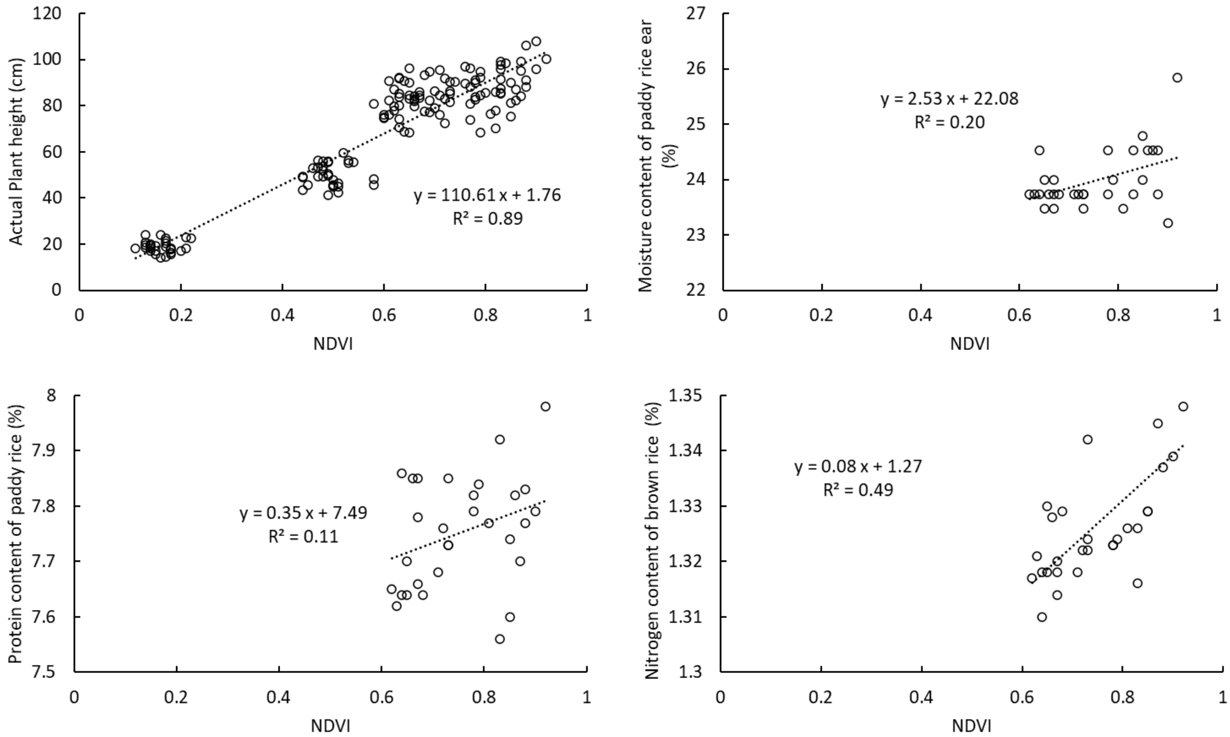

Figure 2 Comparison of NDVI and plant parameters of paddy rice.**
**The number of samples used for plant nutrient estimation was 30.

Discussion and conclusions

To develop a management cultivation method for farmers on rice terraces, we verified whether it is possible to measure the plant information of paddy rice using UAV. Based on our findings, it is possible to nondestructively measure the plant height of paddy rice during cultivation. In addition, it was suggested that the continuous measurement of plant height could predict changes in the growth stage. If this technology is implemented in agricultural fields, farmers will be able to make timely and appropriate agricultural work decisions. However, it remains a challenge to non-destructively measure the plant quality of paddy rice. Therefore, it is necessary to reconsider the measurement conditions.

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P41 - Identification of potato cultivars using multispectral imaging

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Introduction

Phenotyping and cultivar identification are critical for developing improved crop varieties adapted to specific environments, enhancing productivity, yield, and quality. High-throughput field phenotyping rapidly measures plant traits on a large scale. Remote sensing technologies, such as unmanned aerial vehicles (UAVs), provide accurate information about crop growth, health, and performance over large areas at high resolutions [1,2]. Remote sensing increases efficiency and accuracy, reduces labour costs, and enables real-time data collection for rapid decision-making in crop breeding. Additionally, remote sensing provides valuable insights into physiological processes underlying crop growth, enabling more precise and effective breeding strategies [3]. Phenotyping and cultivar identification facilitated by remote sensing play a crucial role in developing improved crop varieties to meet increasing demands for food, fibre, and fuel.

Objectives

The objective of this study was to test the applicability of a multispectral imaging system mounted on an unmanned aerial vehicle (UAV) to identify 68 potato (*Solanum tuberosum* L.) cultivars.

Materials and methods

68 potato cultivars were planted at a field of the Infrastructure centre Jable, Agriculture institute of Slovenia (KIS), near Ljubljana in April 2020. Potatoes were planted in microplots in a randomised design with 30 plants per microplot, and three replicates per cultivar. Seeding material was obtained from regular breeding and phenotyping activities at KIS. Cultivars were grouped into 5 groups (early, late, second early, very early, very late), based on their maturity period.

Multispectral images were obtained using a 5-band multispectral camera with downwelling light sensor (Micasense Rededge-MX), mounted on a quadcopter Skyhero Spyder X4-850 Geo Edition, at an altitude of 50 m AGL, at midday in beginning of July 2020. Positions of ground control points were measured using a Stonex S9i GNSS receiver, and used to increase spatial accuracy of multispectral images.

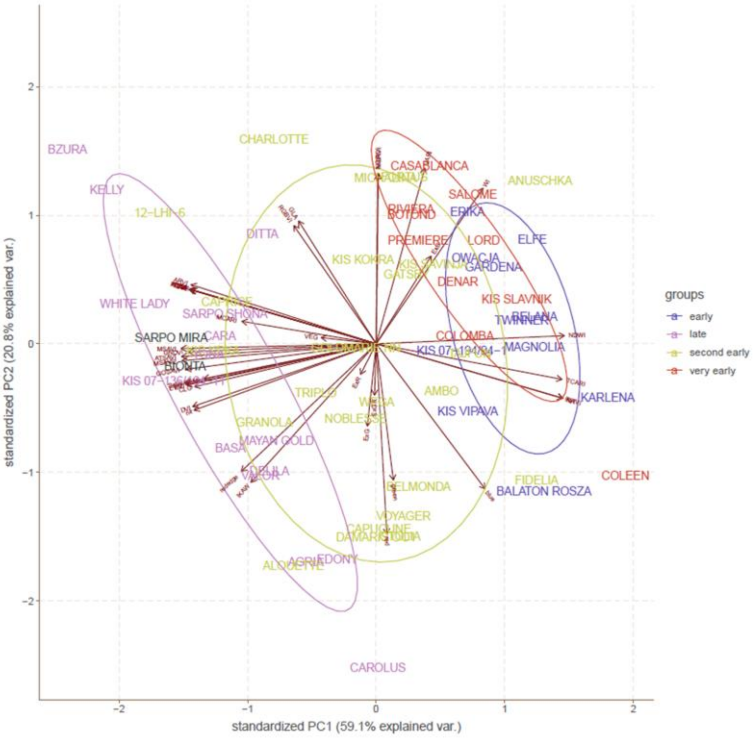
Reflectance images were segmented, leaf area pixels extracted for each plant and labelled for each cultivar and replicate. Two datasets were built, one with leaf-area pixel values, the second with mean spectra of each plant. Using each dataset, 40 spectral indices were calculated. Principal component analysis was used a dimensionality reduction and data exploration methods. Both dimensionally reduced datasets were split into training and test datasets in a 70:30 ratio. The first dataset was used to train an Extreme Gradient Boosting (XGBoost) model [4], which was evaluated using 5-times repeated 10-fold cross validation. Hyperparameter tuning was performed using a grid search. For the per-pixel dataset, majority voting was implemented to determine classification success for individual plants. The test dataset was then used to perform the final evaluation of the developed models.

Results

The first two principal components explain approximately 80 % variance. 22 indices were selected as important, and accounted for most of the observed variance. The selected 10 components explain more than 95 % variance in the data. Cultivar groups were arranged predominantly along the 1st component, with late varieties characterized by high values of indices such as MSAVI, ARVI, GNDVI, DVI, and low values of indices NDWI, TCARI, and WI. The opposite was observed for early and very early varieties, while second early varieties were between these groups. Second early cultivars also had the largest variability of all cultivar groups (Figure 1).

Identification of cultivars using PCA and XGBoost achieved a success rate of 97.1 % on mean spectra of plants. Using per-pixel data, a success rate of 88.5 % was achieved, and then increased to 98.4 % by using majority voting. Moreover, majority voting constrained classification results, thereby reducing confidence intervals in comparison to both per-pixel and mean classifications, with confidence intervals ranging from 94.1% - 99.5%, compared to 83.5% - 98.7%, respectively. These findings highlight the effectiveness of combining per-pixel classifications with majority voting in achieving highly accurate results in classification tasks.

Figure 1. PCA biplot of the first two principal components with 95 % confidence elipses for each group.



Source: author’s data

Discussion and conclusions

These findings demonstrate the potential of spectral data and machine learning techniques in accurately identifying cultivars and enhancing crop breeding programs. The observed differences between cultivar groups change throughout the season, so detailed time series analysis would be needed to accurately characterize these cultivars, their differences, and developmental changes throughout the season. The biggest differences were observed between late, and early and very early cultivars, with second early cultivars between them. At the time of imaging, early cultivars were more developed than late, and second early cultivars were in between. Later in the season the variability within this group would probably decrease, leading to a better differentiation. Further studies are needed, including time series, to validate these results and develop more generalizable models.

Acknowledgements

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P42 – Predicting maize grain yield using UAV-based remote sensing across varieties, row spacings, and irrigation

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Introduction

Corn (*Zea mays* L.) is the most grown and highly productive crop in the United States, especially in the Midwest and Great Plains. However, current agronomic practices still need to be optimized to sustain an increasing corn grain yield in the future to feed the growing population under pressures from climate change. For instance, there has been great interest in planting maize in narrow rows compared to traditional wide rows [1], cultivating drought-tolerant hybrids rather than conventional corn [2], and employing regulated deficit irrigation in semi-arid areas [3,4]. Remote sensing technology has been widely applied to promptly evaluate the efficacy of these practices. Ground-based sensors are convenient but have low spatial coverage of the field. Satellite remote sensing has broad coverage but lacks details in small fields. Unmanned aerial vehicles (UAV) remote sensing has become a dependable tool for the timely monitoring of crop growth and accurate yield prediction. Therefore, in this study, we used high temporal-spatial resolutions of UAV-based multispectral (MS) and thermal imagery to predict corn yield at various growth stages. Three corn varieties were planted in four different spatial arrangements under full and deficit irrigation treatments.

Objectives

The specific objectives of the study are to explore (1) the viability of vegetation indices (VI) derived from UAV MS images for yield estimation at different growth stages; (2) if the estimation model can be improved from the combinations of VI from multiple growth stages; and (3) model performance on yield prediction across diverse varieties, row spacings, and irrigation treatments.

Materials and methods

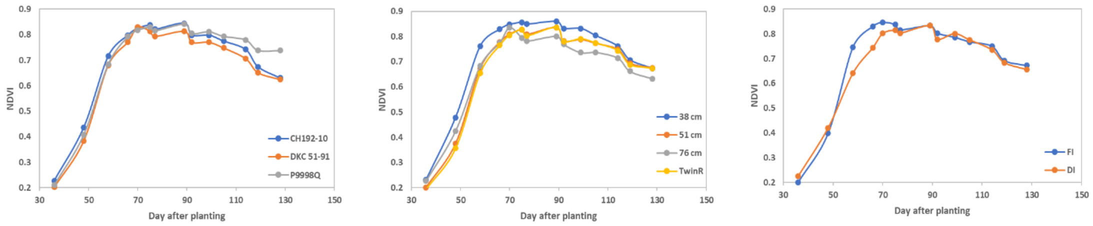
The study was conducted at the USDA-ARS Limited Irrigation Research Farm (LIRF) in Greeley, CO, USA (40.4463ºN, 104.6371ºW, and 1432 m above sea level). On May 11, 2022, three corn varieties -conventional DKC51-91(Dekalb), conventional Ch192-10 (Channel), and drought-tolerant P9998Q (Pioneer)- were planted in four different row spacing (twin-row with 23 cm between paired rows, 38-, 51-, and 76 cm- single-row spacing) and under full (FI) and deficit irrigation (DI) treatments with three replications. The field was irrigated using a linear sprinkler system. The seeding rate for all varieties was 82,780 plants/ha except for fully irrigated 38 cm row spacing plots, which had a seeding rate of 123,553 plants/ha. Irrigation was scheduled following the FAO-56 approach (Allen et al, 1998), and the meterological data was measured using an on-site weather station on Colorado Agricultural Meteorological Network. The cumulative seasonal irrigation amount in DI was about 70% of that in FI ((344 mm vs. 495 mm). Yield data were obtained using the yield monitor on the combine during the harvest on Nov 8-9, 2022.

A DJI S900 hexacopter (DJI LTD, Shenzhen, China) with a FLIR Duo Pro thermal camera (7.5-13.5µm, 640x512-pixel) (FLIR Inc., Wilsonville, OR) and a Micasense Rededge-MX multispectral (MS) camera were used for data collection. The cameras were vertically oriented. The MS camera captured five spectral bands including Blue, Green, Red, Red Edge, and Near-IR, with a ground spatial resolution of 8.33 cm per pixel. Thermal imagery had a ground spatial resolution of 10.74 cm per pixel. Image mosaicking and reflectance conversion were conducted using Agisoft Photoscan Professional (Agisoft LLC, Saint Petersburg, Russia). NDVI (Normalized Difference Vegetation Index), NDRE (Normalized Difference Red Edge), CIRE (Chlorophyll Index Ratio Equation), RVI (Ratio Vegetation Index), OSAVI (Optimized Soil Adjusted Vegetation Index), and DATT (Difference Atmospherically Adjusted Vegetation Index) were computed from MS images. Mean VIs derived from the central area of each plot were correlated with the corresponding corn yield. UAV VIs at various growth stages (vegetative (V9-VT), silking (R1), milk (R3), maturation (R6)) were tested for developing yield prediction models. Statistical analysis was done in R (R Core Team, 2023).

Results

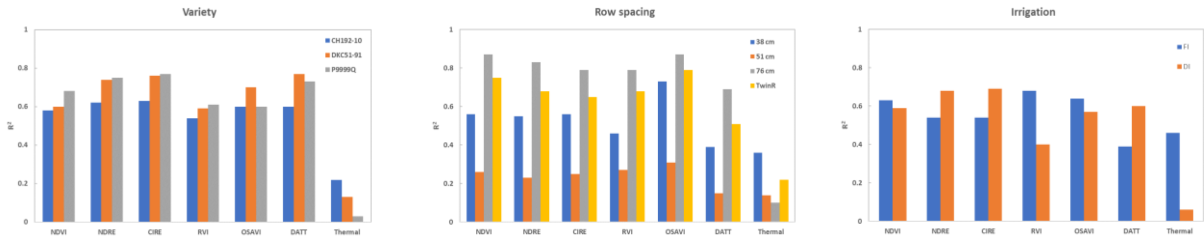
Figure 1 shows the seasonal NDVI patterns among varieties (Vrt), row spacings (RS), and irrigation (Irr). The 38 cm RS achieved full ground cover 20 days earlier than the 76 cm RS, with the former reaching maximum NDVI values 58 days after planting (DAP) compared to 70 DAP for the latter. Towards the end of the season, drought-tolerant corn exhibited higher greenness.

Figure 1. Seasonal NDVI trends among varieties, row spacings, and irrigation treatments.



Upon considering all the cases (Vrt, RS, and Irr), no single VI demonstrated superior performance in yield prediction for all days. VIs at the R3 exhibited the highest R^2 values of 0.48-0.61 (NDVI 0.59, NDRE 0.59, CIRE 0.60, RVI 0.53, OSAVI 0.61, and DATT 0.48)). Figure 2 shows the correlations (R^2) between yield and the VIs and thermal values on Aug 24. Irrigation on that day may have resulted in low correlations between thermal values and yield. CIRE and OSAVI were superior for different varieties and row spacings, respectively. All VIs show relatively low R^2 values for yield prediction in the 51 cm RS. CIRE and RVI performed superior for DI and FI, respectively.

Figure 2. Correlations between corn yield and VIs derived from the imagery on Aug 24, 2022 (R3 stage), for different varieties, row spacings, and irrigation treatments.



Multi-temporal VIs at various growth stages improved yield prediction. R^2 increased 8% using NDVI at V9 or V13 and R3 and 16.7% using RVI at V13 or VT and R6. R^2 increased using CIRE and DATT at V6, R3, and R6. R^2 had no changes when R3 and R6 VIs were combined.

Discussion and Conclusions

The optimal timing for yield prediction was found to be at the milk stage (R3) in this study. CIRE and OSAVI outperformed in yield prediction when considering varieties and row spacings because CIRE is more sensitive to leaf chlorophyll content and OSAVI is adjusted to variations for soil background. All VIs showed higher correlations with yield for 76 cm RS. Multi-temporal VIs were found to enhance prediction accuracy, particularly at vegetative and R3 stages. Thermal values showed significant responses to irrigation treatments only on Aug 11 when both DI and FI plots had not been irrigated for approximately a week. In order to improve the accuracy of corn yield prediction models based on UAV imagery, further development, and validation are required across different varieties, row spacings, and irrigation treatments.

Acknowledgments

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P43 – E-Crops DSS: software architecture, technologies, main functions, and examples of application

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Introduction

In the framework of the on-going research project E-Crops (www.e-crops.it/), coordinated by the Institute of Bioeconomy of the Italian National Research Council (NRC), and founded by Italian Ministry of University and Research, several Precision Agriculture (PA) technologies are under development and testing for different agricultural systems and fields of application, at both farm and district scales. All data and information provided by these PA technologies are integrated in a common cloud platform and elaborated by a unique DSS (Decision Support System).

Objectives

The paper provides a general description of the E-Crops DSS software platform, in relation to: i) general software architecture; ii) key technologies and data integrated; iii) main software functions and interfaces (Web/App); iv) list of relevant fields of application.

Materials and methods

The E-Crops DSS has been based on the existing Bluleaf® software platform [1], by means of the development and implementation of new functions and components. Several data sources related with different PA technologies (weather and satellite data, UAV/UGV, soil-plant sensors, crop imaging, etc.) have been integrated in the DSS platform. In collaboration with research institutions, providing scientific knowledge, specific databases and algorithms have been implemented, with approaches that can be model-driven and/or data-driven, depending on data sources and type of application. Finally, relevant agricultural stakeholders have been involved for the design on main DSS tools and interfaces, and for their preliminary field testing on selected cropping systems.

Results

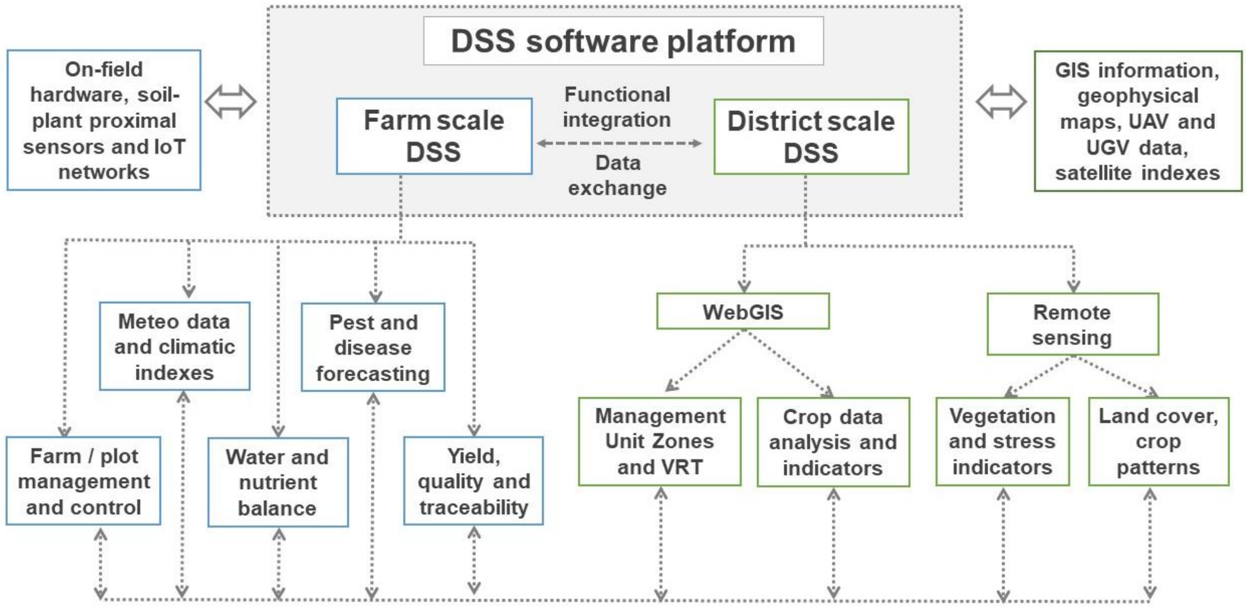
The E-Crops DSS is offered as a cloud-based software, accessible by means of specific Web/App applications. As shown in figure 1, the DSS has two main components, respectively providing specific functions and tools for the 'farm' and the 'district' scale, depending on the type of end-users, and requested level of data analysis and decision support. In table 1, some examples of DSS functions are listed, with information about PA technologies, scientific approach and main references.

Table 1. Examples of E-crops DSS functions, technologies and scientific approaches.

Functions	Scientific approach	PA technologies	D/M *	References
Climate analysis	Agro-climatic indicators, crop phenological and biometric models	Weather stations and climatic services	M	[-]
Irrigation	Crop-soil water balance model, integrated with proximal sensing	Weather sensors, IoT soil/plant sensors	M, D	[1,2,4]
Fertilization	Nutrient balance model, integrated with proximal/remote sensing	Soil sensors, satellite data	M, D	[3,4,9]
Disease control	Pest and disease forecast models, integrated with image analysis	Microclimatic sensors, automatic traps	M, D	[5]
Yield and quality	Yield prediction by statistical models integrated with image analysis	Multispectral and RGB images	D, M	[6,7]
Crop mapping	Proximal/remote monitoring of vegetation development and stress	UAV and UGV ***, satellite data	D	[7,8,9]
MUZ / VRT **	MUZ classification by means of statistical analysis	Geophysical survey, satellite data	D, M	[9]

* Data-driven (D) and/or Model-driven (M) approaches
** Management Unit Zones (MUZ) and Variable Rate Technologies (VRT)
*** Unmanned Aerial Vehicles (UAV) and Unmanned Ground Vehicles (UGV)

Figure 1. E-Crops DSS architecture: data sources, technologies and main functions



Discussion and conclusions

In the framework of E-Crops project activities, the DSS has been tested by different end-users (researchers, field technicians, farmers) against the following case studies and relevant cropping systems: 1) monitoring of water status and estimation of irrigation requirements for wine grape, fruit (kiwifruit) and greenhouse (strawberry) crops, by comparing sensor-based with model-based indicators; 2) mapping fertilization requirements for field crops (wheat, barley), by integrating remote sensing data, geo-spatial information and models of crop-soil nutrient balance; 3) predicting relevant diseases (downy mildew) and pests (moth) in grapevine, by integrating forecast models and automatic traps for real-time monitoring; 4) estimating fruit load and quality parameters in fruit crops (kiwifruit), by integrating image analysis, on-field sampling and laboratory analytical data processing.

The DSS has been considered to be effective for: i) the real-time monitoring of process-related variables and indicators; ii) the assessment of spatial-temporal variability at the plot/farm scale; iii) the computation of crop requirements for technical support; iv) the integration of multiple sources of information within a unique software platform.

Funding

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P44 - Stakeholders' needs and barriers to adoption of advanced digital tracking tools

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Introduction

The double challenge of achieving higher levels of productivity and environmental sustainability [1], has raised the importance of accurately monitor farm performance so that farmers can intervene with appropriate actions. In particular, the precision of field-level data could be deeply enhanced with an automatic digitalization of the field activities exploiting the data already available in most of the existing agricultural machinery. In this context, the major objective of the DATA BUS project is the development of enhanced tools for the proficient exploitation of farm data to improve farm management, budgeting, environmental assessment, and crop traceability.

However, collecting and elaborating activity-level data is not enough to ensure a shift towards higher sustainability as farmers must be helped in the transition to data-driven farming to increase their decision-making efficacy. In fact, farmers do not have the required analytical skills to manage digital information and use precision farming technologies. Indeed, they usually adopt technology only if they are not overloaded by its complexity and perceive the benefits of farm management information systems in relation to their costs [2]. These barriers to the adoption of digital tools in farms can hamper the proficient use of farm data to improve farm management, budgeting and environmental performance [3]. Thus, understanding the factors that affect the adoption of new technologies is required to adequately inform the developers and to promote their use [4]; in fact, these technologies must be compatible with the farmers' practices and needs to be accepted [2].

Objectives

To facilitate a real innovation uptake in the agricultural sector, the DATA BUS research project will analyse the stakeholders' needs and demand for advanced digital tracing tools along the food supply chain and their barriers to the adoption of such tools.

In detail, two main objectives will be pursued: *i*) assessing the stakeholders' demand for the full tracking of farming activities at the field level along the food value chain; *ii*) analysing barriers to and advantages of farmers' adoption of the innovation developed by the project.

Materials and methods

To achieve objective one a two-step procedure is followed. First, a focus group (FG) meeting was held in February 2023. The FG included representatives of farmers' associations, farm entrepreneurs and technology developers and users, totalling 6 participants. In the focus group have been discussed the stakeholders' demands and barriers in relation to the use of tools for the tracing of farming activities at the field level. FG has been preferred here because this approach is recognised as a useful tool to gather qualitative information to answer specific research questions [5] by allowing interaction among different stakeholders.

After the FG meeting, following the suggestions received, semi-structured interviews have been drafted by the research team to be administered among a wider range of stakeholders along the whole food supply chain to obtain feedback about their needs regarding the tracing system and eventual barriers to adoption. This stakeholders' group is composed of twenty people and includes farmers, cooperatives representatives, marketing specialists, machinery producers, but also certification bodies representatives, to focus on the eventual needs for the certification of a superior environmental sustainability of food [6]. Based on the semi-structured interviews, an ad hoc survey will be developed on factors influencing farmers' decision-making process when adopting the innovation developed.

Results

The FG was held in Bologna, on the 3rd of February 2023. The participants discussed two main topics: the need for data for farm management and perceived opportunities and barriers derived by the adoption of precision agriculture technologies. The whole session lasted about 90 minutes. The FG responses were analysed through content analysis [7].

Overall, the environmental benefits deriving from the uses of precision agriculture technology and the social benefits appeared to be poorly understood, but the capacity to implement supply chain relations seems to be well appreciate. The main barriers to the adoption of digital agriculture technologies emerging from the FG were the following: stakeholders' lack of awareness of the benefits of technology; limited economic resources available for farms (especially small ones) in relation to the incidence of technology costs; the presence of cultural barriers; inadequate competencies. Besides, stakeholders highlighted the importance for farmers to know the cost-efficiency of investments in digital tools. Indeed, agricultural data from precision agriculture are not exploited strategically, but are used only to guide current production activity. It also appeared evident that one of the most important drivers of technology diffusion could be an adequate education for a correct management of data complexity.

Discussion and conclusions

Results from the FG are in line with the existing literature highlighting the main barriers to innovative technologies adoption [8-9] and suggest the need of targeted policies and training interventions to encourage the use of digital tracking tools. In fact, the perceived complexity of such tools has a significant role in hampering their adoption. Overcoming this barrier through information can help farmers understanding the advantages and opportunities associated to these technologies also from an economic perspective. The Common Agricultural Policy funds could be useful to promote new measures that support information systems and networks.

These results are propaedeutic to a second step of analysis, where deeper investigations will be performed. Outputs from the FG have been used to draft interviews for the whole supply chain stakeholders' representatives which will be performed from May to June 2023. Based on the semi-structured interviews and a systematic review of the literature, an ad hoc survey will be then developed on factors influencing farmers' decision-making process when adopting innovation and will be distributed among Italian farms by the end of 2023.

Acknowledgements

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P45 - Does the use of multi-year data improve wheat yield prediction?

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Introduction (For the section titles, please use the style "Title 2".)

Obtaining an early and precise crop yield estimation is one of the biggest challenges of modern agriculture. For example, knowing the expected yield in advance allows for more efficient fertilizer management. For optimal fertilization, soil nutrient availability and crop extraction must be in consideration because, in more productive zones, crop nutritional requirements are higher.

To estimate crop yield, various techniques, such as the use of agronomic models like CERES [1], combining meteorological data with proximal sensing data [2], or using information from Sentinel-1 and 2 [3] were used. In the aforementioned studies, yield estimation was done using data from the same crop season. For instance, in wheat (*Triticum aestivum* L.), the highest correlation between the Normalized Difference Vegetative index (NDVI) and yield (t ha^{-1}) was obtained during the heading or ripening phase [4], which makes it unsuitable for adjusting fertilization since basal-nitrogen input in the study area occurs at the start of the stem elongation phase. In 2021, a study was published by [5], where wheat yield for the next crop season was estimated using information collected in previous ones. To achieve this, a Convolutional Neural Network (CNN) algorithm was used in combination with phenological and meteorological data. However, the spatial resolution of this study does not allow for fertilizer optimization since it was conducted at the NUT3 level.

Objectives

The aim of this study is to analyze the potential of the Categorical Boosting (CatBoost) algorithm to estimate wheat yield for an upcoming season using yield information and Sentinel-2 images from various seasons.

Materials and methods

This study was conducted using wheat data collected over four seasons, between 2019 and 2022. Analyzed plots were located across the provinces of Álava and Burgos in northern Spain. Yield data were collected using a yield monitor mounted on a combine harvester equipped with RX-corrected GPS. The 11 vegetation indices used in this study were derived from cloud-free, 2A-Sentinel-2 images available between February and June of each season. Number of images ranged from seven in 2019 to five in 2022. A total of 307 ha of wheat plots were analyzed, resulting in a matrix of 26,000 instances and 56 variables. The CatBoost algorithm [6] was used to estimate wheat yield.

Results

The average yield of the 141 analyzed plots ranged from 3.62 t ha^{-1} of plot 20 of 2022 to 9.94 t ha^{-1} of plot 17 of 2021. There were significant yield differences ($p<0.05$) between seasons. The highest yields were achieved in 2020 and 2021 seasons, with 6.85 and 6.91 t ha^{-1}, respectively, while the lowest was measured in the 2022 season at 5.34 t ha^{-1}. Finally, in 2019 the yield was 6.39 t ha^{-1}.

Figure 1 shows the mean error and its interquartile range error for the four seasons. These errors were obtained by estimating the yield of each plot individually using information from the other seasons. The average error for the 2019 season was 0.86 t ha^{-1}, an error of 13.5%. In the 2020 season, the error was 0.99 t ha^{-1}, representing an error of 14.4% of the average yield, while for the 2021 season, the error increased to 1.18 t ha^{-1}, representing an error of 17.1%. Finally, with an error of 1.22 t ha^{-1}, which represents a 22.9% of yield, the wors results were obtained for 2022 year.

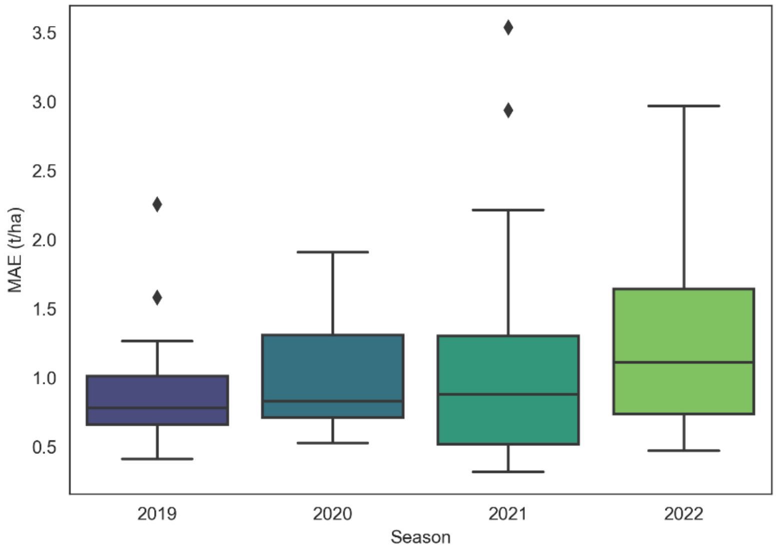

Figure1. Median, interquartile range and outliers of the mean absolute error (MAE) for the four seasons when estimating the yield of a plot using data from other seasons. The yield of each pixel was estimated, and with the data of all the pixels of each plot, its average error was estimated. The error represented here corresponds to the mean of the errors of the plots used each year.

Discussion and conclusions

The highest mean error corresponds to the 2022 season, which is understandable as the yield data for that year differs the most from the others. Consequently, the algorithm lacks similar data to "learn from". On the other hand, it is surprising that the mean error for the 2020 and 2021 seasons is higher than that of 2019, given that the average yield for both seasons does not show significant differences. For the 2021 season, there are two abnormally high errors (2.9 and 3.5 t ha $^{-1}$).

Although the scale of the published data by [5] is completely different, the mean error obtained for the predictions ranges from 0.1 to 77.6%, which is more variable than the results present in this study. The yield estimates presented in this study exceed the acceptable mean error of 10% in all cases, so future work must continue to improve the estimation. With this in mind, it is proposed to improve the estimation by adding additional data sources, such as Sentinel-1 or meteorological information. Nonetheless, this preliminary investigation has paved the way for the utilization of satellite-derived information in predicting yields across seasons, thus potentially enabling the optimization of fertilization practices.

Acknowledgements

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P46 – Working times classification through CAN-BUS data analysis

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Introduction

With modern agricultural machinery, large amounts of data are produced during each operation by several sensors, but most of the time remain unused unless for very technical or specific reasons. Understanding the CAN (Controller Area Network) data has big potential, helping to improve the efficient use of different machinery in different working conditions and comprehend which is the most suitable approach to optimise the operations.

Objectives

The first objective was to estimate working times classification by combining the data collected from the CAN and a GNSS module. The second objective was to evaluate if all the data produced are necessary or if it is possible to slim down the list since many parameters are collected.

The third objective was to find the most appropriate sampling frequency of the data since they can be exported at different frequencies, influencing the amount of data in terms of megabytes produced.

In addition, another classification was performed using only the data coming from the GNSS module, in this case only Speed values, to check whether there was a difference between the classification performed with CAN + GNSS data and the one achieved with only GNSS.

Materials and methods

A ploughing operation was monitored in a 0.6 ha field of the experimental farm of the University of Padova; the tractor used was a New Holland T7 165s (110kW) working with a two-furrow plough, equipped with a data logger to collect the data coming from the CAN and a GNSS module (CANedge 2, CSS electronics).

The logs of the operation were converted using the appropriate library and then resampled at different frequencies, respectively (5hz, 3hz, 1hz, 3s, 5s, 10s, 30s).

The classification was performed with Python using different algorithms, which allowed us to divide the sampling into two clusters: working time and turning time (Figure 1), then, the files were visualised using GIS software for a visual validation of the classification.

Working and turning times were also monitored by an operator in the headland. The time classification carried out by using the operator timestamps was used to train a random forest algorithm on the 5hz telemetry data, based on the parameters selected (Table1). The random forest algorithm was then used to classify data with different frequencies from the CAN and GNSS module.

Results

The results showed no notable difference between the various sampling frequencies obtained with the combination of data from the CAN+GNSS.

It is also important to mention that the results obtained using only the Speed from the GPS module are close to those produced with the CAN+GNSS (Table 2).

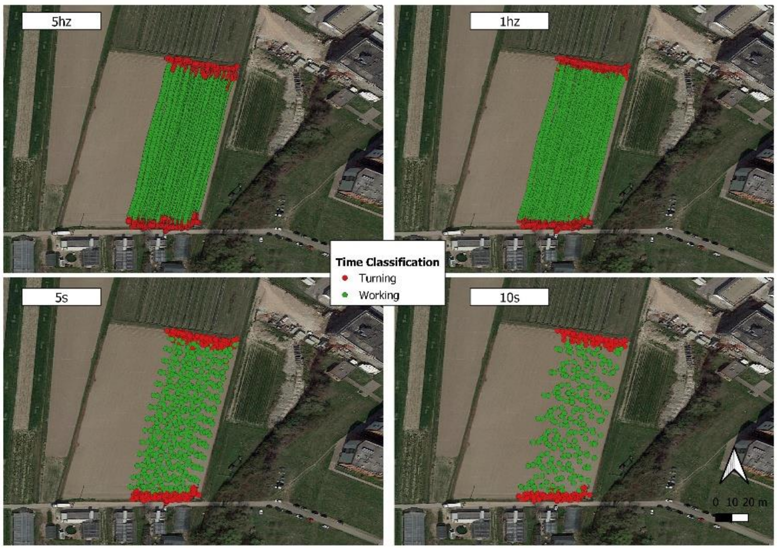
Table 1. Parameters used for the times classification

Parameters used	
GNSS_altitude.Altitude	CAN1.ETC2.TransmissionSelectedGear
GNSS_attitude.Pitch	CAN1.A1SCRDSI1.Atttt1DsExstFdAtDsQtt
GNSS_attitude.Heading	CAN1.FD1.EngineFan1EstimatedPercentSpeed
GNSS_ABS_Delta_head	CAN1.EEC3.Aftrtrtmnt1ExhstGsMssFlwRt
GNSS_speed.Speed	CAN1.EEC3.EnginesDesiredOperatingSpeed
CAN1.TSC1.EngnRqstdTrqTrqLmt	CAN1.EEC3.NominalFrictionPercentTorque
CAN1.ETC1.TransmissionDrivelineEngaged	CAN1.EFLP1.EngineOilPressure1
CAN1.ETC1.TransmissionShiftInProcess	CAN1.CCVS1.WheelBasedVehicleSpeed
CAN1.EEC2.AtlMxmmAvllEngnPrntTrq	Calculated Slippage
CAN1.EEC2.EnginePercentLoadAtCurrentSpeed	CAN1.LFE1.EngineFuelRate
CAN1.EEC1.ActualEnginePercentTorque	CAN1.LFE1.EngineInstantaneousFuelEconomy
CAN1.EEC1.EngineSpeed	CAN1.IC1.EngineIntakeAirPressure
CAN1.EEC1.EngineDemandPercentTorque	CAN1.IC1.EngineIntakeManifold1Pressure
CAN1.ETC2.TransmissionCurrentGear	

Table 2. Times classification

Sampling Frequency	Working (minutes)	Turning (minutes)	Totals (minutes)
5hz	36.68	25.08	61.73
3hz	37.03	25.38	62.41
1hz	36.63	25.08	61.71
3s	36.3	25.40	61.70
5s	36.67	25.08	61.75
10s	37	25	62
30s	36.5	26	62.5
1hz GNSS	37.76	23.95	61.71
5s GNSS	38.58	23.16	61.75
10s GNSS	39.33	22.66	62
30s GNSS	39	24	63

Figure 1. Visualisation of the times classification



Discussion and conclusions

According to the results, both methodologies are suitable for the classification of working and turning times during tillage operations; there is no difference between higher sampling frequencies, such as 5hz and lower, like 5s, indicating that is possible to achieve the same accuracy producing a lower amount of data, which are easier to process.

It is also interesting to underline that it is possible to perform the same task using only the speed data produced by any low-cost GNSS.

In future research, those aspects will be investigated, and the study will be extended to several tillage operations.

P47 - Preliminary Study for the Development of Variable-Tillage Implements for Precision Farming

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Introduction

Energy demand of soil tillage implements has been reported based on different operating conditions and the chemical and physical soil properties[1,2]. However, tillage operations cannot only be evaluated according to their energy consumption; the soil structure improvement and the consequent agronomic benefits must also be considered [3]. Power harrows can adjust soil clod size by varying the velocity ratio (λ) of the machinery which is calculated from the ratio of the peripheral speed of the tine rotors and the vehicle's advancing speed [4]. This peculiarity makes it possible the development of new variable-rate tillage implements, a topic of high interest in recent years [5]. Moreover, according to Berntsen and Berre [6], a good seedbed to achieve a rapid and uniform emergence for cereals should contain roughly 50% of the weight of aggregates in the 0.5-6.0 mm range.

Objectives

This paper aims to gain deeper insight into controlling the soil structure and find correlations with the power harrow's energy requirement in different setups maintaining λ constant. Moreover, a possible correlation was sought between crop emergence and the granulometry of the tilled soil.

Materials and methods

Field tests were conducted on a 5 m working width (b) power harrow coupled with a 230 kW CVT tractor with a working depth (δ) of 15 cm. Tests were performed at constant λ, in particular four different configurations (named Cλ1-4) were performed varying the tractor speed (V_t) and the tines rotational speed (n_{ph}). Through the tractor Controlled Area Network (CAN) SAE J1939 diagnostic port and a datalogger, its speed, engine power, engine speed, fuel rate consumption ($\dot{f}$) and PTO speed were recorded during the tests. In addition, load pins and a torque meter were used to measure the draught force and PTO torque that the power harrow absorbed. Therefore, the power absorbed by the power harrow (P_{ph}), the fuel consumption per hectare (f_{ha}) and the energy required to process 1 m^3 of tilled soil (*E*) were calculated using the following equations:

$$P_{ph} = P_D + P_{PTO} \tag{1}$$

$$f_{ha} = \frac{\dot{f}}{F_c} \tag{2}$$

$$E = \frac{P_{ph}}{V_t\, b\, \delta} \tag{3}$$

where P_D and P_{PTO} are the power used to tow the implement and the power used to run the power harrow rotors through the PTO, respectively. Moreover, F_c is the field capacity of the agricultural operation, obtained by multiplying the working width by the tractor speed.

Following harrowing, soil samples were sieved, and then the granulometric parameter MWD was calculated [7]. Thereafter, the field was sown with maize maintaining constant planter set up all over the field. Then, the crop emergence and phenological stage were manually monitored in the field after a few days by counting the number of plants and the number of unfolded leaves respectively. The infield measurements were repeated three times in each parcel. Then, data from tractor-power harrow system, soil granulometry and crop emergence were correlated to find any possible relationship. Each configuration was randomly replicated three times. The Pearson coefficient was evaluated to correlate MWD and crop emergence (number of emerged plants) data.

Results

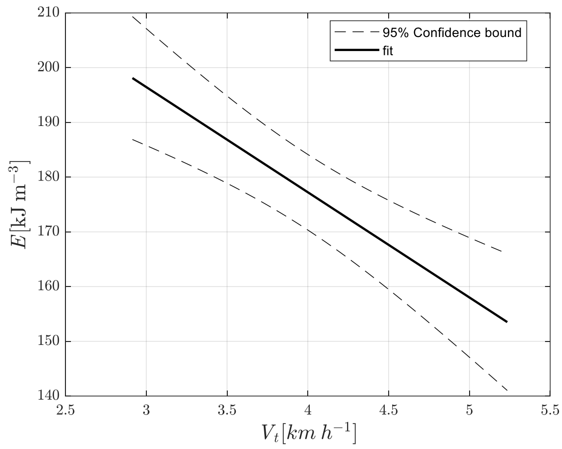
The results showed that the λ parameter was between 2.6 and 2.8 during the field tests (Table 1). The energy required by the tractor-power harrow system per m^3 of tilled soil was affected by the tractor speed and varied from 195.9 kJ m^{-3} at 3 km h^{-1} to 158.4 kJ m^{-3} at 5.1 km h^{-1}. The linear regression of the energy required to process 1 m^3 of tilled soil as a function of the tractor speed is reported in Figure 1 with a coefficient of determination (R^2) equal to 0.73.

The obtained Pearson coefficient, used to correlate the MWD data with the number of emerged plants, resulted to be -0.56.

Table 1. Average of the monitored and calculated data for different configurations. The standard deviation is in brackets.

Test	$\bar{V}_t$ [km h^{-1}]	$\bar{n}_{ph}$ [rpm]	$\overline{\lambda}$	$\bar{P}_{ph}$ [kW]	$\bar{f}_{ha}$ [L ha^{-1}]	$\bar{E}$ [kJ m^{-3}]	$\overline{MWD}$ [mm]
Cλ1	3.0 (1.1 E^{-1})	205 (2.1)	2.55 (7.1 E^{-2})	120.1 (8.3)	25.6 (1.3)	195.9 (11)	13.6 (2.6)
Cλ2	3.4 (4.1 E^{-2})	246 (28)	2.78 (2.9 E^{-1})	136.5 (3.1)	24.8 (7.9 E^{-1})	189.9 (2.4)	10.6 (2.0)
Cλ3	4.4 (1.7 E^{-1})	324 (12)	2.76 (2.1 E^{-1})	153 (11)	23.2 (2.1)	166.3 (18)	9.6 (2.9)
Cλ4	5.1 (1.7 E^{-1})	357 (3.6)	2.66 (7.1 E^{-2})	166.8 (7.8)	20.9 (1.0)	158.4 (13)	8.6 (2.0)

Figure 1. Linear regression of the energy required to process 1 m^3 of tilled soil as a function of the tractor speed.



Discussion and conclusions

The energy values per unit of volume of tilled soil decrease when the tractor speed increases,this is in line with previous results obtained by the Authors[1]. Moreover, $\overline{MWD}$ decrease with the increase of the impact speed of the tines with the soil, as already observed by Varani et al.[4].

The Pearson coefficient shows a reverse strong correlation between MWD data with the number of emerged plants. Therefore, the higher the tractor speed and the tines rotational speed, the higher the crop emergence and the lower energy consumption are respectively.

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P48 - Blockchain Implementations in Precision Agriculture

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Introduction

Today, to increase the productivity of the agricultural sector and improve sustainability conditions, precision agriculture is suggested. A management strategy that helps farmers use production inputs including seeds, fertilizers, pesticides, irrigation water, and tillage more effectively to achieve greater crop yield while considering environmental issues [1]. This technology can be used in all sub-sectors of agriculture to improve the global economy. According to statistical reports, precision farming will grow by 14% in the coming years, and its market growth will reach from 7 billion dollars in 2022 to about 13 billion dollars by 2025 [2].

To improve the performance of the agricultural sector, precision agriculture relies on smart sensors, mobile apps, artificial intelligence, cloud computing, drones, and Internet of Things (IoT) technologies. Considering these technologies, it is possible to process and access real-time agricultural information such as crops, environmental conditions, soil, water, and weather, as well as food safety in the supply chain [3].

Despite the advantages of precision agriculture, this technology faces some challenges. In order to manage many services in precision agriculture, there is a need for decision support systems, data analysis, and mining. Hence, there is an important need for complementary technology to meet the challenges ahead along with precision agriculture. Blockchain technology seems to be promising for overcoming these challenges [4]. An advanced technology that can be supported by several applications in precision agriculture; for instance, smart agriculture, food supply chain monitoring and tracking, financial management, and data security. Based on a market intelligence report by BIS research, the role of blockchain technology in precision agriculture and the food supply chain will be significant (from about 42 million dollars in 2018 to about 1.5 billion dollars in 2028.

Objectives

This study assesses the challenges surrounding precision agriculture, and specifically highlights the role of blockchain technology in overcoming these challenges by focusing empirical studies on this issue.

Materials and methods

A narrative review method to analysis the literature is applied. We conduct a search of the literature within the common electronic databases Science Direct, Web of Science, and Scopus. The search strategy uses two main keywords: blockchain technology and precision agriculture.

Results

We investigated the role of blockchain technology in overcoming the challenges facing precision agriculture in four areas: 1. Farm supervision and optimizing inputs: Setting up a smart farm based on a precision agriculture framework requires sensors for temperature, humidity, light, and crop maturity detection. Based on the obtained digital data, blockchain technology can facilitate the monitoring process for farmers and stakeholders by providing rapid and smooth communication [11]. Patil, Tama [12] in a proposed framework for blockchain-based smart greenhouse farming pointed out that farm monitoring can prevent crop losses after harvest with crop storage monitoring technique. This framework secures communication in smart greenhouse farming by creating a connection between humidity, light, water level and CO_2 sensors [12]. 2. Food supply chain process monitoring and management: Blockchain ledger can play an important role in the transparency of monitoring processes in the food supply chain while using precision agriculture. This technology can increase the trust of consumers and stakeholders in the food producing and also reduces fraud in the food sector by ensuring food safety [13]. For instance, in a study, Li and Wang [14] constructed a traceability system model based on the blockchain technologies. They mentioned that during the supply chain process, blockchain technology can record data between supply chain nodes; track purchases, orders, shipments, all shipping processes and transactions; verify the transactions; link between food products and barcodes, serial codes, digital tags like radio-frequency identification (RFID); and then, share the information on the methods of production, delivery and maintenance of the product with suppliers and sellers [14]. 3. Determining, recording and sharing legal issues related to land: Another feature of blockchain is its use in determining, recording and sharing legal transactions which are related to agricultural land [15]. Because the traditional registry systems have many limitations, including the inability to fully authenticate the traded lands of individuals and organizations. As Luckas [16]'s findings showed, blockchain technology can confirm the authenticity of relevant transaction records by using a decentralized public ledger. This technology analysis the information received from global positioning system (GPS) coordinates and shares it with the relevant people with confidentiality if needed [16]. 4. Improving the efficiency of payments or remittances: Farmers may need a public payment system to receive real-time remittances during their agricultural activities. With compatible mobile blockchain systems, blockchain mobile application or smart contracts, farmers will be able to execute real-time payments for crops and agricultural services. Xiong, Zhang [17] presented a prototype of mobile edge computing enabled blockchain systems with experimental results to justify the proposed concept. They highlighted that in this prototype, the role of blockchain is to create fast, transparent and secure real-time transactions [17].

Discussion and conclusions

Today, precision agriculture is proposed as a management strategy to improve the productivity of the agricultural sector as well as sustainability conditions. To this aim, precision agriculture relies on smart technologies. However, the applied technologies face challenges including the need for decision support systems, data analysis and data mining. Blockchain can overcome the challenges facing precision agriculture such as, farm supervision and optimizing inputs, food supply chain monitoring and tracking, financial management and data security, improving the efficiency of payments or remittances, and improving the efficiency of payments or remittances. This technology with decentralized shared database mechanism creates trust at any given point in the chain, leading to more effective data management and control. Therefore, the capability of this emerging technology, especially its effective application in precision agriculture, can be an attractive topic for the scientific research. Although the intersection of blockchain technology in precision agriculture should be carried out step by step, considering the issues such as energy consumption, scalability, investment costs, and the complexity of its application in the food supply chain as blockchain technology challenges in agri-food.

Acknowledgements

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P49 - Data Models in Precision Agriculture: From IoT to Big Data Analytics

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Introduction

Carrying out (big data) analytics on IoT and precision farming systems requires data models that standardize data formats and relationships. *Data models* describe the *concepts* that belong to a certain *domain* and the instances of a concept are called *entities*; for instance: "Device" and "Farm" are concepts that belong to the "Smart Sensoring" and "Precision Agriculture" domains [1], and the entity "`device-123`" is an instance of "Device". Since data models are mainly oriented to data transmission and representation (e.g., they provide an exhaustive description of a "Device" with all the necessary attributes), the same concept can appear in different domains ("Measurement" is a concept in both "Smart Sensoring" and "Smart Cities" [1]) with different semantics and/or attributes (e.g., some attributes might be useless in the "Precision Farming" domain while they are not in the "Smart City" domain). Additionally, data models usually fuel data silos (i.e., isolated repositories) for specific and independent applications (e.g., smart watering management [4] and autonomous weeding systems [5]).

Decision support systems for precision agriculture would benefit from a unified Data Platform (DP; ecosystems that meet end-to-end data needs) where all data are integrated and managed [2, 3]. However, data models are not suited for automated analysis and integration into a uniform medium due to the issues above. The results obtained in the fields of database and DP could both answer these issues and open novel research directions with the synergy of big data analytics and precision agriculture.

Following our experience in the WeLASER European project [6], where FIWARE data models are employed, we factorize the main issues and their possible solutions. Note that there is no one-size-fits-all solution. We built a modular cloud DP [3] to support heterogeneous applications. The DP must be modular and extensible so that new modules and algorithms for data management can be easily integrated. This requires well-defined and documented application programming interfaces.

(Issue 1) Consistency

The same concept exists in different domains with (possibly slight) different semantics and/or attributes (e.g., a greenhouse can be a Building [7] in the "Smart City" domain or a first-citizen concept [8] in the "Precision Agriculture" domain). Additionally, the same concept can be modeled in different ways even within the same domain (e.g., a sensor measurement is modeled directly in a "Device" [9] or as a first citizen [10].

Solution. Entity resolution is the process of understanding whether data are referencing the same entity. Such algorithms identify data items across multiple data sources that refer to the same real-world entity and link the items together, even without having a unique identifier.

(Issue 2) Data representation

To provide a compact and exhaustive representation of information, data models aggregate different notions (e.g., sensor and measurement) within the same concept (e.g., "Device"). This allows efficient data transmission and representation but also raises several issues, such as redundancy (i.e., the same data could be repeated many times) and vertical applications (i.e., entities are specialized to fulfill a specific workload but not a generic one).

Solution. Aggregate-oriented modeling optimizes ad-hoc applications. However, the DP must support the possibility to query data under unforeseen workloads. To this end, additionally, to the data models, a registry of entities and their relationships could be managed through a knowledge graph to know where entities are spread and reconcile them in case of need.

(Issue 3) Schema evolution

The entity structure can change over time (e.g., attribute renaming/addition/deletion) possibly resulting in unmaintainable data repositories; additionally, an entity can be wrongly filled during their (manual or automatic) generation.

Solution. A schema registry manages the concepts of a domain (e.g., the schema/structure of a "Device") by versioning their evolution. This allows the definition of compatibility between different versions of the same entity and to validate their content (e.g., a temperature measurement must be a numeric value).

(Issue 4) Tracking data flows

Since heterogeneous IoT sources produce data that are collected and transformed into the DP, it is necessary to track the history of this data to ensure privacy regulations, access control, and data quality. However, tracking and querying such data across the transformation processes is computation and storage heavy.

Solution. Data provenance provides a set of techniques to represent and query the data origin, what happens to it, and where it moves over time. For instance, it allows users to understand which entities contributed in producing a specific result (e.g., which devices and measurements have been used to compute the field evapotranspiration?). It also enables replaying specific portions or inputs of the data flow for stepwise debugging or regenerating the lost output.

(Issue 5) Maintaining historical data

Entities are snapshots, i.e. they describe the latest status of the system (e.g., the latest perceived temperature thermometer). However, maintaining historic trends (e.g., showing the temperature trends over time) requires storing multiple versions of the entity at the cost of complex management.

Solution. Updates are usually handled by storing the entire entity at every change (this makes easy the reconstruction of the entity history at the cost of higher memory consumption) or managing delta updates (this saves memory but makes harder the reconstruction of the entity history). A delta update only requires the user to download those parts entities which are new, or have been changed from their previous state, in contrast to having to download the entire copies. This can also save significant amounts of bandwidth.

(Issue 6) Data access and knowledge dissemination

Non-skilled users (in computer science and databases) should be able to access, query, and retrieve knowledge from the DP. This requires defining a unified user-friendly querying metaphor that also supports spatial and temporal data and provides meaningful visual dashboards for the dissemination of such knowledge.

*Solution***.** Online analytical processing (OLAP) provides user-friendly abstractions for multi-dimensional (e.g., space and time) analytical queries. OLAP is part of the broader category of business intelligence techniques to produce and refine dashboards for business users without technical skills.

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P50 – Assessing the environmental footprint of digital agriculture: research perspectives

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Introduction

There are strong expectations around the mobilisation of digital tools to support the transition to agroecological systems to reduce environmental impacts of food sector. Although agricultural digitalisation is promoted by international institutions, little is known about the impacts of their use on the environment and how to assess them. Digital tools are gradually being introduced into agriculture whether for data collection, data analysis or to support field action [1]. This progressive adoption makes it necessary to assess the environmental impacts of digital agriculture.

Several studies have sought to quantify the positive and negative impacts of digital tools for agriculture on the environment [2–4]. Nevertheless, there is a lack of recommendations on how to properly assess digital tools for agriculture taking into account their specificities.

Objectives

The purpose of this study is to establish a state-of-the-art of the digital tools evaluated and evaluation methods used in order to provide general recommendations and highlight the remaining methodological challenges of the environmental assessment of tools for digital agriculture.

Materials and methods

A systematic review was carried out to establish a state-of-the art of the environmental assessments of digital tools for agriculture.

A query was executed on Web of Science and Scopus databases. This query combined words related to agricultural, environmental assessment and digital field. Only english litterature from journals and conference proceedings were selected. The records obtained by the query were filtered following the PRISMA method [5] with Rayyan software [6]. Some records coming from other sources were added to the pool of records to review.

Current situation of the environmental assessment methods and the digital tools assessed

A total of 56 papers were reviewed. 68% of the papers concerned plant production and 20% livestock farming. Livestock farming is underrepresented likely because the first functions of livestock digital tools are about animal welfare and human wellbeing, not environmental impacts mitigation. 75% of the studies focused on the plot or farm scale, while 11% assessed the implementation of digital tools at the basin, national or global scale. Furthermore, 77% of the digital tools reviewed were used for input management. This could be explained by the historical development of precision agriculture for input management, which can mitigate the environmental impacts of agricultural practices. Another significant aspect of the review is that 30% of the digital tools were related to the firsts steps of the data chain (collecting, transferring, storing and analysing) while only 13% concerned the operating step, i.e. automation tools and robots. These results suggests that there is a need in assessing a more diversified range of digital tools in order to catch a better insight of the environmental footprint of digital agriculture.

The main environmental assessment method observed in the litterature is the Life Cycle Assessment (LCA) [7]. It is a standardised method to quantify the environmental impacts of a tool or a product. LCA concerned 28 records. A main feature of LCA is to identify environmental impacts tranfers between the different stages of a life cycle. LCA is also a multicriteria approach, which puts forward any environmental transfers between the different impact categories (e.g. climate change, acidification, water use...). Due to these specificities, LCA is a promising approach to assess the environmental impacts of digital tools in agriculture. Yet, it is not widely used in the review.

The methodological challenges of LCA applied to digital tools for agriculture

Methodological challenges related to LCA were identified throught the systematic review based on the 28 LCA records. Challenges were sorted according to the four standardised stages of LCA : goal and scope, life cycle inventory (LCI), life cycle impact assessment (LCIA) and interpretation (ISO 14040/44).

The goal and scope step aims at defining the objectives of the study and the system boundaries. During this phase, it is necessary to define a functional unit (FU). The FU quantifies the function of the tool assessed, which serves as a comparative unit between the baseline or "business-as-usual" scenario and the digital scenario. 54% of the study chose a mass-based FU, 14% a surface-based and 7% used both. None of the authors discussed the relevance of the FU chosen given the use of the digital tool, although digital tools have multiple functions like animal and farmer wellbeing, input management, time savings etc. The system boundaries turns out to also challenge the goal and scope step. Only 21% of the studies included in the system boundaries both the impacts of the introduction of a digital tool in the agricultural system and the impacts of the production, use and end-of-life of the tool. These latter impacts must be included in the boudaries because it may overtake any environmental benefits of using this tool.

LCI is the step where necessary data are collected. Given the emerging use of digital tools in agricultural sector and the recent interest in their environmental footprint, data concerning the production, use and end-of-life of digital tools may lack. In that case, proxies should be used to approximate the impacts of the digital tool instead of not taking it into account.

At the LCIA step, it is highly recommended to present all the environmental indicators, called midpoints, that are provided by the impact assessment method. Only 6 papers presented them all. Six other papers used a single midpoint, the climate change. This latter was the favourite midpoint in the review, used by 96% of the studies, while some other midpoint indicators were little used. For example, mineral resource consumption appeared in 32% of the papers, althought digital tools relies on metals and rare earths. Water use and ecotoxicity are hardly assessed (25% of the papers) in spite of the negative consequences of agriculture on these midpoinds.

The last step of LCA is the interpretation of the results. The reliability of the results must be evaluated through incertainty analysis, which was carried out by only 39% of the studies. However, the uncertainties are often high, given that LCI data come frome various sources and must often be approximated. Another challenge is to communicate the results to stakeholders and the public. LCA relies on many indicators. It is thus difficult to say whether a scenario is definitely better to one another. Stakeholders may also like to be informed about the in-site environmental impacts of using a digital tool for agriculture, i.e. impacts induced by direct consumption of resources such as water or direct emissions of polluting substances such as pesticides. To date, no distinction is made when providing results between impacts generated locally and those generated in other territories.

Conclusion

The diversity of digital tools for agriculture have been poorly assessed yet. The current studies focused on tools for input management in crop production. Further research must be carried out to have a better insight into the environmental footprint of digital agriculture in all its forms. Furthermore, guidelines must be provided in order to consider the specificities of digital agriculture in environmental assessment, such as multifunctionality, consistent system boundaries, and helpful indicators for stakeholders.

Acknoledgment

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P51 - On the use of the driver-in-the-loop simulator approach to demonstrate the benefits of precision agriculture

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Introduction

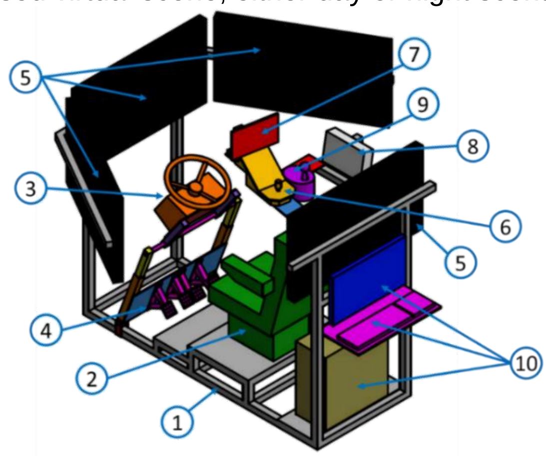
From literature ([1],[2],[3]), it's clearly stated the importance of Precision Agriculture (PA) for future food sustainability and environment protection. Several researches and activities have been carried out to prove and quantify the benefits in adopting PA. Nevertheless, the effort in the attempt to objectify the advantages of this process has a limit in the possibility of performing tests due to (e.g.) field availability, weather conditions, impossibility in repeating in-filed operations close-in-time (due to limitations of fertilizer, pesticide... that can be only once distributed on the same field in a short term). Even if the direction is to bring tractors and implements to a highly automated systems, today human driver plays anyway a key-role. Thus, a driver-in-the-loop simulation platform could be decisive to support farming in providing different scenarios and relevant data aimed to objectify and to quantify the benefits of adopting different levels of PA ([4]). Moreover, compared with field tests, it has the advantages of low cost, high reproducibility, safety, and controllability. The same advantages can be easily recognized thinking about the possibility to use the driver-in-the-loop simulator to train professional farm drivers in performing agricultural operations.

Objectives

The target of this research is to demonstrate that the usage of the proposed simulation platform (AgriSIm©) installed on driver-in-the loop simulator is useful in providing reliable data aimed to objectify the benefits of fertilization with PA criteria. A digital twin of both an existing farm and a real agricultural tractor combined with a fertilizer spreader have been implemented, aimed to realistically replicate in-field operations. The operator has physically driven the virtual tractor into the digital-twin of the farm, replicating the target operations as performed in reality. A comparison between numerical and experimental data have been carried out, to ensure the reliability of the results. Finally, additional investigations have been performed changing several parameters in order to demonstrate the benefits in using the digital platform. Results, in terms of distributed fertilizer, fuel consumption, field capacity have been shown and compared aiming to provide objective information about the advantage of the PA approach.

Materials and methods

A static simulator has been designed and realized. The challenge was to include the real driver in the simulation loop as much as on real operating situations, through dedicated human machine interfaces. The schema is proposed in Figure 4. When possible, real tractor parts have been used to bring the driver to a more realistic driving experience. A real suspended seat, a dual brake pedal system - able to generate yaw torque by operating the single side brakes independently - and a real steering wheel have been installed. Front and rear screens have been installed to guarantee a highly immersed virtual scene; either day or night scenarios can be replicated.



Id	Description
1	Main frame
2	Seat
3	Steering Wheel
4	Pedals
5	Screens
6	Control Platform + Joystick
7	Monitor touch for PA
8	Console
9	Gear lever
10	Host PC + service monitor

Figure 4 Schema of the static simulator with relevant components.

Results

A reference use case has been considered and it has replicated both experimentally and numerically. It includes a tractor vehicle, variable rate fertilizer with 24m width spread, a GNSS sensor and auto-guide, a georeferenced field with a three zones prescription map; the trajectory considered in the reference use-case is parallel to one border of the field, north-south direction and it is followed at 12km/h constant speed. The measured variables were hectares worked, fertilizer distributed, working precision as fertilizer distributed. Numerical results differ less than 8% with respect to experimental data. This ensure the possibility to use the proposed simulation platform to achieve reliable data.

Table 1 proposes some additional numerical investigation to show possible relevant use cases that can be easily investigated thanks to the proposed solution. Different variants with respect to the reference case have been considered. Deviations from target use case have been referred in terms of: (A) total amount of fertilizer, (B) time required to complete the operation and (C) average error in fertilizer distribution.

ID	Reference use case and variants description	(A) Deviation in the total amount of fertilizer [%]	(B) Deviation from duration of operation [%]	(C) Deviation in fertilizer distribution per hectare [%]
#1	Reference - target	1170 [kg] – 0%	1323 [s] – 0%	8.3 [kg/ha]
#2	Constant rate distribution	+6.0%	-2.2%	+378.3%
#3	No precision agriculture	+15.1%	+0.4%	+433.7%
#4	Wider fertilizer	+2.6%	-19.5%	+14.5%
#5	Narrower fertilizer	+0.4%	+27.9%	-37.3%
#6	No section control	+10.4%	-1.7%	+109.6%
#7	Different path	+3.0%	-1.1%	+1.2%
#8	Faster tractor	+1.6%	-29.8%	-6.0%
#9	Slower tractor	+1.5%	+68.5%	+6.0%

Table 1: amount of fertilizer distributed on the field.

Discussion and conclusions

The designed and realized static simulator has been able to emulate in-field significant fertilizing operations. Vehicle and implement dynamics models, together with fertilizer operations logics have been implemented and correlated to experimental evidence. PA simulation suite (AgriSIm©) was used to both quantify and rank results of operations between several variants. Three main relevant indices have been analyzed: the working time saving per day, the waste of fertilizer per day and the operation' quality (waste of fertilizer quantity per hectare), direct related to field's vigor and consequent harvesting quality. The constant rate configuration demonstrated to have the worst operations' quality, while the absence of sections' control resulted in the highest waste of fertilizer distributed per day. The wider the fertilizer, the shorter the operations time (the highest the working time saving per day), but the worse the operations' quality and the higher the amount of waste distributed per day. The numerical analyses demonstrate the possibility to use the proposed simulation platform to objectify and quantify the benefits of PA and to test new operations logics in a repeatable environment, speeding up the development process.

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P52 - Low-cost terrestrial photogrammetry for orchard sidewards 3D reconstruction

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Introduction

Large-scale fruit tree canopy geometric and structural characterisation is of interest in Precision Horticulture to assess spatial variability in fruit tree orchards. Canopy architecture and structure is strongly connected to light interception and tree status and should be considered in management decision making processes. Aerial [1] and terrestrial [2] laser scanning are usual solutions when it comes to 3D canopy characterisation. However, results may be of poor resolution (when aerial) and expensive to be adopted by farmers. UAV-based digital aerial photogrammetry is becoming popular but monitoring tall fruit tree crops (> 3 m) may result in a loss of canopy information such as shape and porosity.

Objectives

The authors present an method to obtain 3D point clouds in orchards based on digital terrestrial photogrammetry (DTP) which consists in using three mobile phone RGB cameras attached to a ground-based vehicle traveling along the orchard alleyways to monitor canopies sidewards. The resulting point cloud will be compared to a LiDAR-based system derived point cloud.

Materials and methods

In order to obtain sufficient image vertical overlap in tall fruit tree orchards (> 3 m tall with 5 m row spacing), a vertical structure was designed to attach 3 mobile phones (Xiaomi Mi Note 10 Lite) at different heights (Figure 1). A mobile app was used to take 64 Mpixel pictures at a 1 Hz frequency of an 8 m long row section (8 trees) using the wide-angle lens option. The creation of the 3D point cloud from the multiple 2D images was carried out by using multi-view Structure-from-Motion (SfM) based on bundle adjustment [3]. To do so, the software Metashape v1.8.5 (Agisoft LLC, St. Petersburg, Russia) was used. The resulting point cloud was scaled and georeferenced in CloudCompare software v2.12.2 (EDF, Paris, France) using a reference point cloud obtained with the bMS3D 4Cam mobile terrestrial laser scanner, MTLS, (Viametris, Laval, France). After registration, the two point clouds were compared using the Cloud-to-Cloud tool which computes the distance of each point of one cloud to the nearest neighboring point of the other cloud.

Figure. 1. Vertical structure with 3 mobile phones (highlighted with circles) at different heights.

Results

Once clipped to the region of interest, the resulting point cloud resembled quite well the scene and had 82 100 975 points (Figure 2) while the MTLS-derived point cloud had 316 375 points. The average difference between both point clouds (only including points of the 8 m long row section and 0.5 m above the ground) was 0.018 m and ranged from 0 m to 0.31 m. The 95 % of the points presented differences smaller than 0.04 m. However, the methodology based on DTP missed some vegetation in top parts and close to the cameras.

Figure. 2. Point cloud created with digital terrestrial photogrammetry with about 82 million points.

Discussion and conclusions

The methodology developed provides with very realistic and accurate point clouds with much more point resolution than the reference MTLS-derived point cloud. However, the system presents some flaws related to the low image acquisition rate as a consequence of high image resolution, the large number of images to process and the overall processing time. The former could be solved by using faster cameras as the mobile phones required too much time to safe 64 Mpixel images, the most suitable for photogrammetry. The last two flaws are an important concern when an entire orchard should be captured. They could be solved with the real-time reconstruction capabilities of some photogrammetry programs. That will be explored in future research. Digital terrestrial photogrammetry has been proved to be accurate enough to monitor orchard canopies and even to detect apple fruits [2]. However, data acquisition in published works to date was done manually. When solving the mentioned flaws, this methodology could be a good alternative to MTLS and UAV digital aerial photogrammetry as it is cheaper and easier to use.

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P53 – Facilitating Economic Analyses of Digital Agriculture: The Role of National Statistical Offices (NSOs) and Data Collection at Scale

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Introduction

The precision agriculture (PA) sector, and the digital agriculture (DA) industry more broadly, has undergone vast change in the past decade [1,2]. Innovations in nearly all technologies, in addition to greater availability and applicability of high-speed internet, have helped to facilitate the ongoing digitalization of agriculture. Precision tools are increasingly able to address concerns about climate change, labor shortages, rising production costs, and growing global food demand [3,4].

Despite these rapid developments, many questions remain about how PA technology use impacts commercial farms' efficiency and profitability. Though considerable evidence exists in the economics literature for the United States [5,6,7], less is known about the impacts of these technologies in European countries [8]. Such open questions could be addressed, in part, through improved collection of detailed, coordinated, and harmonised data by Europe's national statistical offices (NSOs).

Objectives

The objective of this research is two-fold. First, the study provides an illustrative overview of farm-level data collection underlying PA technology adoption estimates from NSOs within the EU-27 and the United Kingdom (UK). Second, this study details trends in adoption using information from the set of European NSOs that collect relevant data.

Materials and methods

Website data were collected for sets of PA technologies adopted by individuals for use on farms or related agricultural businesses from each country's NSO(s). In most instances, the relevant NSO is the main statistical agency within the country's federal government tasked with performing major national surveys (e.g., household censuses, manufacturer surveys). However, the relevant NSOs in some European countries are national agriculture agencies.

Given that the focus is on national data collection for a mid-sized set of countries (i.e., the 28 nations comprising the EU-27 and UK), there were few pre-specified limits underlying the study's inclusion criteria. That is, to avoid potential bias, national estimates were not excluded based on: 1) specific unit of observation (e.g., field, farm, farm household, agricultural business), 2) sectoral aggregation (e.g., farming only vs. agriculture, forestry, and fishing (AFF)), or 3) perceived digital sophistication of the PA technologies. Rather, the approach was designed to be as broadly representative of European, government-conducted PA data collection efforts as possible, while focusing mainly on advanced technologies to assist site-specific agricultural management [2,4,10].

Results

Few European NSOs collect large-scale, representative data on PA use (Table 1). Notable exceptions include Denmark, Estonia, France, Hungary, Portugal, and the UK (specifically England), though the data are not harmonised regarding coverage levels and technology categories.

Table 1. Precision agriculture data by national statistcal offices (NSOs)

Country	NSO	Years	Sample technologies
Denmark	Statistics Danmark	2018-22	UAVs, guidance, sensors
Estonia	Statistics Estonia	2014-22	Robots, data analyses
France	Agreste, Ministry of Agriculture, Agrifood, and Forestry	2021	Guidance, VRT, maps
Hungary	Hungarian Central Statistics Office	2020	Robots, guidance, UAVs
Portugal	National Statistics Institute	2019	Sensors, VRT, maps
UK	Department for Environmental, Food, and Rural Affairs	2011-21	Nutrient tests, VRT, maps

Source: Author's synthesis of data from NSOs' websites

For England, across 2009, 2012, and 2019, the fraction of farms using yield maps increased from 7% to 17%; soil map adoption increased from 14% to 29%; adoption of variable rate technologies (VRT) rose from 13% to 25%; and remote sensing use increased from 1% to 10%.

Moreover, between 2009 and 2012, global positioning systems (GPS) use increased from 14% to 22% of farms, while controlled traffic farming was 8% in 2019.

In Denmark, across years 2018-2022, use of tractors/harvesters with RTK-GPS increased from 20% to 24% of farms; automatic section control increased from 14% to 23%; software to plan/document nitrogen needs rose from 6% to 9%; satellite/drone imagery increased from 5% to 8%; and use of crop sensors on equipment—2% of farms—was unchanged.

In Estonia, surveys of firms within the AFF sector indicate that use of a broad mix of technologies has been increasing since 2014. In 2022, use of industrial and/or service robots stood at 13% of AFF firms. Between 2016 and 2019, analysis of own big data from smart devices/sensors rose from 2% to 5%, though analysis of geolocation data from portable devices was relatively unchanged at 6% of firms. Purchase of cloud computing services rose from 2% in 2014 to 67% in 2020.

In France, the 2021 data are not yet available. However, adoption rate estimates are forthcoming for the following technologies: guidance systems, VRT, precision weed control, remote sensing, sensors, soil mapping, high-precision GPS use, and disease risk modeling tools.

For Hungary, 2020 data indicate the following adoption rates, in units of percent of farms: drones (8%), robots (4%), precision feeding (12%), plant condition surveys (29%), environmental sensors (17%), automated steering (18%), yield mapping (14%), and decision support sofware (13%).

In Poland, similar data collection efforts in 2019 suggest the following adoption rates, in units of percent of utilized agricultural area: georeferenced farm data (4%), soil moisture sensors (4%), VRT (2%), NDVI charts/vegetation indices (2%), soil electrical conductivity charts (1%), and productivity charts for annual crops (1%).

Discussion and conclusions

Other countries, such as the Netherlands, have made strides in collaborative efforts with the private sector to obtain data from farmers' equipment, though these remain "experimental" in nature. The evidence suggests national data collection efforts fundamentally differ by: 1) year of first technology survey (never, early, middle, late), 2) collection mode (traditional vs. public-private collaboration), and 3) technology focus (machinery and equipment vs. digital and/or cloud-based). Cost, authority, respondent burden, and lack of subject matter expertise could be some of the main barriers NSOs face in their agricultural PA data collection efforts. However, these data gaps will narrow in 2023—the first year of EU-wide, harmonised data collection on precision farming under Regulation (EU) 2021/2286, presenting important opportunities for new economic analyses.

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P54 - Data fusion for the decision-making process for a digitized experimental farm in Hungary

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Introduction

Site-specific management of an experimental farm requires several input data such as soil parameters, yield data from earlier years, or in-season plant nutrition status data fused with remotely sensed data [1]. For management zone delineation historical yield data as well as remotely sensed images are available however, in practice, soil data plays an important role in the decision-making process [2] for variable rate applications such as variable rate seeding (VRS) or variable rate top dressing fertilization. Other than that many factors affect the yield rate of corn such as sowing date, fertilization treatments, hybrid, etc. [3]. Depending on the data availability and earlier variable rate application (VRA) management zones can slightly differ from year to year. Every year differs in available data as yield is measured and data is collected throughout the season. This paper reports the decision-making process of one experimental farm located in the Northwestern part of Hungary.

Objectives

In the on-farm experimental fields precision agriculture (PA) technologies applied for more than 10 years, so not only satellite images, but field measurements – such as yield data – are available for more than a decade. Experiments in zone delineation by apparent soil electrical conductivity measurement as well as including information derived from satellite-based images were carried out in the earlier years, however, they were applied only for some designated fields, not for the full farm. In 2022 the owner of the farm decided to rethink the management of the decision-making process and carried out site-specific, zone-delineation-based soil sampling for the full farm, in order to include the soil data into the decision-making process. In this study, the process of data flow and decision-making is introduced with one chosen field from the experimental farm.

Materials and methods

In 2022 corn (Zea Mays L.) was grown in about 250ha in the experimental farm. On the described field named "Kurcsi12", forecrop in the 2021 season was also corn however, no site-specific practice was applied. Management zone delineation was carried out on a multi-layer-based data fusion, where a time series of remotely sensed images collected by Sentinel-2 satellite and earlier yield map (2021) data was used. Three different management zones were detected: low, medium, and high potential zones. Based on the defined management zones, soil samples were collected and analyzed. For variable rate seeding, the field was divided into three management zones: (i) 66, (ii) 70, and (iii) 75 thousand seeds per hectare for low, middle, and high potential management zones, respectively. Seeding was carried out with a John Deere 1775NT ExactEmerge seeding machine. For top dressing variable rate carbamide application was planned however, the application failed, and therefore uniform 150 kg carbamide was applied. The season was extremely dry, precipitation was very low during the growing season, therefore very low yield was expected. In October yield data was collected to create a yield map.

Results

Data analysis showed that the success rate for the seeding was high (Table 1), in each management zone the realized seeding rate difference was lower than 1000. Yield in low potential areas - 66 000 s/ha - yield was extremely low – 1.87 and 2.23 t/ha in management zone 2 and 4, in middle potential areas - 70 000 s/ha - 2.15 t/ha (management zone 1), well below the economic return of investment. In the high potential areas large difference was experienced: in a smaller zone (Management Zone 3) 2.81 t/ha yield, and in a larger zone (management zone 5), 6.29 t/ha yield was measured. Overall, the field average was 4,1 t/ha, which is 4 to 6 t/ha lower than the average yield in not dry conditions.

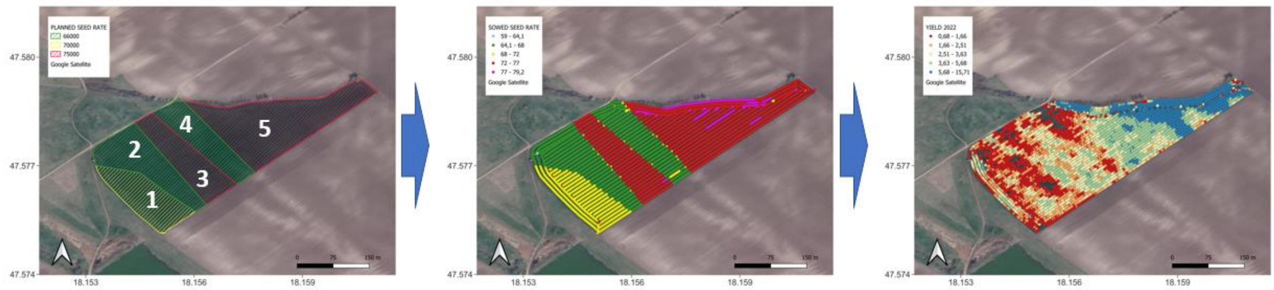
Table 1. VRS rate applications and yields in the experimental management zones

Management Zone	Seed rate (planned)	Seed rate (realized)	Yield (t/ha)
1	70000	70444	2.15
2	66000	66643	1.87
3	75000	75642	2.81
4	66000	66733	2.23
5	75000	75780	6.29
Totals	70000	72000	4,10

Source: author’s data

The yield difference between management zone 3 (2.81 t/ha) and management zone 5 (6.29 t/ha) was due to the geographical position of the management zones. Zone 3 is located on the top of the local hill, while Zone 5 is on a slope facing to the north, therefore drought did not affect Zone 5 as much as Zone 3.

Figure 1. Planned and realized seed rate map, and yield map of the experimental field



Source: author’s data

Discussion and conclusions

Data fusion in the experimental farm increased the productivity of plant production by lowering the applied seed rate in the farm average. Due to the failure of the top dressing equipment VR head fertilizing was carried out with a uniform 150 kg/ha, therefore differences in the supply of fertilizer rate could not compensate for the different seed rates during the growing season. Extreme dry conditions hit the area during the growing season, therefore field average yield was 4-6 t/ha lower than the long-term average. In the 2023 growing season, the farmer/owner of the field expects a similar dry year and lowered the seed rate from a farm average of 72000 to 70000.

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P55 - Development of depth-of-tillage control system with data linkage

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Introduction

In the Web 2.0 world, a business model has been established in which farmers can upload field observation data to a cloud service and download recommended work plans for harvesting, fertilizing, and other operations based on estimated models. However, as a practical matter, it is difficult to explain the characteristics of each field with a single parameter (Ostergaard, 1997)[1]. In this study, a feasibility study was conducted to develop a variable tillage depth navigation system based on soil depth data in paddy fields by linking soil depth data at planting and drive harrow height data, which represent tillage depth in paddy fields, and mapping each of them to examine their availability.

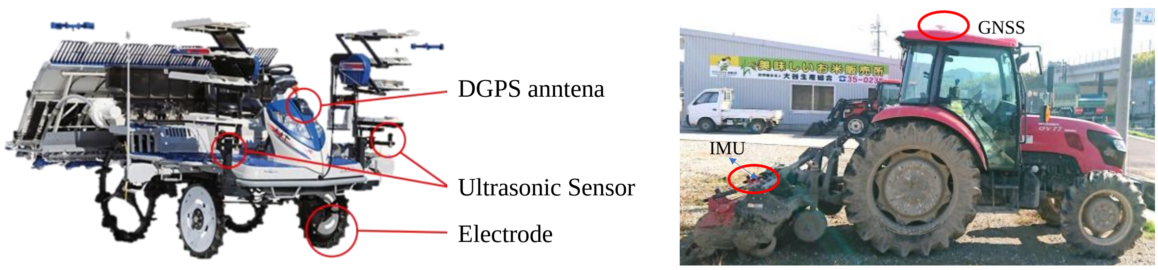
Objectives

The objectives of this study were (1) to estimate drive harrow height using an inertial measurement unit (IMU) and (2) to develop a method to verify the usefulness of drive harrow height control based on topsoil depth information from the follow ing year's soil depth data when applying soil depth obtained at rice planting as a control parameter.

Materials and methods

An ultrasonic sensor (UM30-213113, SICK) was mounted on the smart rice transplanter (PRJ8, ISEKI) tested as shown in Figure 1 to measure soil depth. Basic tests to apply the inclination sensor to depth-of-tillage estimation were conducted under the following conditions. A test tractor (GV77, Mitsubishi Mahindra Agricultural Machinery) and a drive harrow (TXV415, Kobashi Kogyo) were used, and a GNSS antenna (ANN-MB-00, u-blox) connected to a GNSS module (ZED-F9P, u-blox) was installed on the tractor's roof to measure latitude and longitude at 4 Hz. An IMU (WT901BLECL, WitMotion) was installed on top of the drive halo frame to acquire data at 2 Hz. Since the working widths of the rice transplanter and tractor are different, the information on soil depth and drive harrow angle obtained from the test plots cannot be simply compared. Therefore, the test plots were divided into a 2m x 2m mesh, and a grid map was created using location information. The grid value was the average of the sensor data within the grid. In the process of creating the grid map, there are grids that contain no data within the grid. Mean replacement, regression analysis, and other methods are often used to supplement these missing values (Kotsiantis et al., 2006)[2]. In this study, mean value replacement, which stores the mean value of the surrounding 8 grids in the missing values, was applied. When missing values were adjacent to each other, the mean value of the surrounding grid excluding that grid was entered, and when all surrounding values were missing, no completion was performed. On farm experiment, the Ohtani agricultural cooperative in Tottori Prefecture (N134.299927, E35.569264) in 2021 and 2022 A drive harrow height control test was conducted in rice paddies (1.4 ha). Tillage depth adjustment was manually controlled by the operator by applying the soil depth map created by the smart rice transplanter in 2021 and checking the current position and soil depth as if using a car navigation system. Tillage depth adjustment was set at two levels: 0.13 m when the soil depth was below the average value and 0.05 m when the soil depth was above the average value.

Figure 1. Smart rice transplanter and Tractor with drive harrow and IMU



Results

In the first year, topsoil depth was measured using a smart rice transplanter and 3411 data points were obtained to represent spatial variability, which revealed that the topsoil depth in the center of the field was relatively greater, with maximum, minimum, and average values of 0.33, 0.13, and 0.21 m, respectively, for soil depth. In the second year, variable depth adjustments during tillage based on the soil depth map indicated that the maximum, minimum, and average estimated tillage depths were 0.28, 0.11, and 0.21 m, respectively. Next, a grid map of topsoil depth was created in the second year and compared to the first year, with results suggesting a decrease in the variability between the deep and shallow layers as shown in Figure 2. Numerical evaluation confirmed the trend shown in Figure 3 between the depth of topsoil in the first year and the amount of change in the second year, with a correlation of coefficient of determination R2 = 0.53. The slope of the approximate curve showed that the sites with greater than average topsoil depth in the previous year tended to become shallower in the following year, and the standard deviation improved from 3.3 cm to 2.2 cm, suggesting that variable tillage was effective.

Figure 2. Topsoil depth in 1st year (right), variable rate tillage control in the 2nd year (center) and topsoil depth in the 2nd year (left) distributions of grid map at Ohtani Farm

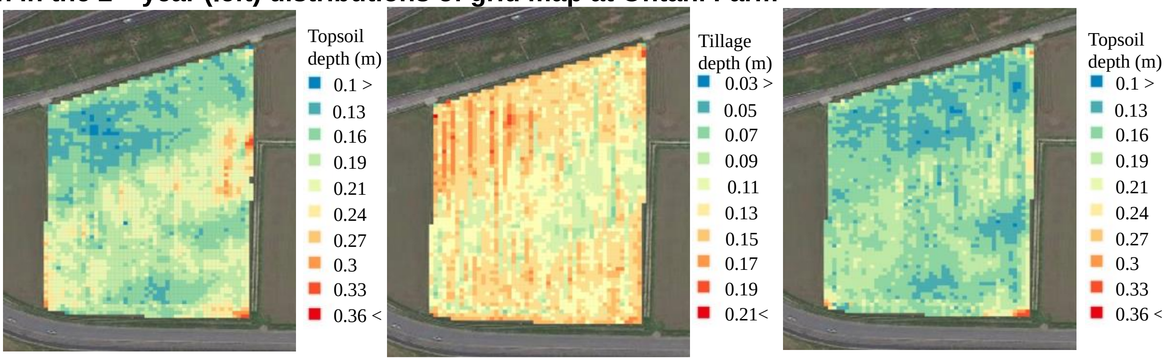
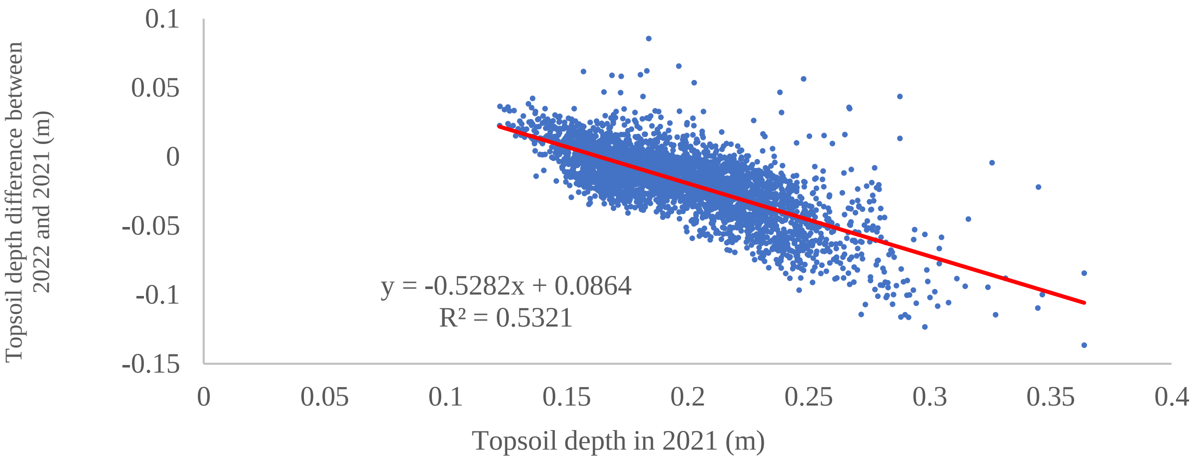


Figure. 3 Numerical evaluation confirmed the trend shown in Figure 4 between the depth of topsoil in the first year and the amount of change in the second year



Discussion and conclusions

This study discusses the possibility of improving the field through data interoperation between different farm machines applied to variable tillage of tractors, based on a grid map of soil depth of rice transplanters. Results: Variable tillage control based on soil depth maps improved soil depth variability by 30%. This is the first successful case of data interoperation between rice transplanters and tractors in Japan.

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P56 - Data to Decisions: Efficient Implementation of Eco- Schemes, a Use Case for AI in Agriculture

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Introduction

The Common Agricultural Policy (CAP) introduced new rules regarding subsidies for agriculture in the EU in January 2023. One of the new features are the so-called eco-schemes. Eco-schemes are climate and environmental protection measures that go beyond the minimum requirements set by conditionality and can be voluntarily implemented by farmers. In return for implementing such measures, farmers receive compensation payments. For example, they can take parts of their arable land out of production or sow flowering strips [1,2]. Farmers are thus faced with the challenge of deciding which eco-schemes they can implement efficiently, i.e. without financial disadvantages, on their fields. Farmers typically make such decisions by drawing on their extensive experience in managing their fields, as well as through field-level assessments. However, this approach does not ensure the identification of all field segments that are potentially suitable for implementing eco-schemes. To support the decision-making process, a long-term, site-specific economic analysis of production data is necessary to identify sub-areas with below-average productivity and/ or high production costs.

Objectives

The main goal of this project is to develop a prototype of a web-based decision support system for farmers. Fortunately, modern agricultural machines are equipped with sensors that collect site-specific data in large quantities. Thus, the necessary data are available for development. However, given the large amounts of data involved, a high degree of automation is necessary for analyzing this data. Additionally, the application of traditional data processing methods, such as filtering of raw data or interpolation, requires expertise in parameterization. AI algorithms could provide a solution, making it easier to automate data analysis without making static assumptions. Yield data collected by yield monitoring systems of combine harvesters are of high importance in this context as they describe the productivity of the field. Therefore, in the first phase of this project, multiple AI algorithms for filtering and interpolating yield data are tested and compared with traditional methods.

Methodological Approach

To train the AI models, multi-year yield data (up to 5 years, approx. 105 hectares) and the corresponding field boundaries of two farms from northern Germany were acquired. The decision support system consists of four modules. The user interface and database will allow for the import of field boundaries and yield data from yield monitoring systems of combine harvesters in ISOXML or Shape file formats. The imported and processed data should than be visualized within the interface, and a zone map can be exported for the spatially optimized arrangement of selected eco-schemes.

Raw data from combine harvester yield monitoring systems are prone to errors, which effects the accuracy of yield maps. Various random and systematic sources of errors as well as diverse methods for error-specific data filtering have been extensively described in the literature [3–8]. Typically, multiple of these specific filtering methods are combined and applied. The majority of these methods require parameterization, for example, upper and lower yield thresholds or the multiple of the standard deviation for filtering need to be set. Subsequently, the result of the filtering must be inspected by the user, and the parameterization adjusted if necessary. This requires expertise and entails a significant amount of time. Thus, these methods are only suitable to a limited extent for the automated filtering of large amounts of yield datasets. In order to address the limitations and inconveniences, various ML/AI algorithms are being experimented with. Currently, DBSCAN is being tested for unsupervised noise detection, while a comprehensive algorithm evaluation for supervised learning approaches is underway. In order to obtain clean data for supervised learning, the raw data has been filtered by an expert using conventional methods.

After filtering the yield data, an interpolation method must be applied to create the yield maps. Kriging is commonly used for this purpose. However, due to the need for parameterization (Lag spacing, limiting distance), this method is also only suitable to a limited extent for automation. Several AI algorithms, such as Deep Neural Networks, Random Forest, and Support Vector Machine, have already been successfully tested for the interpolation of spatial data [9–12]. The methods described by Chen et al. [9] and Hengl et al. [10] are adapted and tested for the decision support system, and the results are compared with those of a Kriging interpolation.

Based on the yield maps, the site-specific contribution margin calculation is carried out. By comparing the contribution margins with the compensation payments for eco-schemes, the site-specific cultivation recommendations are derived and output as a zone map via the user interface.

Conclusion and Outlook

The development of a web-based decision support system for farmers provides a solution to identify sub-areas with below-average productivity and high production costs. AI algorithms facilitate the automated filtering and interpolation of yield data, enabling efficient eco-scheme implementation on farmlands. This system will promote maximum environmental protection while ensuring financial benefits for farmers, making it an important tool for sustainable agriculture. For future development stages, additional modules are planned. Variable rate applications for fertilization and seeding should be taken into account in the cost structures. Furthermore, it is planned to introduce a module that optimizes the geometry of the zones on which eco-schemes are implemented to adapt to the main working direction and lanes of the field, in order to minimize turnaround times and overlapping zones.

Acknowledgements

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P57 - Low-cost 3D modelling of crop-weed interactions

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Introduction

New sensors and phenotyping techniques have improved plant characterization through 3D modelling. 3D imaging systems can be used to measure plant architecture, plant tags can be used to capture the exact shape of a plant, and even computer vision and machine learning algorithms can be employed to create geometric models of plants from images. These approaches provide valuable insight of plant characteristics and phenology, which if properly managed could improve crop performance and yield.

Light Detection and Ranging (LiDAR) is the most common sensor for 3D imaging. Depth cameras (RGB-D), such as the Kinect v2, are low-cost alternatives frequently used for plant characterization. Additionally, RGB-D cameras capture both color and depth information, enabling a more detailed analysis. Weed infestation detection is possible using RGB-D, performing similarly to expensive laser scanners [1]. Algorithms were developed to reconstruct plant models, extract plant height, leaf area, and shape using a combination of cameras and Structure from Motion (SfM) techniques [2]. This method produces a sparse set of points in 3D and estimates the common position of the cameras and the set of points. This dense cloud was then processed with a 3D reconstruction algorithm to generate a 3D model of the weed plants.

Objectives

The objective of this study was to explore the capabilities and limitations of Kinect v2 and photogrametry of high resolution RGB images to extract physical parameters of weed species, comparing with manual measured plant parameters. For this purpose, multple SfM were combined with MVS techniques and RGB-D systems to characterize weed plants among crop plants.

Materials and methods

The study was implemented on a commercial maize field in Arganda del Rey, Madrid, Central Spain. Three weed species were chosen for image processing: *D. ferox*, *X. strumarium*, and *S. halepense*. The purpose was to observe the contrast in shape and plant structure between the three species; these weeds were chosen for their potential to cause economic losses in maize. Image acquisition was conducted during May 2022 at maize growth stage 14 (BBCH scale) while weeds ranged from BBCH 12 to 20. Weed heights ranged from 6 to 30 cm, and samples were chosen to represent different stages of the weeds. Ten samples per weed species were monitored. The monitoring plan aimed at providing data define weed management strategies. 3D Plant reconstruction was completed with SfM of an input set of images, taken from two different oblique angles in a concentric track around the plant axis. Two rounds of images were taken, ensuring a minimum of 90% overlap between images (30 to 50 images, depending on plant size), required for a detailed and accurate plant reconstruction. A plant was placed in the center of a triangle formed by three 10 cm graphic scales located on the ground. Camera positions were then not predefined, and variations were corrected by the SfM algorithm. Images were taken from different angles and heights to ensure a full coverage.

A system based on a Microsoft Kinect® v2 RGB-D sensor was also evaluated. The sensor has a 1080p RGB camera, an infrared (IR) camera and several microphones. The distance calculation is based on the time-of-flight (ToF) principle. The distance is calculated simultaneously for each captured pixel of the scene. This new Kinect model can automatically adapt the exposure time of the RGB sensor, thus generating brighter images than the previous version. The RGB has a resolution of 1920×1080 pixels, while the IR camera resolution is 512x424 pixels. The IR camera sensor has a field of view of 70° horizontally and 60° vertically for depth information, and can capture information from 0.5 m to 4.5 m (0.5 ft to 15 ft). The frame rate of the 3D scanning system can be adjusted up to 30 frames per second (fps), ensuring that the overlap between images is sufficient for reconstruction processes. Image acquisition was similar to the previous method, using a concentric path. A reconstruction software was used to fuse the different consecutive and overlapping depth images, creating a 3D model from the scan. Using the cylinder method, manual measurements were taken on each individual plant. The maximum height of each plant was then calculated from the base of the stem to the end of the main stem. This measurement indicates the maximum height of the stem. The data collected from these measurements was then used to determine the average height of the plants in the sample.

Results and discussion

The 3D reconstruction systems created different weed models (Figure 1). The models in all cases were very similar to reality with small errors that were slightly different between the Kinect-based models and those created by photogrammetry. Although in all cases errors appeared at the end of the leaf and branch edges, the Kinect v2 measurements were more inaccurate than those of photogrammetry. Although the last final details were not correctly reconstructed, the reconstruction showed high fidelity.

The interaction between weeds and crop was also characterized by a height-based protocol within the 3D models. Parameters measured using the modeling systems showed a high correlation with ground truth data. Although the overall values were similar between both 3D methods, small differences emerged when the sampled crop was analyzed independently. These small differences may be due to manual camera movement and hidden areas during scanning. Therefore, the final detail can be improved by increasing the sample size or reducing the distance from the camera to the target plant.

Figure 1. Different examples of plants reconstructed from different viewing angles using Kinect-based systems (top) and photogrammetry (bottom)

Source: authors' data

Conclusions

The results demonstrated the feasibility of using low-cost tools to reconstruct weed plants, with good accuracy and high resolution. This work is an important step forward in using low-cost depth cameras to reconstruct plants in real-time with easy-to-handle budget hardware.

Acknowledgements

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P58 - Farmwissen an innovative concept and platform for competence enhancement in Smart Farming

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Introduction

Today's agriculture has plenty of digital technologies at its disposal. But how does the farmer know which application or technology is the right one for him and his farm?

In Germany, the Federal Ministry of Food and Agriculture (BMEL) funds projects that help to research digital technologies and test their practicality; these are called experimental trial fields. The focus is on knowledge transfer, i.e. putting the acquired knowledge into practice and building up competencies. Two of these projects, the project "Farm Management and Material Flow Management - Networked Agriculture in Schleswig-Holstein" (BeSt-SH) and "Experimentierfeld Südwest" (EF-Südwest) have taken this as an opportunity to bundle the knowledge and competences of all projects and make them available on the central, freely accessible platform "FarmWissen" on www.farmwissen.de (translates FarmKnowledge). Because if we take a closer look at digitisation in agriculture, it quickly becomes clear that some challenges to the successful establishment of a new technology inhibit its use [1].

The basic idea of FarmWissen is to bundle knowledge about established and future-oriented digital applications and technologies and to present them in a way that is easy to understand. The benefit of such a knowledge transfer strategy lies in the possibility of individual farm-specific knowledge transfer, independent of time and place. The content on digitalisation in the agricultural sector should also play a decisive role in vocational, technical and higher education as well as in training and further education.

The components of FarmWissen consist of practical examples, which include detailed step-by-step instructions with a detailed list of ingredients, similar to a recipe for cooking, a FarmWiki, in which a detailed explanation of the individual ingredients of the practical examples or recipes takes place, and complicated preparatory work for individual examples is explained with images and video material in detailed tutorials.

Concept and competence enhancement thru FarmWissen

The FarmWissen strategy is made up of different components. The practical examples, the FarmWiki, the OpenDataFarm and edu@FarmWissen have different focal points in knowledge transfer. The focus is on informing, demonstrating and qualifying users.

The idea behind FarmWissen is to bundle knowledge about digital technologies in agriculture and present it in a comprehensible way; this has given rise to the concept of a "recept platform". Here, findings from practice, extension, trials and manufacturer presentations are used as a basis for developing concepts, explanations and examples on specialist topics relating to digitalisation in agriculture. The target group here is the practitioners themselves, but the content can also be used in further education and teaching to impart knowledge. The so-called practical examples have emerged from this idea. These function as "recipes" for solving practical problems on farms. Thus, the focus is not on the technology used, but on the benefits behind it. As with a recipe, the necessary ingredients are listed within the practical examples. It is precisely listed which data, which technology and which application are used and, above all, which skills the practitioner needs to implement this example on his farm. This is followed by step-by-step instructions on how to use the digital technology.

In addition to the practical examples, the FarmWiki consists of a glossary and tutorials. The glossary explains technical terms related to digitisation in agriculture. These terms were written on the basis of scientific sources and go through a correction process so that technical accuracy is guaranteed. The amounts are linked to the practical examples, so that one immediately receives a practical example for interesting terms. The tutorials serve to explain preliminary work within the practical examples; these can take the form of instructions or a video. In order to make the knowledge visually experienceable, the concept of the OpenDataFarm was developed in a further step.

The core objective of the digital farm "OpenDataFarm" is to build up the Hofgut Neumühle teaching and experimental farm (LVAV) as a 3D model and to back it up with real data, thus capturing and dynamically demonstrating the operational data and material flows from a wide variety of data sources. This type of visual information and data preparation establishes an understanding of the data and data flows that occur on a farm.

Another important point is to bring the generated knowledge about digital techniques in agriculture into practice. One strategy is to start with this directly in vocational and technical schools. This is where edu@FarmWissen comes in. A concept has been developed that prepares the contents of the platform in a didactic way for vocational and technical schools and converts it into a curriculum.

These individual modules can be integrated into edu@Farmwissen for competence-oriented teaching to provide early competence development in digital agriculture [2].

Figure 1. Structure and Modules on FarmWissen

Outlook

FarmWissen has already become an overall concept for all digital experimental trial fields. The project is clearly pursuing the platform idea. The open community of the experimental trial fields is the beginning of a success story for FarmWissen. Through the successful cooperation, a basic concept has emerged and the foundation for further cooperative approaches has been laid. From this point of view, new collaborations can emerge in the future. In order to answer as many practical questions as possible on FarmWissen, there is also an openness towards third-party providers. In addition, FarmWissen will continue to develop. At the moment, the content is only available in German. A filter and search function is already being developed in order to find solutions to individual questions more quickly. In addition, a live format for FarmWissen is conceivable, so that experts from extension, science and practice can exchange views on certain specialised topics. Another idea is workshops for the users of the platform, so that the practical examples can also be used as practical exercises and detailed questions can be clarified in direct exchange.

Acknowledgements

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P59 - Site-Specific Yield Prediction of Red Fescue (*Festuca rubra* L.)

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Introduction

Yield mapping is an essential component of precision agriculture. Yield maps give farmers information about growth conditions and can be a tool for site-specific crop management. Although combine harvesters can provide farmers with detailed yield maps for cereals, they are generally unable to do so for grass seeds due to the low weight of the intake, which makes it difficult to detect variations in yield. Therefore, we suggest a method to create grass seed yield maps based on drone imagery and local regression models.

Objectives

This study aims to evaluate whether it is possible to predict yield in red fescue (*Festuca rubra* L.) based on regression models using crop yield from plots with extreme yields and Vegetation Indices (VI) from drone RGB imagery in specific fields. It is hypothesized that an increasing number of plots used for training increases the predictive power.

Materials and methods

We studied seed yield variation in two red fescue (*Festuca rubra*) fields with variation in soil fertility and management, respectively. We estimated five vegetation indices (VI) based on RGB drone images to describe yield variation, and trained prediction models based on relatively few harvested plots. The plots were 1.5 × 12 m. In 2018, 10, 20, and 48 plots were used to train a regression model and in 2020, 6 and 10 plots were used for training. Only results from the VI showing the strongest correlation between index and yield are presented (Normalized Excess Green Index (ExG) and Normalized Green/Red Difference Index (NGRDI)).

Results

In 2018, the average yield was 1548 kg ha^{-1} with a standard deviation of 209 kg, and in 2020 the average yield was 1160 kg ha^{-1} with a standard deviation of 260 kg. Hence, the absolute and relative crop yield variation was larger in 2020.

ExG correlated slightly better with yield than NGRDI in 2018, whereas it was the opposite in 2020. When half of the plots were used for training (48 plots in 2018 and 10 plots in 2020), the correlation coefficients were 0.71 for ExG (Table 1) and 0.69 for NGRDI in 2018. In 2020, the correlation coefficients were 0.77 for ExG and 0.80 for NGRDI (Table 1).

The timing of the UAV image capture was unimportant in 2020 in weeks before harvest. The correlation between NGRDI and yield was 0.49 ($P < 0.05$), 0.68 ($P < 0.001$), 0.76 ($P < 0.001$), 0.79 ($P < 0.001$) and 0.77 ($P < 0.001$) on 3 March, 13 May, 24 May, 24 June, and 17 July, respectively. The results did not support the hypothesis that the yield prediction accuracy was increased by using an increasing number of training plots. This was found when training was carried out on systematically selected plots (extreme values) (Table 1) and randomly selected plots (not shown) [1].

In both years, parameters in the regression models based on extreme values were not statistically affected by the size of training data sets, which means that RMSE for predictions were almost unaffected by the size of the training data sets (Table 1). A large training set means that the regression model was tested on medium yields only. The opposite trend appeared in 2020, where the largest RMSE were for the extreme yields (Table 1).

Table 1. Correlation between vegetation indices (VI) and yield in training data sets and yield predictions for the remaining part of data sets. Selection of data from extremes.

Year VI	Training				Yield prediction for remaining data set	
	Number of plots used for training	Correlation coefficient[1]	RMSE[2] (kg ha^{-1})	RMSE (%)	RMSE (kg ha^{-1})	RMSE (%)
2018 ExG	10	0.76*	178	11.5	171	11.1
	20	0.81***	193	12.5	184	12.5
	48	0.71***	145	9.4	192	12.4
2020 NGRDI	6	0.84*	118	10.2	231	20.0
	10	0.80**	182	15.7	222	19.1

Source: [1]

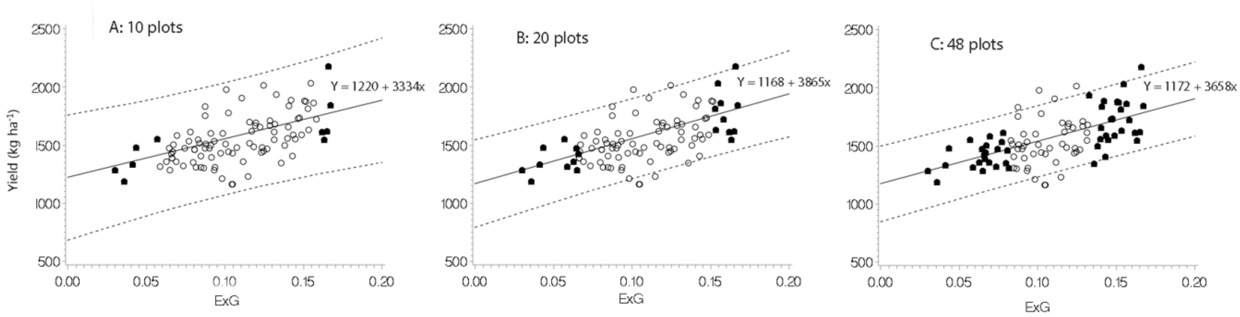

Figure 1. Linear regression models (solid line) with prediction intervals (dotted lines) for specific VI values based on an increasing number of plots in 2018. The model in A is based on 10 plots, B is based on 20 plots and C is based on 24 plots. Plots used in regression analyzes are denoted with dots and validation plots are denoted with open circles. The selection of training data was based on extreme ExG values (From Andreasen et al., 2023).

Discussion and conclusions

The study indicates that it is possible to predict the yield variation in a grass field based on relatively few harvested plots, provided the plots represent contrasting yield levels. The prediction errors in yield (RMSE) ranged from 171 kg ha^{-1} to 231 kg ha^{-1}, with no clear influence of the size of the training data set. Using random selection of plots instead of selecting plots representing contrasting yield levels resulted in a slightly better yield prediction when evaluated on an average of ten random selections of plots. However, using random selection came with a risk of poor prediction due to the occasional lack of correlation between yield and VI. The exact timing of unmanned aerial vehicles (UAVs) image capture showed to be unimportant in the weeks before harvest

Acknowledgements

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P60 – Yield and texture based management zones in a heterogeneous Old Morainic landscape

Bönecke E [1], Schröter I [2], Meyer S [3], Kling C [2], Vogel S [4], Post S [2], Kramer E [2], Rühlmann J [1]

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Introduction (For the section titles, please use the style "Title 2".)

While economic and environmental pressures still increase rapidly on farming, site-specific crop and soil management provides efficient and cost-effective methods by delineating sub-field productivity zones - so-called management zones (MZ). To apply inputs, common approaches determine the MZ through decreasing variability of a single site condition solely that represents either the nutrient storage potential or the nutrient withdrawal potential. However, MZs should be determined on a combination of both.

The measurement of above ground biomass is a crucial factor in determining crop yields or net primary productivity. In recent times, there has been a growing interest in utilizing vegetation indices instead of productivity maps. The NDVI (Normalized Difference Vegetation Index), which is calculated from satellite imagery [1], has gained widespread use globally due to its strong correlation with crop productivity [2,3]. Moreover, high-resolution satellite images can be obtained inexpensively, enabling the mapping of large areas with minimal investments.

In practice, farmers often use class based soil texture systems in order to determine fertilizer amounts. As was shown by [4,5], the soil clay, silt and sand content can now be determined very accurately and with a high degree of spatial accuracy using on-the-go soil sensors and digital soil mapping techniques. However, when using class-based systems with these highly accurate input data for fertilizer determination, much of the input information is lost because the classes of this system are rather coarse. To consider the clay, silt and sand content equally, this study uses, moreover, the mean particle size diameter (MPD) according to [6] and applied by [7].

Objectives

Therefore, this study tests the delineation of soil MZs based on a combination of soil texture (as for the storage potential) and relative yields (as for the nutrient withdrawal) on a 62 ha field in a heterogeneous old morainic landscape in northeast Germany.

Materials and methods

Level-2A data of Sentinel-2/MSI (10m resolution) of the study area and for the harvest periods of the years 2016 to 2020 were obtained and NDVI values calculated from the reflectance in band 4 (red; center wavelength: 665 nm; bandwidth: 30 nm) and band 8 (NIR; 842 nm; 115 nm) after excluding cloud pixels. NDVIs were averaged over the observation period and expressed as relative yields with a mean yield set as 100. Clay, silt and sand content maps were derived from combining spatially high-resolution soil electrical resistivity and gamma data and point reference samples as described by [4,5] and the MPD derived [6,7]. Management zones were obtained by applying fuzzy k-mean clustering on the MPD and relative yield maps of 2x2 m resolution. The number of cluster zones were set fix to 6.

As the soil pH is a central element in soil fertility and therefore an indicator for nutrient availability, MZs determined in this study were evaluated by the variability (variance, coefficient of variation CV%) of the soil pH from a calibrated pH sensor map. The pH map was generated using a mobile in-situ pH soil sensor before the crop cycle.

Results

Both maps (MPD and relative yields) showed similar spatial patterns. In the centre of the field, lower MPD values indicate a higher clay content while higher MPDs to the field border indicate higher silt and sand contents. Relative yields were highest in the field centre, but lower in the south and the northeast. Correlation between MPD and relative yields was lower than 0.65 (Fig.1).

The clustering showed MZ in accordance with the both co-variates with zones of lower MPDs and higher yields in the field centre and zones of lower yields and higher MPDs to the northeast and the south.

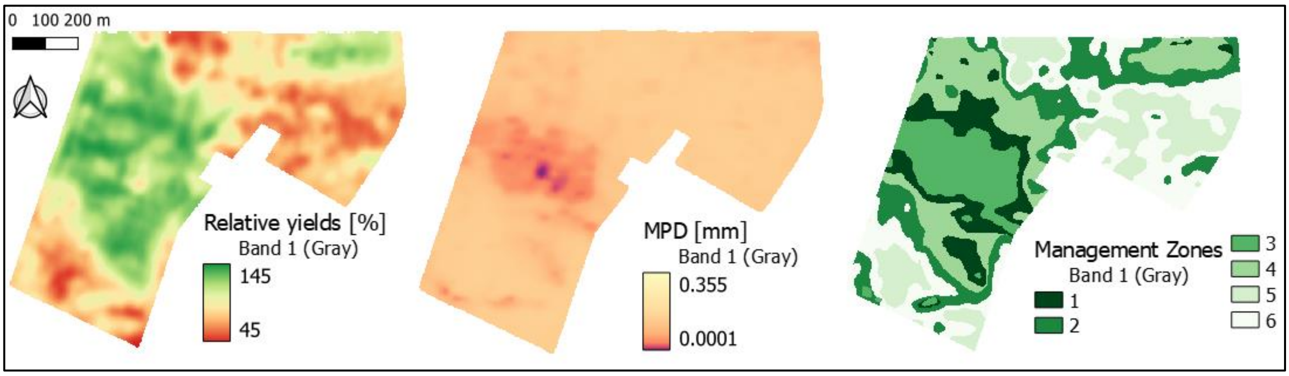

Figure 1. Management Zones (right) based on the spatial distribution of relative yields (left) and the Mean Particle Diameter (MPD) (middle).

PH variance and pH CV% over the whole field ranged from 0-0.1 and 0-5.5, respectively. While average zone size increased linearly by 0.11 ha per 5% yield class range increase, pH variability increased only marginally by 0.13 CV% per 0.1 ha average zone area increase. In 15-20 ha of the field, pH variability was greatest (>4.5 CV%, Var: 0.075-0.1) in zones of weak loamy sands (clay: 5-12%, silt: 0-50%) and positive yield deviation (30-60%) from the mean relative yield. Areas with lowest yield variability (<2 CV%, Var < 0.15) decreased exponentially with increasing class range of yield deviation.

Discussion and conclusions

Further analysis in these MZs were conducted with nutrient variability of P, K, Mg and SOC from mass sampling (n = 250) distributed over the whole field and pH sensor measurements over the observation period.

Acknowledgements

The project is part of the EIP-AGRI project ‘pH-BB: precision liming in Brandenburg’ (Project No.: 204016000014/80168341) funded by the European Agricultural Fund for Rural Development of the European Commission and by the Ministry of Rural Development, Environment and Agriculture of the state of Brandenburg in Germany.

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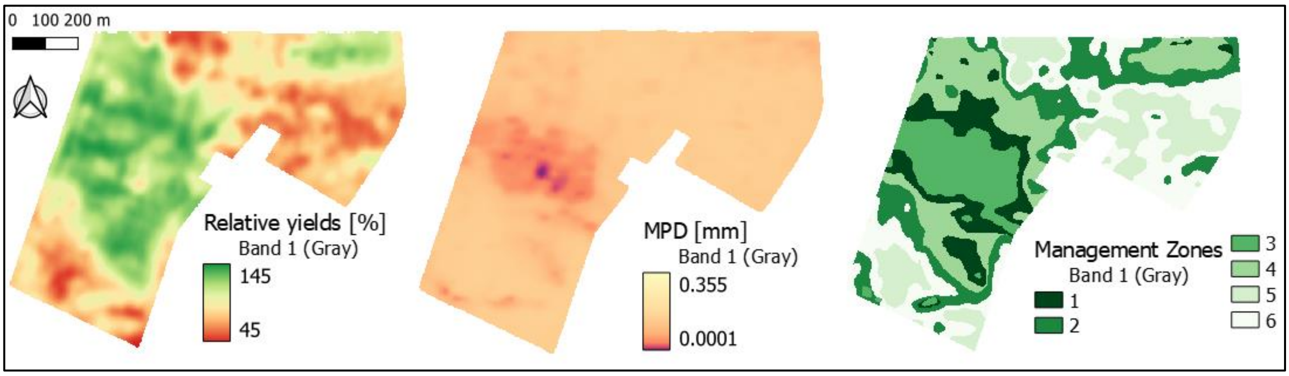

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P61 - Cropland Reference Ecological Unit for Comparative Soil Studies

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Introduction

The Soil Health Gap concept allows us to compare soil health in cropland and native undisturbed land, measuring the decline in cropland soil health since cultivation began and simultaneously setting potential soil health targets [1]. However, comparing croplands with reference native sites or among themselves can be confounded with agroecological variations, including the heterogeneity in soil and climate. Significant changes in soil properties can be observed across different soils [2]. Climate, especially precipitation, significantly affects soil biological functions, nutrient cycling, and native vegetation. Precipitation gradient and soil series based on pedogenetic differences or soil genoform [3] can create differences in soil health potential. For that reason, the soil health response to different management practices is site-specific [4]. Therefore, when comparing soils, they should belong to an ecologically discrete unit that accounts for soil heterogeneity and climate variability.

Objectives

The objective of this project is to create a landmass classification that enables comparative soil studies. The project demonstrates how to create a Cropland Reference Ecological Unit (CREU), a land area with presumably uniform pedogenetic and climatic properties and where sites can be compared unconfounded by extenuating agroecological variation.

Materials and Methods

In the United States Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS) Land Resource Hierarchy or Hierarchical Land Classification System (HLCS), a Major Land Resource Area (MLRA) is a broad classification of geographically associated land [5]. The MLRA is divided into ecological sites (ES), distinctive lands with specific soil and physical characteristics [6]. Benchmark ES are selected for their potential to yield data and information about ecological functions, processes, and climate change [7]. Thus, the NRCS Hierarchical system presents the framework vital for delineating CREU (Figure 1a).

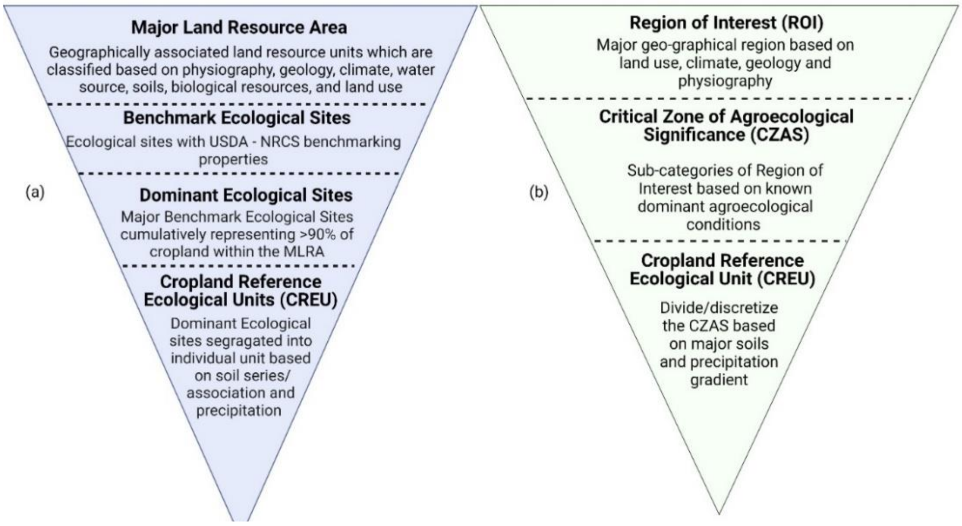

***Figure 1**. A flow chart showing the development of Reference Ecological Units (a) using the USDA-NRCS hierarchical land classification system (USDA NRCS, 2021) and (b) when organized and hierarchical land classification is absent.*

In the region where organized land classification based on soil, ecological functions, and vegetation characterization data is lacking, a critical zone of regional agroecological significance (CZAS) needs to be determined within the Region of Interest (ROI) before identifying the CREU (Figure 1b). The ROI will be analogous to MLRA, a distinct area with dominant physical and climate characteristics and important in regional agricultural planning.

Individual dominant ES or CZAS are then divided into discrete landmass units as a function of soil association, topography, and precipitation range to determine the CREU. The CREU selection methodology involves the following:

i) Creating the geospatial layers: where shapefiles of MLRA, cropland cover, benchmark ES, soil associations, and precipitation are created using public data sources such as the National Agricultural Statistics Service (NASS), and High Plains Regional Climate Center,

ii) Geospatial analysis: which involves the geospatial intersection of the shapefiles mentioned above to determine the dominant ES for crop production that encompasses top-ranked benchmark ES representing >90% of cropland in an MLRA, and

iii) *Determination of CREU*: segregation of dominant ES as a function of selected precipitation range and soil associations in an MLRA.

Results

For the illustration in this paper, we used the generalized soil map for Nebraska, which divides the state into 80 soil associations using the Soil Survey Geographic Database (SSURGO). For example, Tripp – Mitchell – Alice (TMA) in Figure 2 is the association of the Tripp, Mitchell, and Alice soil series. Theoretically, CREU would represent uniformity from perspectives of soil genesis (geology), biotic community (plant community), physical properties (topography and hydrology), and climate (precipitation). For each CREU, croplands or rangelands associated with the specific ES designation within the same MLRA, can be paired and compared against each other. One can use an Ecological Site Description (ESD) that includes the reference plant community to inform the reference site selection (NRCS - USDA, 2022a; Salley et al., 2016). The concept of CREU is based on current and available soil pedogenetic and climate data; a collaborative effort of the soil scientific community is warranted to cross-validate the extent of applicability of CREU.

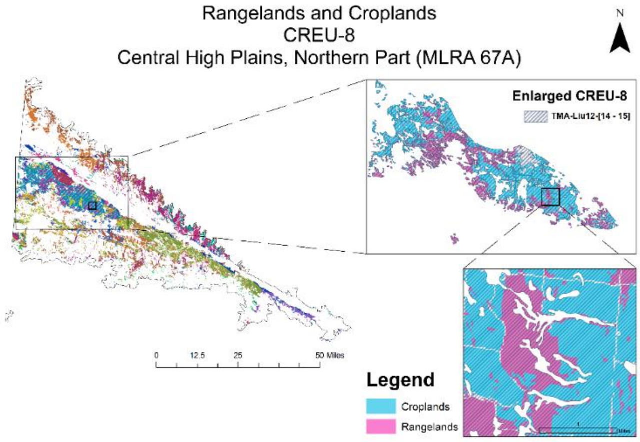

Figure 2. *MLRA 67A with one of 45 identified CREU (CREU-8; in box) in Nebraska Panhandle (left). Right Top: CREU-8 enlarged and divided into cropland and rangeland. The CREU consists of soil association-Trip-Mitchell-Alice (TMA), Liu12; Limy upland, and [14 – 15]; 14–15-inch precipitation zone. Right Bottom: Enlarged section of CREU-8 showing cropland and rangeland.*

Discussion and conclusions

There are several past and current ongoing efforts in paired comparisons of sites to measure the success of management practices. However, it is very unlikely to always find a reference site near croplands for paired comparison. The CREU Framework builds on the existing and tested NRCS land classification system and its ecological sites (ES) and sets the land boundary within which croplands and reference sites can be matched and compared.

Acknowledgment

Authors acknowledge Carlos Villarreal, State Soil Scientist and Aaron Hird, Nebraska State Soil Health Specialist, Nebraska, USA, for their advice and support.

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P62 - Monitoring of insect pests and their interactions with the environmental conditions in vineyards

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Introduction

Apart from abiotic environmental factors, many biotic interactions also influence the grapevine. One of these factors is the presence of various organisms being either beneficial or harmful to the grapevine. Vineyards are agroecosystems, which can host a large number of pests [1]. Likewise, many biotic and abiotic conditions influence grapevine diseases and pests [2]. Historical records set prerequisites to studying the complex interactions between the pests and their host plant. If they are not understood sufficiently, they may have devastating consequences on the grape-growing (e.g., phylloxera epidemic in the mid-19th century).

The spatial distribution of insect pests in vineyards, especially invasive species, has received considerable attention in the past years [3,4]. Early detection and monitoring are essential practices in preventing the spread of invasive species, as well as adopting the most appropriate management measures for established populations.

Objectives

The aim of paper was to monitor the incidence of insect pests in selected vineyards of the Nitra region (Slovakia) and identify their relation to environmental conditions The occurrence of the European grapevine moth (*Lobesia botrana*) and the American grapevine leafhopper (*Scaphoideus titanus*) was investigated. The research was carried out in the model vineyards in Jelenec, Ladice and Topoľčianky during the period from April to September 2021 and 2022.

Materials and methods

The research was performed on different dates during the growing season of 2021 and 2022. Jelenec and Ladice had six monitoring sites, Topoľčianky had seven monitoring sites during both years. Data were collected in approximately 30-day cycles. Based on aim studying the link between insect pests and climate conditions, traps were dispersed at the place of installation of the microclimatic datalogger and the automatic weather station. Pheromone traps were used throughout the research. Climatic data (mean, maximum and minimum temperature) were obtained from dataloggers and automatic weather station (temperatures, total precipitation and wind speed). The distance of the locality from the forest was measured using DEM. Data on the occurrence of the pests were subsequently evaluated in the context of the climatic variability and the other environmental conditions using RDA Analysis.

Results

In total, 783 individuals of *L. botrana* and 557 individuals of *S. titanus* were identified. During the research, significant differences in the number of detected insect pests were found between individual vineyards (Table 1). Both years, Topolčianky was the least affected vineyard. Both, *L. botrana* and *S. titanus* appeared to be significantly different over the localities and years. Using RDA, we were able to explain the bonds in a maximum of 40 % insect pests-environmental factors relationships. However, only two years of monitoring do not allow any precise appreciation of variability effects.

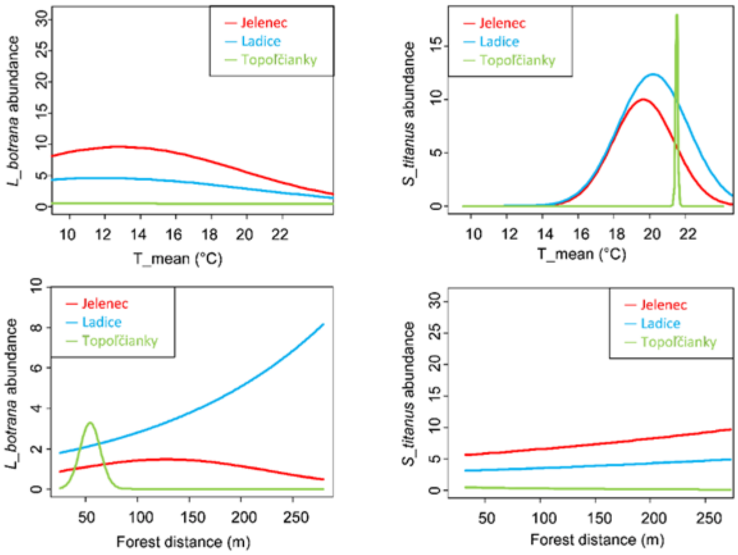
Table 1. Abundance of *L. botrana* and *S. titanus* in studied vineyards

	2021			2022			Total
	Jelenec	Ladice	Topoľčianky	Jelenec	Ladice	Topoľčianky	
L. botrana	433	219	48	31	48	4	783
S. titanus	59	173	129	32	125	39	557

Source: author's data

In Jelenec and Ladice vineyard, species *L. botrana* showed the highest abundances at temperatures of 12 - 14 ºC with a gradual decrease in abundance with temperature increase. Species *S. titanus* shows the highest abundances at temperatures of 19 - 21 ºC, in Jelenec and Ladice this pest started to get active around 14 - 15 ºC. In Topoľčianky vineyard there is a sharp increase of this species at a temperature of 21 ºC, but the presumed reason is the generally low abundance of the species compared to two other localities. A positive correlation of abundance in *L. botrana* with increase of forest distance was found in the Ladice vineyard, whilst on other two localities, this relationship was not relevant. Similarly, in *S. titanus* only a slight abundance increase with the increase of distance from the forest was observed. The increase of *L. botrana* abundance especially in Ladice vineyard may be due to the declining number of potential forest predators with the increase of distance from the forest (Figure 1).

Figure 1. Response curves showing the relationship between in abundances of *L. botrana* and *S. titanus* and significant (threshold level α = 0.05) environmental gradients identified in the RDA analysis.



Source: author's data

Discussion and conclusions

This paper confirmed that the insect pests are unequally distributed in the studied region. Presented results shows that each plot of the vineyard is unique, and the distribution of insects' may changes depending on the stage of development, the season, the phenological state of the crop, and the climatic conditions. The causes of nonuniformity in insect populations are often difficult to understand, being determined by several factors [5]. [6] focused on *S. titanus* investigated the effect of temperature changes for its occurrence in Switzerland. In accordance with our knowledge from Slovakia, they noted the spread of this pest in connection with global warming, as well as the need to use microclimatic data to monitor their occurrence and for the subsequent adoption of adequate measures.

Acknowledgements

This research project was funded by FOMON project ITMS2014+: 313011V465 from EFRD.

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P63 - DIGINVASIVE: a digital system to map invasive weed plants

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Introduction and Objectives

Invasive plant species are a major cause of crop loss and have high potential to disturb the existing ecological systems [1]. *Amarantus palmeri* has been recently detected in Mediterranean basin countries, triggering highest alerts of the European Plant Protection Organization [2] and national plant health services, as it is an extremely competitive species native to North America with a high fertility rate and adept at developing herbicide-resistant biotypes [3]. In Spain, *A. palmeri* has been included among the exotic species that pose a serious threat to productive sectors, pointing to the need for containment efforts and early detection of new cases [4].

In recent years, agricultural web-based tools have made the process of crop monitoring and surveillance easier and more accessible. They are online digital platforms that combine Geographic Information Systems (GPS) technology and big data collected by remote sensing platform or meteorological station, among others, analyze them, and provide graphical and text information in the form of maps and databases. However, they have not been developed for invasive weeds in agricultural domain.

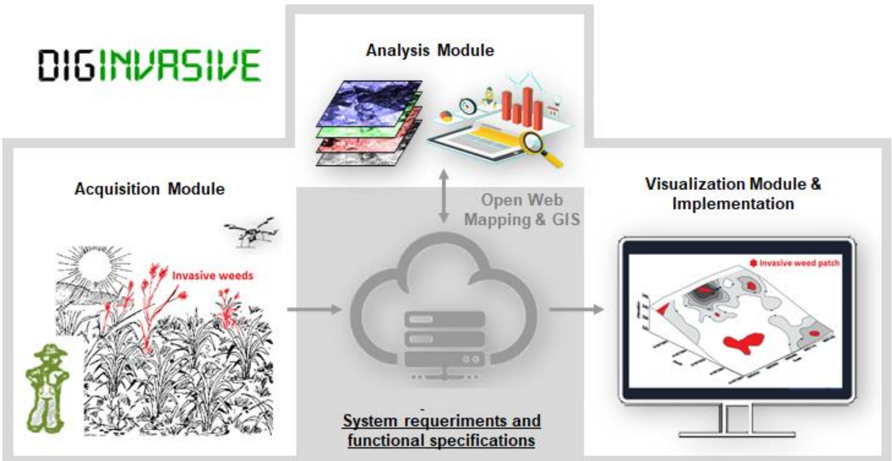
Unmanned Aerial Vehicles (UAV) and Artificial Intelligence (AI), as object-based image analysis-OBIA and machine learning (ML) procedures, are required to detect and map weeds in challenging scenarios, such as in early season herbaceous crops due to the high spectral similarity of different plant species and the small size of plants in such early stages of development [5,6].

To this end, an **open source web-based interface system**, called DIGINVASIVE, is being designed to assist end-users by providing an open web mapping and GIS platform to upload, analyze and visualize geo-spatial data that will be able to map the presence of invasive weed plants.

Materials and methods

DIGINVASIVE uses *A. palmeri* weed and maize crop as model weed-crop scenario due to the high ecological risk posed by this weed species in the Spanish agriculture. This digital system takes advantage of innovative digital technologies as remote-sensed images acquired with UAV, GPS, Information and Communication Technology, AI, OBIA and ML procedures. It consist of several modules (Figure 1) for mapping and monitoring invasive weed species and infested crop-fields, and developing an open web-based platform to integrate, analyze, and deploy weed and crop information.

Figure 1. General scheme of DIGINVASIVE web-tool



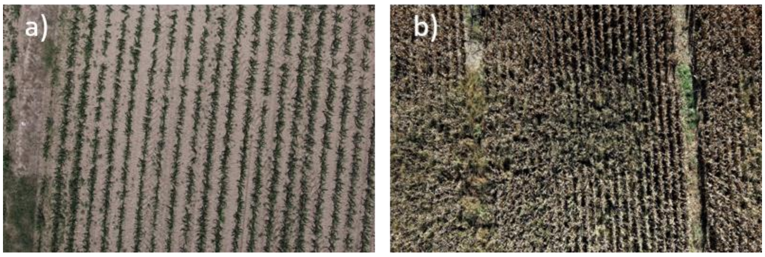
DIGINVAISIVE consists of several modules:

- *Acquisition Module*: with capability to incorporate UAV-based image and manual vectorization of the geographical data with the location of invasive weeds.

- *Analysis Module*: to detect and map *A. palmeri* patches within UAV-based images and manage the manual input data with the location of invasive patches and the outputs of the image analysis phase.
- *Visualization Module*: the GIS desktop tool with an intuitive and user-friendly Graphical User Interface-GUI.

For DIGINVASIVE development, UAV images have been acquired on ten maize fields located in Lleida (Spain) at two crop phenological stages (early and late) (Figure 2) infested with *A. palmeri*. Moreover, an automatic image analysis procedure, combining OBIA and ML algorithms, has been created to map invasive plants, taking into account specific patterns typical of these species, such as morphological (plant height, distribution in patches, etc.) and phenological characteristics (flowering, senescence).

Figure 2. UAV images of maize crops at early (a) and late (b) stage infested by *A. palmeri*



Results

The technical specifications and configuration of the UAV and sensors to discriminate *A. palmeri* have been determined in terms of flight altitude and route design, optimal spatial and spectral resolution. Based on the first field campaign data, an OBIA- and IA-based procedure is currently being developed to map *A. palmeri* patches in maize crops at any development stage. In addition, data on the current location *A. palmeri* at the county scale are being gathered for the Plant Health Services technicians. It is expected that the full system will be updated and improved with new data from the next field campaign. Currently, we are working on the design of the Spatial Data Infrastructure considering the dimension (computing resources), connectivity, communication rules and specification of each afforementioned module.

Discussion and conclusions

The DIGINVASIVE open web mapping platform is currently being developing to provide geo-referenced and digital information to stakeholders, delivering up-to-date data on the location, mapping and spread of *A. palmeri*. Moreover, the provided information will allow optimizing crop management thought more efficient and sustainable crop protection strategies based on PA strategies at timely weed control and improving knowledge about invasive weeds. Although the first approach has focused on *A. palmeri*, the system will be extended to other invasive species and crops in further research.

Acknowledgements

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P64 - A Processing Method for Adhesive Droplets on Images of Water-sensitive Papers

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Introduction

Over the last decades, water-sensitive papers (WSP) have been widely used to assess droplet deposition. Although more precise methods exist, WSP are simple to use and represents a suitable tool for spraying application by farmers. To analyze droplets on WSP, lots of dedicated software were launched and more research focusing on better algorithms was reported in recent years [1,2,3,4]. At present, the adhesive droplets problem is still a thorny issue, which significantly impairs the accuracy of droplet analysis. In this study, an image-processing code using Python and OpenCV was developed, in order to overcome the adhesive droplets problem.

Objectives

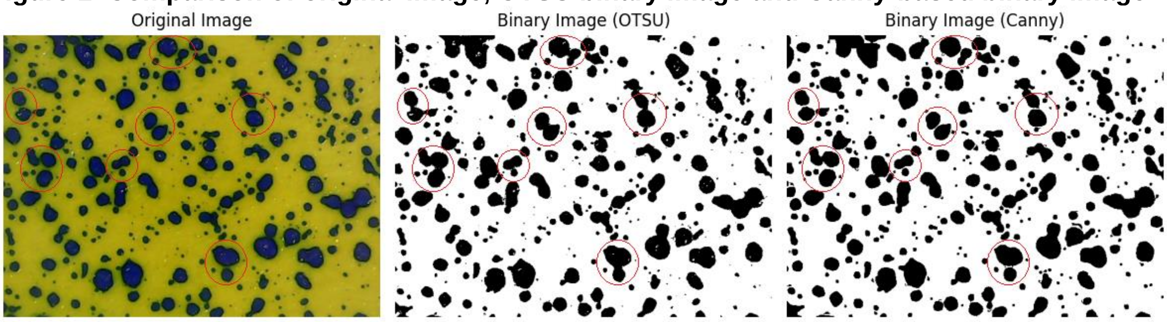
The objectives of this study contained three steps: (1) to apply a droplet segmentation algorithm that reduced adhesive droplets caused by the image segmentation; (2) to explore an approach that identified connecting points of adhesive droplets, then split their contours with the points; (3) to choose a suitable algorithm that rebuilt completed contours of single droplets.

Materials and methods

WSP in this study were obtained by testing 4 sprayers in a commercial vineyard in San Vito al Tagliamento (Italy) in July 2022. A total of 30 papers were used (Syngenta Group Co., Ltd., Shangai, China). The paper is 76 by 26 mm, which is the standard size of WSP. For digital image processing, Jiusion 1000x microscope (Jiusion Ltd., Shenzhen, China) was used to collect images of the papers. The camera field of view was 12.7 by 9.6 mm, and the pixel resolution was 640 by 480 pixels, which means the image resolution was 1280 PPI. All the images were output to *.jpg format.

Despite the OTSU algorithm [5] being proved to be a suitable binarization algorithm for WSP [6], the algorithm still contributed to considerable adhesive droplets in droplet analysis. The adhesive droplets are shown in Figure 1. The reason for the phenomenon is the halo around the droplets. When two droplets are too close, the halo between the droplets will be binarized to 0 value if global thresholding and binarization algorithms are applied. To reduce these adhesive droplets, the Canny algorithm [7] was transplanted into the image-processing code to detect the contours of droplets. Then, the binarization would be accomplished after the contours are filled. Although the Canny algorithm outputted some opened contours that were unable to be filled, the morphological dilation operation was applied to modify these opened contours. The Canny-based segmentation is shown in Figure 2.

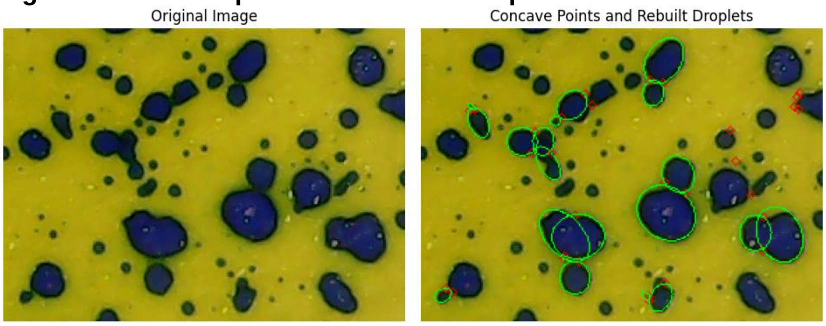
Figure 1. Comparison of original image, OTSU binary image and Canny-based binary image



After image segmentation, to suppress redundant points on droplet contours, the polygonal approximation algorithm in OpenCV was adopted to detect dominant points. Then, the connecting points were obtained on the presumption that the concave points in the sequence of dominant points are always the connecting points. To determine the concave points, the image-processing code calculated the midpoints of adjacent two points of arbitrary dominant points. The midpoints outside contours showed that the corresponding dominant points were concave points. The concave points are showed in Figure 2. With the connecting points, the contours of single droplets within adhesive droplets were segmented.

Assuming that all the adhesive droplets are elliptical, with the segmented contours, an ellipse fitting algorithm based on the least square method was adopted into the image-processing code to rebuild the single droplets. Since some segmented contours were too short that the fitting ellipses were totally unavailable, the image-processing code filter some unsuitable contours. The rebuilt droplets are shown in Figure 2.

Figure 2. Concave points and rebuilt droplets



A trial was designed to verify the validity of the image-processing code, which used 3 WSP images with droplet coverages of 31.36%, 19.82% and 11.07%, respectively. To obtain the real contours of droplets, each image was binarized manually by using Microsoft Paint, and the adhesive droplets were counted manually as well. The accuracy of segmentation was defined as the percentage of consistent pixels between two binary images. The accuracy of the OTSU segmentation and manual segmentation, the Canny-based segmentation and manual segmentation are calculated respectively.

Results

The result of the trial is in Table 1. It showed that the accuracy of segmentation of the image-processing code is higher than OTSU segmentation in all the given coverage of the WSP images. The accuracy difference between the two is 1.91% on average. For adhesive droplets, the image-processing code identified around half of the total adhesive droplets.

Table 1. Example of table illustrating the main results

Coverage	Accuracy of OTSU segmentation	Accuracy of Canny based segmentation	Identification of adhesive droplets (Identified / Total, Percentage)
31.36%	94.13%	95.35%	77 / 152, 50.66%
19.82%	95.18%	97.47%	47 / 91, 51.65
11.07%	96.58%	98.81%	23 / 51, 45.10%
Average	95.30%	97.21%	49.14%

Discussion and conclusions

This study developed an image-processing code for WSP images, which was proved to be able to overcome the problem of adhesive droplets. For further work, enhancing the identification percentage for adhesive droplets could be meaningful.

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P65 - Early assessment of tomato bacterial spot through proximal hyperspectral sensing

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Introduction

Plant diseases are responsible for causing major losses in numerous crops worldwide, affecting their yield, and their economic and nutritional value. Early disease detection, promoted by applied predictive classification methods, allows a more immediate and precise intervention, preventing a crop from being severely affected. A reduction in the usage of phytosanitary products is expected, which translates into a beneficial impact on the protection of the environment and ecosystem services, on the producer’s income and on the quality of the product that reaches the final consumer. Proximal hyperspectral spectroscopy approaches combined with applied predictive classification models are a helpful solution for assisting producers in early disease diagnosis in vivo tomato plants. In this regard, spectral data must be collected and evaluated to retrieve qualitative and quantitative information, identifying divergences between samples with different health statuses.

Objectives

The aims of this research were i) to verify if the spectral behaviour of healthy and diseased tomato leaves presented differences; ii) to investigate the capacity of applied predictive models to early detect bacterial tomato diseases (diagnose in pre-symptomatic stages); iii) to develop applied predictive models to classify leaves according to their treatment group (control vs. inoculated plants), and their health status (healthy, pre-symptomatic, and symptomatic).

Materials and methods

Tomato plants were cultivated in a walk-in plant growth chamber, and divided into two groups, one of them being inoculated with *Xanthomonas euvesicatoria* LMG 905 (Xeu) bacteria and the other being treated with sterile distilled water only (control group, Con) according to [1]. Plants were monitored daily for symptom development for 18 days. Hyperspectral data were randomly collected in vivo from the adaxial side of leaves using an in-house compact benchtop system composed by laptop, mini spectrometer (TM Series C11697MB, Hamamatsu Photonics K.K., Japan), and a transmission optical fibre bundle with a reflection probe. The probe was placed 1 cm above the sample, in a dark room, and a white LED light was used to provide even illumination to the abaxial surface of the leaf. Measurements were taken from 2430 points, belonging both to healthy and diseased leaves.

To assess the predictive modelling of bacterial diseases in tomato leaves, only the spectral region of 400 to 800 nm was used. Raw and normalized spectra were used for data analysis. The normalized spectral signatures were obtained through the division of leaves raw spectral signatures by the spectral signal of the white LED source (according to the time of exposure of the spectral acquisitions). Spectral modelling was then applied to classify tomato leaves pooled according to their health status (HS, independent variable): HS1 (control and Xeu disease plants), and HS2 (healthy, pre-symptomatic and symptomatic). For each approach, class discrimination was performed by date (days after inoculation, DAI). The datasets were randomly divided into training data and validation data (70/30%), following a holdout method [2], for each measurement date. To determine which wavelengths predictors were more relevant to diagnose tomato bacterial disease caused by Xeu a Flexible Discriminant Analysis (FDA) was computed (using a repeated 10-fold cross-validation). Different metrics were retrieved to investigate model performance, namely accuracy, Confusion Matrix, Kappa coefficient, and F1-Score according to Reis-Pereira et al. [3].

Results

Tomato plants infected with Xeu bacteria showed the first visual typical chlorotic disease symptoms between 12 to 15 DAI, only evolving to the necrotic stage at 17 to 18 DAI. Healthy leaves presented a spectral signature divergent from diseased leaves in raw and normalized data, even before symptom appearance. Spectral divergences were more evident in the ranges of approximately 425-460 nm, 520-585 nm for the raw data, and 425-515 nm, 640-710 nm, 710-770 nm for the normalized set.

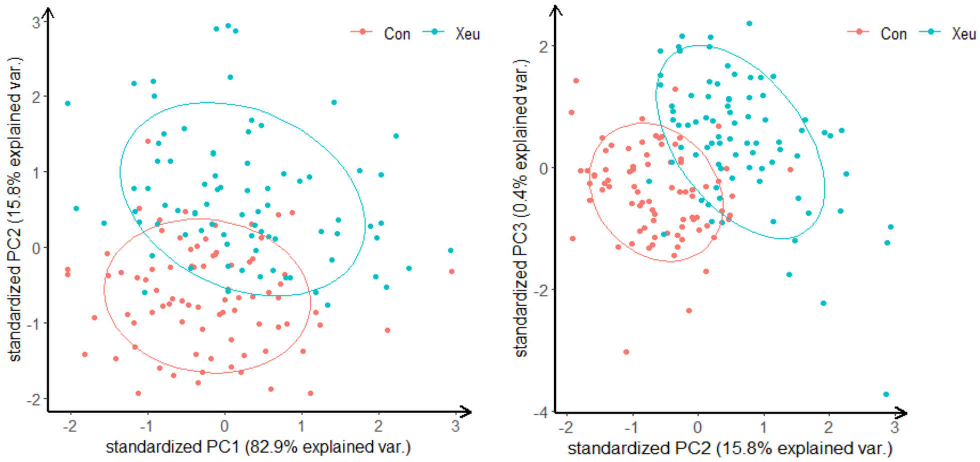

Figure 5. Biplot of PCA results of raw data at the 8th DAI (before symptom appearance).

The best modelling approach before symptom appearance, for Control and Xeu HS1 classification, was achieved by applying FDA predictive model in both spectral data sets at the 8th DAI, demonstrating an accuracy of 0.90, kappa of 0.79, and f1-measure of 0.90. For ‘healthy’ and pre-symptomatic discrimination, the best strategy involving the computation of the same model presented an accuracy of 0.85, kappa of 0.71, and f1-measure of 0.85. After the first symptoms 10 DAI appeared, the best HS1 classification was achieved when normalized data was used. The model registered an accuracy of 0.96, kappa of 0.92, and f1-score of 0.96. In HS2 prediction, is possible to see a NaN value of f1 for the ‘symptomatic’ class due to the reduced number of symptomatic samples (Table 1).

Table 2. Model evaluation metrics (accuracy - Ac, kappa score - Kp, and f1-measure - F1) for test sets, when raw and normalized data were used, at 6, 8, and 10 days after infection (DAI).

	Health Status 1			Health Status 2				Health Status 1			Health Status 2			
DI	6	8	10	6	8	10		6	8	10	6	8	10	
Ac	0.77	0.90	0.94	0.75	0.85	0.75	**Raw**	0.77	0.90	0.96	0.75	0.85	0.75	**Norm**
Kp	0.54	0.79	0.75	0.50	0.71	0.55		0.54	0.79	0.92	0.50	0.71	0.56	
F1	0.80	0.90	0.94	0.77	0.84	0.70,0.86,0.29		0.80	0.90	0.96	0.77	0.85	0.73,0.88,NaN	

Discussion and conclusions

In-vivo hyperspectral spectroscopy combined with applied predictive classification was explored to diagnose bacterial tomato leaf disease caused by Xeu bacteria. Even in early infection stages, spectral separability between healthy and diseased leaves was observed, allowing for accurate classification of the HS1 group (90% accuracy) and HS2 discrimination (85% accuracy). These results demonstrate the potential of applied predictive classification modelling using hyperspectral point data to early detect bacterial crop diseases on leaves.

Further research is suggested to better understand the host-pathogen interactions, and their impact on the crop's spectral signature. This can lead to the development of more cost-effective devices, and agricultural practices (e.g. phytosanitary treatments), leading to more efficient and environmentally friendly agricultural practices. Spectroscopic sensors can, withal, be coupled with different measuring platforms, allowing for spectral data studies from the leaf to the canopy scale.

Acknowledgements

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P66 - High power 2 µm wavelength fiber laser for precision weeding

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Introduction

We present a new generation of fiber lasers operating in the 2 µm wavelength range that provides the highest available output power with single mode beam quality. Due to administrative regulations and customer demands herbicide usage in agriculture must be drastically reduced in the future. Fiber laser systems emitting at 2 µm wavelength offer many benefits for precision herbicide free laser weeding e.g., high absorption in plant tissue, small focus spot diameter and high overall efficiency. The laser wavelength is overlapping with a strong water absorption peak, which provides high absorption in all kinds of weeds [1]. The penetration depth of a few hundred µm enables highly efficient weeding. With energy doses provided by millisecond pulses the regrows of weeds is suppressed [2].

Objective

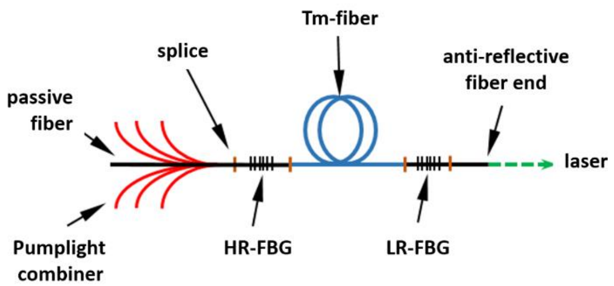
Weed control is one of the most important objectives for crop production with high output yields. Weeds typically only constitute a small proportion of the target area, and herbicide application increases the risk of environmental contamination, as most herbicides hit non-target material or are lost to spray drift. Also, problems with herbicide-resistant weeds are increasing worldwide. The negative side-effects of pesticide use have resulted in stricter regulation and political initiatives to reduce pesticide use [3]. Therefore, there is a need for developing new techniques supplementing or replacing present weed control methods.

A laser beam can be directed toward a weed plant and deliver high-density energy on the meristem and warm up the tissue resulting in harming or killing of the weed plant [4]. Using recognition tools based on artificial intelligence, it is possible to distinguish weeds from crop plants in real-time. The meristem can be detected using high-resolution cameras, while precise scanners can position the laser focus.

Futonics high power 2 µm laser

Here we present the actual 2 µm laser systems from Futonics, which provide output powers up to 750 W in pulsed and up to 500 W in continuous operation. The newest fiber laser systems based on an all-fiber design provide single mode beam quality over the whole power range. The all-fiber design enables a robust design without free space optics (Figure 1). This provides a stable output power and long-term continuous operation in the field. Also, the maintenance costs are minimized. Outside the laser the application fiber is protected by a metal hose and the fiber end, with its anti-reflective coated output window, which is held in a robust connector. The high beam quality in combination with the emission wavelength enables spot diameters below 200 µm at a working distance of 0.5 m. With such a working distance the beam diameter is only doubled in some cm from the focus.

Figure 1. Schematic of the “All-Fiber” design used in the Thulium fiber laser systems from Futonics

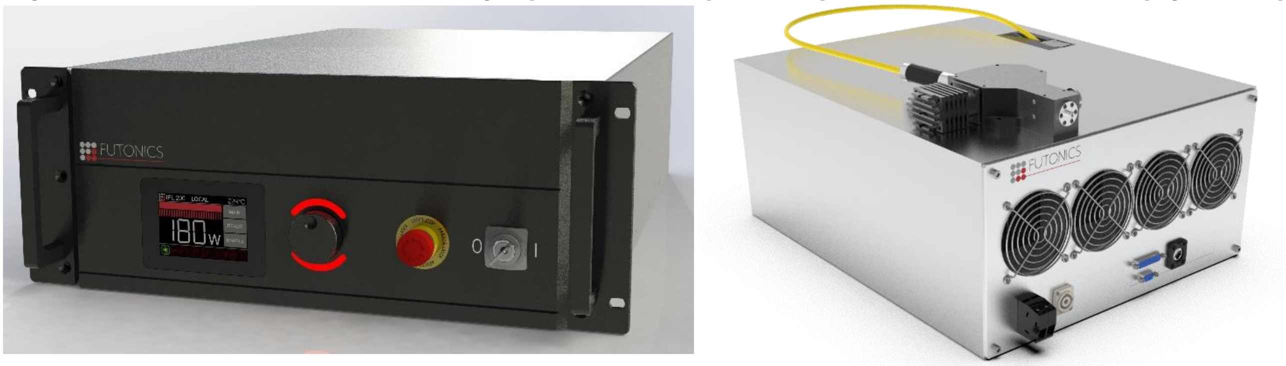


Futonics 2 µm fiber lasers reach a high overall laser efficiency, as they utilize the two for one cross relaxation process in thulium. In this process for one pump photon two laser photons are generated. Together with highly efficient fiber coupled pump diodes an overall efficiency of up to 20 % is achieved, which is significantly better compared to other weeding lasers. For operation on autonomous vehicles or other agriculture equipment the laser systems can be operated directly with the vehicle electrical system voltage of 48 V DC.

Laser weeding application

The 2 µm laser sources from Futonics are used within the WeLASER project for weed control experiments [5]. During the project water cooled systems with up to 500 W average power are tested and air-cooled systems with lower power are developed (Figure 2). The laser is mounted on an autonomous vehicle and the power is guided by fiber to an attached scanner system. Artificial intelligence is used to identify and locate crop and weed plants and direct the laser beam to the targets. A fast control electronic of the laser systems allows turning on and off of the full laser power within 50 µs. This enables precise hitting of weeds.

Figure 2. Futonics water cooled high power laser (left side) and air cooled laser (right side)



Weeds were treated with different energy densities and treatment times to analyse regrowth. In the field weed species have different temperature requirements for effective treatment. Seeds from weed species with higher temperature requirements (e.g., *Solanum nigrum* L. and *Urtica urens* L.) need longer treatment times to suppress regrowth. The best weeding results were obtained when the meristem of the target plant is exposed on the cotyledon stage or the two permanent leaf stage. At these stages, only the apical meristem is developed for most weed species. The laser spot directly hits the weed and does not trigger weed seeds to germinate on the whole area. Good treatment results were observed, because the 2 µm radiation penetrates through the epidermis of plants cells and is mainly absorbed by the water inside the plant. In contrast the energy from a CO2 laser, is solely absorbed on the surface of the plant, therefore more energy for treatment is needed.

Discussion and conclusions

Laser treatment of weeds is a suitable alternative or supplement to, for example, herbicide application or mechanical weed control. The effect of the laser treatment depends on weed species, laser spot position, growth size, laser spot area, and applied laser energy. Due to the very small laser spot diameter the area directly exposed for weed control is drastically reduced. Therefore, this method interferes substantially less with the biodiversity and environment.

Futonics high power 2 µm laser sources are ideally suited for weed control applications. The absorption of the 2 µm radiation very strong in all types of weeds. The high beam quality of the new fiber lasers enables small spot diameters in long focal distances and the design of the lasers ensures a stable operation also in harsh environments.

Acknowledgements

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P67 – How do farmers prefer laser-weeding? A pan-European survey

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Introduction

Sustainable agriculture has increasingly attracted public attention due to the rapid population growth and the negative impacts of current agricultural practices on the environment [1,2]. Indicatively, pesticide use reduction and organic farming expansion are among the main targets aimed by the European Green Deal to "improve the well-being and health of citizens and future generations" [3].

The emergence of new precision agriculture technologies has played a critical role in achieving a more sustainable agricultural system [4]. Remarkably, the recent development of laser weeding treatments using artificial intelligent (AI) recognition systems shows the potential to sophisticatedly eradicate weeds for sensitive crops, which normally cannot tolerate heavy mechanical weeders [5]. Such an innovative system may facilitate the establishment of organic farming for sensitive crops by providing an economically feasible solution to organic weed control.

Given the novelty of this laser weeding system, insights into farmers' perceptions and preferences for it remain lacking. The identification of farmers' needs for the new agricultural machinery would lay a solid foundation for the successful development and implementation of such a system. Besides, it would be scientifically of interest to investigate the factors affecting the transition from conventional weeding technique to laser weeding treatment.

Concerning the mentioned literature gaps, this study aims to explore farmers' preferences for laser weeding systems as well as to identify the determinants of their preferences for such an innovative system.

Materials and methods

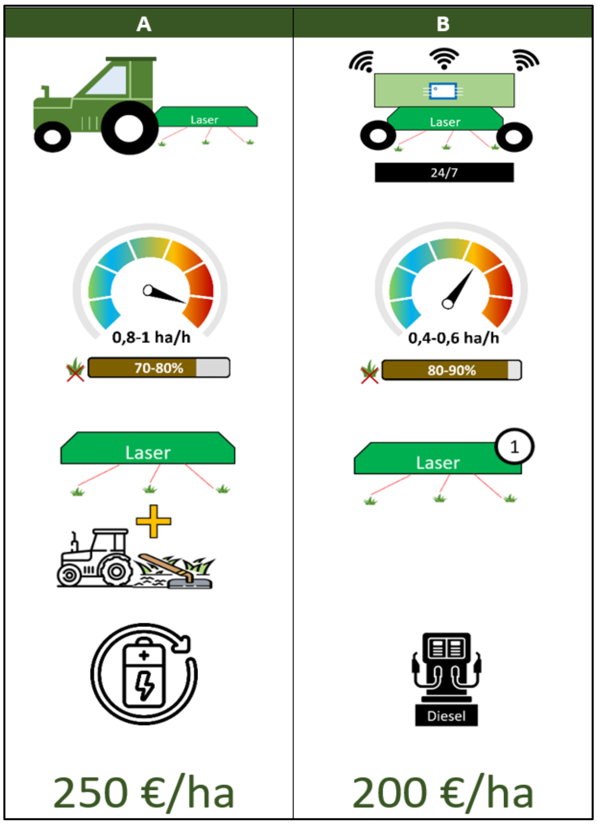
An online-based survey was designed to obtain a convenience sample of growers in four European countries namely Denmark, Poland, Italy, and Spain. The original survey was in English, which was translated into Danish, Polish, Italian, and Spanish for data collection.

A choice experiment was employed to measure farmers' preference for different tentative attributes of a laser weeding system. Five attributes were considered namely (1) mobility mode (autonomous vehicle or mounted laser systems on tractors), (2) efficacy (two weed-killing rates), (3) service type (alone service of only laser-weeding or hybrid service with mechanical weeders), (4) energy source (fossil fuel or rechargeable batteries, and (5) weeding costs with 4 levels (€100,150,200, and 250/ha).

Farmers could choose between Options A or B (as shown in **Figure 1**) or a *status quo* in a choice set. There are 8 choice sets in total, which were designed by using Ngene.

Choice data were analysed using Randomised Parameter Logit (RPL) models in RStudio using *mlogit* and *gmnl* packages.

Figure 1. Example of a choice set



Results

The findings show that the surveyed farmers were ethusiatic about laser-weeding as 24% farmers would want to adopt laser-weeding immediately if available (**Figure 2**), while only 5% stated they did not have any intention to use laser-weeding.

The analysis of choice data was conducted for the total sample and two sub-groups: adoption group and non-adoption group, created by dividing the sample with the cut-off at 4 of the "intention to adopt" variable (indicating "likely to adopt laser-weeding"). Across the examined groups, the cost coefficients were significantly negative indicating that low weeding costs are crucial for laser-weeding to be desirable. The coefficients of *status quo* were significantly negative which implies that farmers preferred alternative weed control solutions such as laser-weeding. Interestingly, prospective farmers in the adoption group showed an positive preference for a rechargeable battery. Meanwhile, other attributes did not significantly affect farmers' preference for laser-weeding. Nevertheless, significant preference heterogeneity of the examined attributes were observed.

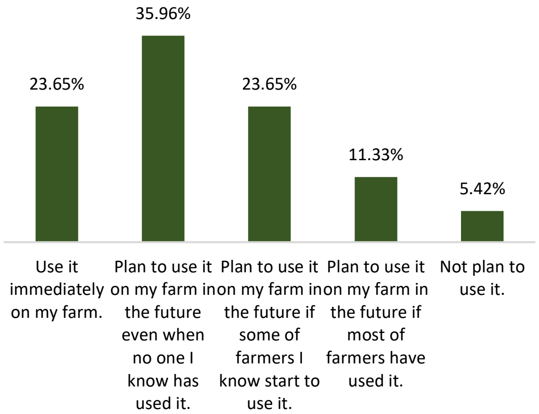


Figure 2. Intention to adopt laser weeding (n=203)

Table 1. Choice experiment data analysis (Randomized Parameter Logit models)

	Total sample (n = 203)		**Adoption group (n= 68)**		**Non-adoption group (n=139)**	
	β (SE)		β (SE)		β (SE)	
Cost	-0.004	***	-0.01	***	-0.002	*
Status quo	-1.68	***	-3.35	***	-1.00	***
Mobility	-0.06		-0.18		0.010	
SD Mobility	0.89	***	1.22	***	0.76	***
Efficacy	-0.03		-0.05		-0.02	
SD Efficacy	0.59	***	0.54	**	0.63	***
Service	-0.01		-0.09		0.03	
SD Service	0.54	***	0.49	**	0.60	***
Energy	0.01		0.37	*	-0.13	
SD Energy	0.94	***	1.10	***	0.84	***
Goodness-of-fit						
AIC	3215		942		2230	
BIC	3269		985		2280	
Observation	1624		544		1080	

Discussion and conclusions

This study sheds light on the nuances of the preference of European farmers for more sustainable weeding practices via a choice experiment. As farmers are primarily concerned about the weeding cost for the new laser solutions, it is crucial to illustrate the cost-effectiveness of the solution to farmers with concise performance results. Machinery builders should keep in mind that a green energy source (e.g., rechargable battery) is desirable for prospective adopters of laser-weeding. The result interpretation should be done with caution given the hypothetical bias (due to the hypothetical products) and selection bias (due to the convenience sample). Larger sample size is needed to explain the preference heterogeneity among farmers for the examined attributes of laser-weeding.

Acknowledgements

This research was performed in the framework of the WeLaser H2020 project Grant Agreement N. 101000256. https://cordis.europa.eu/project/id/101000256.

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P68 - Development and validation of a method for detection of four NTX-related pesticides in plant foods

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Introduction

Nereistoxin (NTX)-related pesticides have been used to control pests on agricultural products due to their low toxicity and high efficiency. However, the excessive use of NTX-related pesticides may pose a risk to the environment and human health [1]. Although sensors and mapping technology can determine the type, amount, and location of pesticide application according to the needs of specific locations, it can't accurately detect the concentration of pesticide residues in either crops or food and can't evaluate the risk of pesticides to human health [2]. Therefore, there is clear value in establishing a method for the simultaneous determination of NTX-related pesticide residues in plant foods to guide agricultural production and verify whether the optimization is appropriate with precision agriculture.

Objectives

The specific objective of this study was to develop an efficient method for the analysis of residual NTX-related pesticides (i.e., cartap, thiocyclam, thiosultap-monosodium, and thiosultap-disodium) in 20 types of plant food, including cereals (brown rice, wheat, and corn), oil crops (soybean), vegetables (cabbage, celery, tomato, eggplant, potato, radish, and kidney bean), fruits (apple, peach, grape, and orange), nuts (walnut), edible fungi (mushroom), plant oils (corn oil), tea (green tea), and spices (Sichuan pepper). The intermediate precision of the method was evaluated by repeating the method confirmation experiment 5 times in laboratory. Besides, the reproducibility of the established analytical method was also verified in five laboratories.

Materials and methods

Thiocyclam (95.0%, w/w), thiosultap-monosodium (98.3%, w/w), thiosultap-disodium (94.3%, w/w), and NTX oxalate (99.0%, w/w) were purchased from Dr. Ehrenstorfer GmbH (Augsburg, Germany), whereas cartap (98.1%, w/w) was purchased from the Shanghai Pesticide Research Institute Co., Ltd. (Shanghai, China). Individual standard stock solutions of cartap, thiocyclam, thiosultap-monosodium, and thiosultap-disodium were prepared at 1000 mg/L in methanol. The NTX oxalate standard was dissolved at 1000 mg/L in a methanol/water mixture (50/50, v/v). All solutions were stored at –20 ◦C until analysis.

A gas chromatography equipped with electron capture detector (GC- ECD; Shimadzu GC-2010, Shimadzu Corporation, Tokyo, Japan) was employed with an HP-5 (5% diphenyl and 95% dimethyl-polysiloxane) capillary column (film thickness 0.25 μm, 30 m × 0.25 mm i.d., Agilent Technologies, Inc., USA). The oven temperature was first maintained at 70 ◦C for 1 min, and the temperature was then increased to 220 ◦C at a rate of 20 ◦C/min; it was held at this temperature for 1 min. The carrier gas was nitrogen (greater than 99.999%) at a flow rate of 50.0 mL/min. The injection temperature was 250 ◦C, the injection volume was 2 μL and a splitless injection mode was used. LabSolutions software (GC solution version 2.40.00) was used in this study to collect and analyze the data.

Results

Oil crops (soybean), nuts (walnut), plant oils (corn oil), and spices (Sichuan pepper) contain large volumes of oil, whereas cereals (corn, wheat, and brown rice) and potatoes contain a large quantity of starch. Oil is easily dissolved in hydrophobic n-hexane, and thus blocks the chromatographic column and reduces the reliability and accuracy of the results. Starch reduces the polarity of the water phase, which impedes the separation of the water phase from the n-hexane phase, leading to emulsification. The addition of NaCl can reduce emulsification, thus allowing the two-phase system (n-hexane and water) to be separated. In addition, it also increases the surface tension of starch and conducive to demulsification. The recoveries of cartap, thiocyclam, thiosultap-monosodium, and thiosultap-disodium, which was 80 – 99% with RSDs ranging from 4.2% to 13.5%, met the requirements (70 – 120%, and RSDs ≤ 20.0%) when 2 g of NaCl were added (Figure 1).

The polarity of water is stronger than that of general solvents, which is beneficial for the extraction of pesticides. Moreover, it can contribute to an increase in the contact area between the extraction solvent and matrix and provide a good reaction environment. After addition of 5 mL and 10 mL of water, the recoveries were significantly higher, rising to the range of 72% to102% (RSDs of 2.1%–9.8%) (Figure 1).

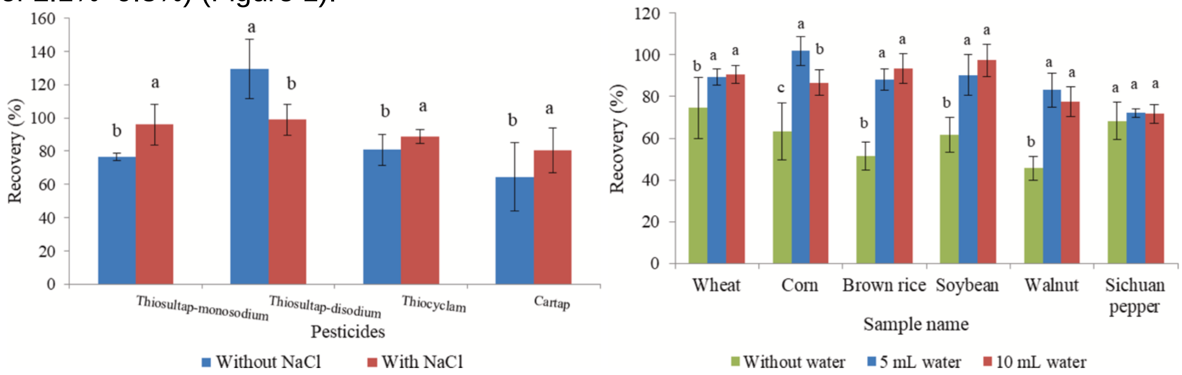

Figure 1. Comparison of the recoveries of NTX-related pesticides in corn with and without NaCl (left); Comparison of the recoveries of thiosultap-monosodium in corn, brown rice, soybean, wheat, walnut, and Sichuan pepper after no water, 5 mL of water, and 10 mL of water were added (right)
Source:author's data

Many factors in the laboratory cause variation in the results of the determination method, such as the time of measurement interval, recalibration of the same instrument, operator, and equipment or reagents. In this study, we evaluated the intermediate precision of the measurement interval.

Moreover, to validate the reproducibility of this method, method validation experiments were conducted in four other laboratories.The results indicates the good intermediate precision of the interval of continuous measurement as well as the good reproducibility of the method.

Discussion and conclusions

A GC-ECD method was developed for the detection of cartap, thiocyclam, thiosultap-monosodium, and thiosultap-disodium in 20 plant foods. In this study, samples were analyzed and the conditions such as the extraction solution, extraction time, derivatization pH, derivatization temperature, derivatization time, type of catalyst, and pretreatment of starch-containing and oil-containing crops were optimized. The recoveries of cartap, thiocyclam, thiosultap- monosodium, and thiosultap-disodium in all samples were in the range of 72 – 108%, with RSDs of 0.3–14.7% ($n = 1200$, $p < 0.05$). These results demonstrated the good sensitivity, accuracy, and precision of this method. The intermediate precision of the method was evaluated by repeating the method confirmation experiment 5 times in our laboratory, and the reproducibility of this method was tested in five different laboratories. All the experimental results passed the Cochrane and Grubbs tests ($n = 2400$, $p < 0.05$). The RSDs of intermediate precision and RSDs of reproducibility among different laboratories met the requirements for pesticide residue detection. This indicates that the accuracy and precision (i.e., repeatability, intermediate precision, and reproducibility) of the established method were satisfactory. Therefore, this method can be used to detect residues of cartap, thiocyclam, thiosultap-monosodium, and thiosultap-disodium in plant foods.

Acknowledgements

We appreciate the help of the National Grain and Oil Quality Supervision and Inspection Center (Beijing, China), Beijing Pesticide Identification Institute (Beijing, China), Beijing Disease Control and Prevention Center (Beijing, China), and Beijing Food Inspection Institute (Beijing, China), who assisted us in completing the repeatability and reproducibility tests for the established analytical method.

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P69 - Importance of Unmanned Aerial Vehicles Settings for Spray Bait Treatments on Citrus Orchards

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Introduction

Since its inception, agriculture has been threatened by pests. Currently, according to the FAO, they give rise to annual losses of 40% of production. A problem that is accentuated by climate change, the intensification of farming systems and the increase in monocultures, and the global exchange of material that produces the entry of pests from third countries.This makes crops protection essencial. Despite the enormous advances in biological control and ecologically sustainable alternatives, today the application of plant protection products (PPP) is still necessary, especially in tree crops, such as fruit trees, citrus and vineyards, which are subject to a particular pest pressure. There is currently a social and political commitment to reduce the risks of the PPP use, as included in the "Farm to Fork" strategy of the European Green Deal, which promotes strategies to improve the sustainability of the application of PPP.

Unmanned Aerial Vehicles (UAV) are foreseen to be an important new technology for PPP application. Their greatest limitation for this task at a technical level, especially in tree crops, is their low load capacity and low flow rate. This makes them inadequate for treatments that require a good coverage of the vegetation and penetration inside the canopy, which entail high volume rates. However, they can be suitable for low or ultra-low volume treatments, such as bait treatments, in which it is the pest that comes attracted to the PPP distributed over the vegetation. It is important, however, to take into account the specific requirements of each application, in order to properly configure the ensemble formed by the UAV-spraying system so that the biological efficacy and efficiency of the operation is maximum.

Citrus are characterized by being perennial and presenting high leaf density, usually with elliptical-shape trees which reach large dimensions with a non-negligible crop width. It is highly affected by *Ceratitis capitata*, the Mediterranean fruit fly. The female medfly lays her eggs in the fruit subsequent larvae feed on the citrus flesh, reducing their marketability. Bait treatments are regularly used to control this pest. They are mainly applied by terrestrial equipment, fitted with a single nozzle working at low pressure (3 bar) and high forward speed (6-8 km/h), aimed at distributing coarse bait impacts (1-6 mm diameter, as suggested by Vergoulas and Torné [1]) on the external part of the canopy in one row out of every two, depositing 6 L/ha in each treated row. The use of UAV to perform this task is seen as a good alternative to avoid operator exposure, reach hard-to-reach areas, and increase working capacity, so proper settings to maximize medfly control and reduce PPP losses have to be identified.

Objectives

The aim of this work was to evaluate the deposition on the citrus canopy and the ground spray losses of bait treatments applied with UAV at diverse forward speeds and fitted with different nozzle types. The final goal was to know how these factors affect the spray distribution with UAV to optimize this application in citrus crop.

Materials and methods

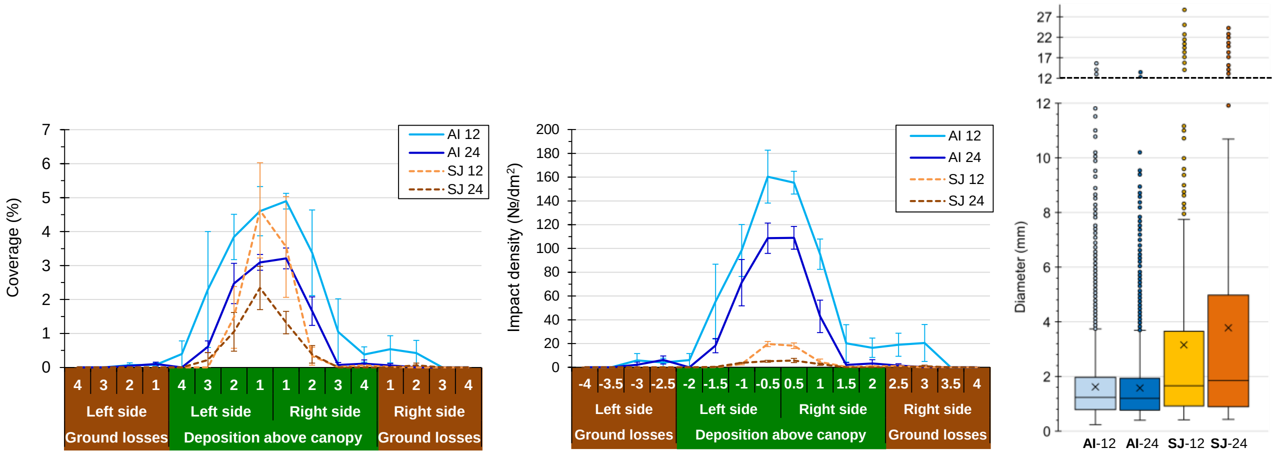
An UAV (AGR Qifei, model Q10, China) with 10 L tank capacity was used, which was flown manually 2m above a citrus row. The spraying system was manipulated so that one working nozzle was located in the centre of the UAV. To study the effect of the nozzle, two types of nozzles that produce coarse droplets , were selected: one air induction nozzle AI9504EVS and one fertilization streamjet nozzle SJ7-04-VP (TeeJet Spraying Systems Co., Wheaton, Illinois, USA). Forward speed effect was studied at 2 levels, 12 km/h and 24 km/h. Therefore, 4 treatments were performed AI12, AI24, SJ12, and SJ24, with 3 replicates.

The spray distribution was evaluated through the characterization of spray deposits collected on filter papers located perpendicular to the advance of the UAV, both on the external face of the top of the canopy and on the ground of the two adjacent swaths. Filter papers were digitized and image-analysed, and the following parameters were calculated: coverage (%), impact size (mm) and density of impacts (#/dm^2).

Results

The results showed that the density of impacts from the air induction nozzle was higher and their size was lower than the ones from the streamjet nozzle. The streamjet nozzle produced very few droplets and they were very big. On the other hand, the lower the forward speed, the higher the droplet density for both nozzles (Figure 1).

Figure 1. Impact density (#/dm²) and coverage (%) for each treatment depending on the position of the collector. And Box-and-Whisker distribution plot of impact diameter (mm) for each treatment.



Source: authors' data

Discussion and conclusions

The lower impact size obtained with the air induction nozzle fulfilled the requirements for bait treatments, because they were similar to the obtained by Chueca et al. [2], therefore were considered big enough to attract the target pest. On the contrary, the size of impacts from the streamjet nozzle was that big that they would likely runoff from the leaves. The droplet density at 24 km/h was also enough increasing by 2 the work capacity and reducing the PPP losses. Therefore, in the conditions of the study, the best option would be to use the air induction nozzle at 24 km/h.

It has been demonstrated that the application of bait treatments with UAV is possible but it is important to set up the system adequately to improve its efficiency.

Acknowledgements

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P70 - Efficiency of a smart spraying technology in a fodder crop production

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Introduction

The current Common Agriculture Policy (CAP) foresees a reduction of 50% in the use of herbicides by 2030. In Mediterranean regions, usually weed control in rainfed fodder crops under no-till, is necessary before sowing and after crop emergence. It is therefore important to adopt new management approaches and instruments such as remote sensing and variable rate application technologies capable of reduce the amount of herbicide used with the environmental and operation cost-benefit, and without affecting agricultural yield [1]. Weeds do not appear homogeneously in the plot, to know and quantify its presence at each of these points with a high level of certainty, the collection of close images can be a crucial technique due to its high level of resolution. The classification of the images must be evaluated and validated. An example of these validation methods is the Kappa Coefficient [2] whose objective is to provide a basis for comparing, classified and reference data, and verifying whether they agree.

Objectives

The objectives of this trial were i) to demonstrate how remote sensing using a low-cost RGB sensor combined with variable rate technology can contribute to the best efficiency productivity of a herbicide in a fodder crop, and ii) to determine the variable rate efficiency of a herbicide in a fodder crop.

Materials and methods

The field surveyed, covering three plots of 7.5 ha each, was conducted in Southern Portugal at the geographic coordinates 38° 53’ 39’’N, 7° 03’ 03’’W.

Sowing rate of 43 kg ha^{-1}of a winter rye grass (Lolium multiflorum Lam.) under no-till took place in mid-October, weed control of a fixed rate of a glyphosate-based herbicide with 3.0 l ha^{-1}, and a basal dressing of 150 kg ha^{-1} NPK 7-21-21 fertilizer. The field was sampled at one point per hectare approximately where crop biomass was evaluated under three different grass weeds control: no herbicide application (Plot I), variable rate application of 0.5 to 0.75 l ha^{-1} of post-emergence control of broad-leaved weeds based in Florasulam (Plot II), and fixed rate application of 0.75 l ha^{-1} of the same herbicide (Plot III). Image segmentation and classification per sampling area followed an image obtained at 0.80 m height from the soil by an RGB sensor in a camera with 12 MP of a smartphone Xiaomi Redmi 8 and performed using QGis software version 3.16.9 (http://www.qgis.org/). From each image Excess Green Index (ExG) was determined, and GRASS GIS module *r.neighbors* was used to calculate maps using the spatial neighbourhood set to 9 pixels. The value of this index was determined for the classification of the image into 3 zones i) soil, ii) crop, and iii) weeds. Descriptive statistics and Student t-tests for identification of significant differences followed by a Tukey’s test for post hoc results were undertaken using Statistica software, version 12.0 (StatSoft®, Tulsa, USA).

Results

Data of the percentage of crop plants and weeds per plot before and after the herbicide application are summarized in Table 1, and the validation of the kappa coefficient, and the estimated precision for the identification of soil, crop, and weed are in Table 2.

Table 3 summarizes the descriptive statistics and coefficient of variation (CV) of the crop production of the three plots.

Table 1. Percentage of crop plants and weeds per plot before (M1) and after (M2) the herbicide application

	Plot	I (No herbicide)						II (VRT)					III (Fixed-Rate)									
	Sample point	1a	2a	3a	4a	5a	6a	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Ryegrass	M1	54,0	79,3	7,4	74,6	48,7	42,0	86,1	62,1	43,9	91,2	95,3	5,1	76,7	69,4	37,1	87,4	97,6	75,3	43,5	75,7	83,3
	M2	60,7	74,2	3,4	75,7	65,9	28,2	91,5	81,5	63,1	95,8	100,0	74,1	2,7	95,5	79,3	87,1	93,8	85,6	80,6	96,9	92,6
Weed	M1	42,1	20,7	92,6	25,4	51,3	55,4	4,6	20,4	13,5	2,6	0,0	85,1	16,1	11,1	62,9	1,1	2,4	22,0	53,6	24,3	8,8
	M2	33,3	25,8	96,6	24,3	34,1	62,4	3,4	0,0	8,3	2,1	0,0	20,3	97,3	0,3	3,1	3,8	3,6	0,0	0,0	0,0	0,0

Table 2. Validation of the kappa coefficient (left), and the estimated precision for the identification of soil, crop, and weed (right)

N = 150		Precision (%)		
K1	0.78		Soil	99
K2	0.58	Estimation	Crop	20
K3	0.48		Weed	45

Table 3. Descriptive statistics and CV of crop production per plot (kg ha^{-1} DM)

	Plot I (n=6)	Plot II (n=8)	Plot III (n=7)
Min	64.0	212.2	457.1
Max	1280.0	1289.8	1926.5
X±sd	394.7$^{a)}$ ±453.3	844,9$^{b)}$ ±365.7	1322.4 $^{c)}$ ±557.0
CV	114.9	43.3	42.1

Different letters mean significantly different means ($p<0.05$)

Discussion and conclusions

Our study although with a lower value in the accuracy showed a similar value of kappa [3] demonstrating that using the RGB sensor of a smartphone as a low-cost sensor and computed an image for later classification in a GIS software allows a moderate distinction performance of the soil, weeds, and crop even considering it earlier growth stage.

The percentage of weeds clearly decreases in Plot II and III with the application of the herbicide, as well as increase crop production and homogeneity of the crop. Despite a lower production, the results of Plot II there was an average reduction of 0,22 l ha^{-1}demonstrate that a clear reduction in the weed population was achieved, providing a friendly and light computational solution to the farmer to collect the quantities of weeds along the plot making possible to know their variation in space, as well as facilitates the zoning areas to adjust the doses of herbicide to the needs of each specific point.

Acknowledgements

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P71 – Development of a new Cotton Defoliation Sprayer using Unmanned Ground Vehicle

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Introduction

Cotton (Gossypium hirsutum) falls under the Malvaceae family and is an important industrial crop in the United States (US). Cotton is a perennial crop but is grown as an annual crop in the US. The United States is the world's third largest cotton producer after China and India and the largest exporter of cotton. It produces almost 20 million cotton bales, and the cotton industry contributes almost $7 billion to the US economy [1]. Cotton is grown in the Southern states of the US, known as the Cotton Belt, where the largest cotton-producing state is Texas.

Chemical spraying is among the most important and frequently performed intercultural agricultural operations. Some chemicals are used to accelerate the harvesting process, e.g., harvest aid and defoliant. Cotton defoliation is the shedding of leaves and is an essential factor influencing mechanical harvesting, fiber quality, and the cost of cotton production. Although the cotton crop defoliates by the natural process, due to the inconsistency and inadequacy of the falling of leaves, growers resort to using chemical defoliants. Defoliation is done approximately two weeks before the expected harvest date or when more than 60% of cotton bolls are open [2,3]. A tractor-mounted sprayer [4] or a drone sprayer [5] are being used for defoliation. Although the tractor-mounted sprayer has been used for quite some time, Weicai et al. [6] showed that a small amount of chemical droplets reach the lower canopy of the plant as the upper leaves block the droplets, thereby reducing the volume of chemicals to reach the bottom part of the crop. To completely defoliate, all leaves, including the lower part, must be in contact with the chemical defoliant [3].

Current defoliation spraying practices only spray the top canopy of cotton plants with the presumption that the defoliants will penetrate deeper into the crop. There needs to be more work related to the study of the effect of spraying the bottom part of the cotton crop. Therefore, to address this research gap, we are developing a new spraying system using unmanned ground vehicles and pulse width modulation technology [7]. This work focuses on a new cotton defoliation sprayer with three spray nozzles on each side of the spraying system. Each nozzle can be controlled independently using pulse width modulation.

Objectives

To our knowledge, work has yet to address an autonomous ground vehicle for cotton defoliation that covers the entire canopy of the plant. The objective of this work is to study the effect of the different spray flowrate (duty cycles) on the rate of defoliation.

Materials and methods

An unmanned ground vehicle (UGV) was used for this work. The UGV (Husky A200, Clearpathrobotics, CA) has multiple sensors for autonomous navigation [7]. The sprayer unit is an off-the-shelf pull-behind sprayer (1598042, County Line, USA) with a built-in 12V diaphragm pump. The sprayer unit was retrofitted with 6 nozzles, where three spray nozzles on each side of the spraying system. The three nozzles on each side are designated as low, middle, and top, with distances from the ground at 38 cm, 84 cm, and 145 cm, respectively. An aluminum extrusion was used to hold the nozzles and the sprayer controller. A sprayer controller was developed to control the sprayer and was designed as an independent controller from the UGV. The sprayer controller used an ARM Cortex-M4 (MK66FX1M0VMD18, NXP, Netherlands) with GPS and wireless transceivers.

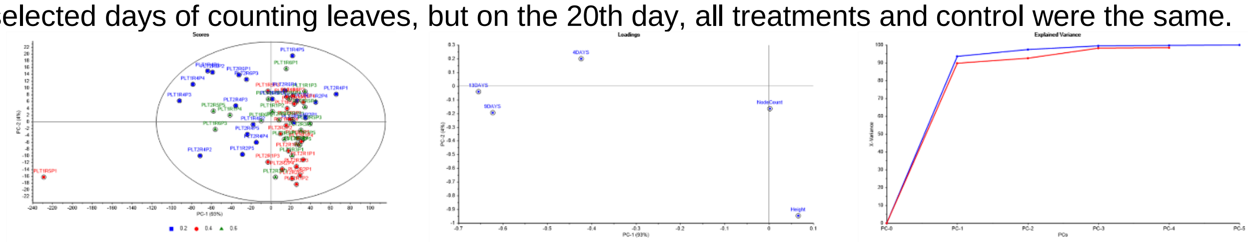
The field experiment was conducted in two cotton fields at Edisto Research and Education Center farm (Field 1: Field 1: 33.347, -81.319; Field 2: 33.353, -81.310) using two different cotton cultivars at each field; DP 2038B3XF, and DP 2055, respectively. Field 1 was planted in early May 2022, while Field 2 was in late May 2022. A completely randomized design with 4 replications was used in Field 1 and 2 replications in Field 2. Three duty cycles (20%, 40%, and 60%) were used as a treatment, and the control was a conventional tractor-mounted sprayer. A total of 120 plants, 80 in Field 1 and 40 in Field 2, were randomly selected and tagged. A mixture of chemicals was used for the defoliation, two cotton defoliant (Folex 6 EC and Free fall SC) and one boll opener chemical

(Super Boll). The same mixture was used for the control. The spraying on both fields was done 20 days before harvest in September of 2022. Data on plant height, node count, and leaves count was collected on the 0th day (at the time of spraying), 4th, 8th, 12th, 16th, and 20th days. The defoliation rate was calculated using the formula

$Defoliation\ rate = \frac{lfc_n - lfc_{n+1}}{lfc_n} x\ 100\%$, where *lfc* is leaf count, and *n* is the days when the count was done. Principal Component Analysis was used to interpret which variables (node, height, etc.) were essential for the defoliation test. A random cross-validation method with 20 segments and 3 samples per data segment was used for the validation.

Results

Results for the spray test showed that there is no significant difference in defoliation across the three treatment levels, as shown in the score plot with one outlier for Field1(PLT1), row 5, and Plant1. (See Figure 1a). The score plot showed that the flowrate of 40% has more contribution on PC-1, while the 20% flowrate shows contribution on PC-2 calibration. The loading plot showed that the height of the crop is important based on the current placement of the nozzles (Figure 1b). The explained variance plot showed that the principal components (PC-1 and PC-2) already captured most of the information needed at 97%. Overall, the control had a faster defoliation rate during the selected days of counting leaves, but on the 20th day, all treatments and control were the same.



(a) (b) (c)

Figure 6. Results of the PCA; (a) score plot, (b) loading plot, and (c) explained variance plot.

Discussion and conclusions

There is no significant difference in defoliation across the three treatments (20%, 40%, and 60%). Although the control has a faster defoliation rate, results showed that on the 20th day, both fields; Field 1 and 2, showed the same defoliated plants as in the control. There was slight rain after the spray on the treatment plot and two consecutive freezing nights, which could have affected the defoliation rate of the cotton plants under study. The results also provide an interesting insight that 20% is enough to defoliate the plant as long as it covers the whole plant. This is a significant finding and will definitely help cotton growers in their defoliation. Although this work is focused on cotton, the technology developed in this project has the full potential to be used with other crops.

Acknowledgements

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P72 – Can UAV spraying systems assist in precision crop protection?

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Introduction

In recent years, unmanned aerial vehicles (UAVs) have been seen as bringing about a new era in the agriculture industry. However, from today's perspective, the most significant impact of the application of UAVs in agriculture can be in two domains: high-throughput field phenotyping and precision aerial applications with spraying systems, the latter subject to regulations depending on the country of use.

The European Commission's Farm to Fork strategy aims to reduce the use of chemical plant protection products (PPPs) in the EU by 50% over the next decade. Spraying drones are a powerful tool that can potentially increase the spatial resolution and flexibility of PPPs spraying. This technology allows PPPs application with precision and reduces the amount of product applied, going faster to friendly environmental agriculture. The advantages of these systems have increased the interest of research centers, growers' associations, and public and private organisms to develop their full potential and apply them together with new technologies, such as artificial intelligence, to assess some of the main challenges in the agri-food and forestry sectors [1, 2, 3].

This project includes trials to assess drift, residues, product efficacy, and human health and safety with drone application compared to conventional terrestrial spraying. The selected crops, olive and vineyards, are representative of the diversity of three-dimensional crops cultivated in Spain that could benefit from drone technology towards sustainability. Furthermore, pine is the chosen specie to validate the use of this technology in plant health management in cultivated forests. Trials took place across the Spanish territory, comprising different climates and conditions representative of the heterogeneity typical of agricultural systems.

Objectives

The "GO PhytoDron" project aims to promote spraying drones as a precise and safe tool for applying PPPs. This allows its classification as precision agriculture instead of the aerial application under specific scenarios.

Our trials aimed to assess and compare the airborne drift, sedimented drift, and soil and crop depositions produced by spraying drones to the drift generated by conventional terrestrial sprayers typically used for each studied crop.

To compare the residues and efficacy, we conducted comparative trials to assess the differences between spraying drones and conventional terrestrial spraying systems.

In addition, we carried out trials to assess human health and the safety of spraying drone operations.

Materials and methods

The experimental design used in the airborne and deposition drift trials followed the standard ISO 22866:2005 and ISO 22522:2007.

The experimental design used to assess efficacy followed PP1/280(1) standard for trials carried out in olive, and PP1/301(1) standard for the trials carried out in citrus.

The experimental design to assess the exposure for operators, workers, residents, and bystanders followed the guidance of EFSA [4].

Drift and deposition trials were carried out using tartrazine as a tracer. In addition, efficacy, residues, and exposure for operators, workers, residents, and bystanders tests were carried out using Spintor (Spinosad, 0.24g/l).

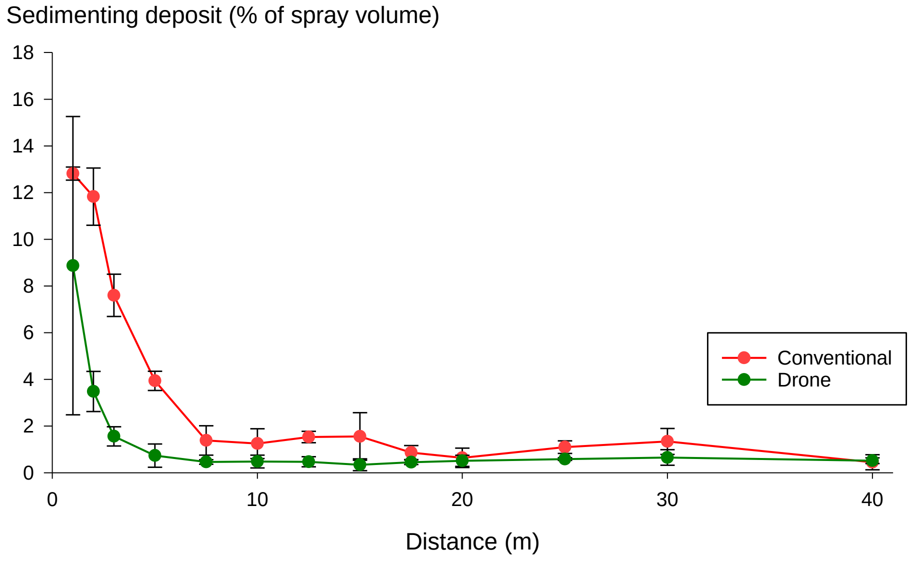
Results

During our trials, we observed a significant reduction in airborne and sedimented drift when spraying drones (Figure 1). Soil deposition results show no statistical difference between conventional and drone sprayers. However, crop deposition was significantly reduced when using spraying drones.

The efficacy results of our study show no statistical difference between a conventional and a drone application for bait treatments against *Bactrocera oleae* and *Ceratitis capitata* in olive and citrus. In addition, results from the residue analysis show no difference between the studied spraying systems.

The results obtained from the exposure for operators, workers, and bystanders trials show that the exposure to PPPs is reduced when spraying drones compared to the reference exposure models.

Figure 1. Sedimented drift results obtained in super-high-density olive orchard trials.



Discussion and conclusions

Our results suggest that, under our conditions, the drift generated by drone spraying systems is significantly lower than the drift generated by the conventional atomizers typically used in olive orchards. Furthermore, the sedimented drift trials in olive orchards suggest that the buffer zone required for sprayer drones is narrower than for conventional terrestrial systems. Since, under our conditions, the efficacy and the residues are comparable to those of a conventional terrestrial sprayer, spraying drones show up to farmers as a real alternative to conventional sprayers. According to our results, drone spraying systems will contribute to the security of operators and the health of workers and bystanders by reducing their exposure to PPPs.

However, not all treatments are suitable for drone spraying. In some cases, the low crop depositions and ultra-low volume application that drone sprayers provide might limit the efficacy of treatments requiring considerable crop coverage. Therefore, drone spraying systems might be more suitable for bait or systemic treatments that do not require full crop coverage.

Our data infers that drone spraying systems can contribute to the sustainability of the European agricultural sector by introducing precision agriculture techniques, such as spot spraying while reducing the use of PPPs and their environmental risks.

Acknowledgments

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P73 - Enhancing nitrogen management through remote sensing and self-driving robots for precise N application to reduce leaching

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Introduction

Precision agriculture has been applied for the site-specific N management by utilizing in-season sensors to detect the spatial variability of crop growing conditions and adjust in-season N input. However, there is a need to improve N input recommendation. One way to do it is the inclusion of weather and soil effects into machine learning and AI techniques with the aid of remote-sensing methods that allow more efficient screening of spatial variability within the field. Machine learning and AI based algorithms can predict location-based N uptake and needs within 10-20 kg N/ha. Based on the concept of critical N dilution curves and crop N uptake interaction with drought stress, this method achieves better estimation of N uptake in crops. The field experiment in central Denmark aims to compare conventional fertilizing to the more precise method of using robot-assisted split fertilization (ROBOTTI, Agrointelli, Denmark), utilizing unmanned aerial systems (UAS, Multispectral Micasense RedEdge Dual with 10 bands and thermal camera Zenmuse H20T). The test crop is table potato. The remotely sensed data is then used to derive relations to the measured variables, such as soil nutrient content, soil organic matter, bulk density, soil water content, crop biomass, leaf area index, and chlorophyll content. This approach can accurately detect plant N requirement and supply fertilization according to its needs, reducing N pool in the soil during and after the growth season to limit nitrous oxide emissions and N leaching by keeping soil nitrate concentration low. By understanding the effects of abiotic stresses, especially drought, further improvements in N application recommendations can be achieved. Self-driving robots for precise leaf surface N application are gaining popularity and offer benefits over soil-applied methods.

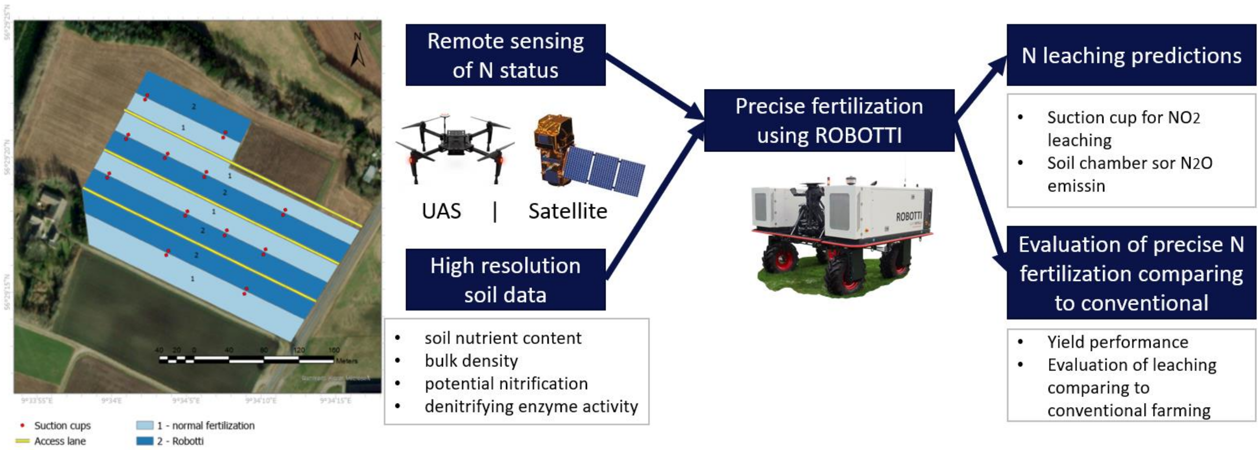
Objectives

The objective of this study are:

- investigate the use of a self-driving robot for precise leaf surface N application and compare it to the performance of the conventional farming techniques;
- explore the potential of machine learning and AI techniques for N input recommendations in precision agriculture using multispectral data obtained from unmanned aerial systems;
- evaluate the possibility to use UAS in N leaching predictions.

Materials and methods

Figure 1. Experimental setup



An 8 ha field experiment (Figure 1) will compare conventional and precise N application methods (using ROBOTTI) on potato crops in central Denmark in 2023. Prior to planting, detailed soil mapping was conducted, including nutrient content, organic matter, water content, nitrification potential, denitrifying enzyme activity, and electromagnetic conductivity. This information will guide the precise application of N fertilizer using the ROBOOTTI, aiming to assess yield, nitrogen use efficiency, and environmental impact. Crop growth and N uptake will be measured to assess N balance and the applicability of sensor-based robotic fertilization. Data processing algorithms will be developed for emissions-based farm regulation and to estimate the effect of precision fertilization on N leaching.

For the in season fertilization using ROBOTTI, the approach of Peng et.al. [1] study will be used the approach of accurately detecting plant N requirement.

Step 1: Determine crop biomass based on f_{Ipar}: Fraction of Intercepted Photosynthetically Active Radiation [2]

Step 2: *Random forest regression (RFR)* analysis in order to assess crop N status [1].

Step 3: Critical nitrogen (Nc) dilution curve construction.

N_c: critical nitrogen concentration, minimum nitrogen for maximum dry matter

For the evaluation of the N leaching, suction cups are installed across the field and the samples are taken every 2 weeks and chamber based GHG measurements performed to estimate emissions.

Discussion

Precision agriculture has been proposed more than 30 years ago [3], and two different approaches have been generally used in site-specific N management: sensor-based and map-based. The former, utilized in-season sensors to detect the spatial variability of crop growing conditions and adjust in-season N input; the latter, utilizes spatial maps, like yield monitors, proximal soil or remotely sensed images to define uniform zones within the field and modify the N amount for each zone [4]. However, despite the significant development in such techniques, the adoption of site-specific N management in many places of the world is low, with about 20% of farmers adopting it [5]. Incorporating weather and soil effects into machine learning and AI techniques using remote-sensing methods has the potential to greatly improve N input recommendations in precision agriculture. The use of unmanned aerial systems and multispectral data can accurately detect plant N requirements and supply fertilization accordingly (e.g. with the use of ROBOTTI), which can ultimately help reduce nitrous oxide emissions and N leaching while maintaining crop yields. However, further investigation is needed to determine the exact benefits and potential impact on leaching of using self-driving robots for precise leaf surface N application.

Acknowledgements

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P74 - Site-specific nitrogen management in winter wheat

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Introduction

An important factor in sustainable agriculture is the efficient use of fertilizer. It not only affects crop productivity but also reduces environmental pollution [2]. Site-specific nitrogen (N) management adjusts within-field N fertilizer rates aiming at optimizing grain yield, mitigating leaching problems, and the emission of greenhouse gases [1]. In this study, we evaluated four strategies, including sensor and crop model simulations, to calculate the optimum amount of wheat nitrogen demand on a site-specific level.

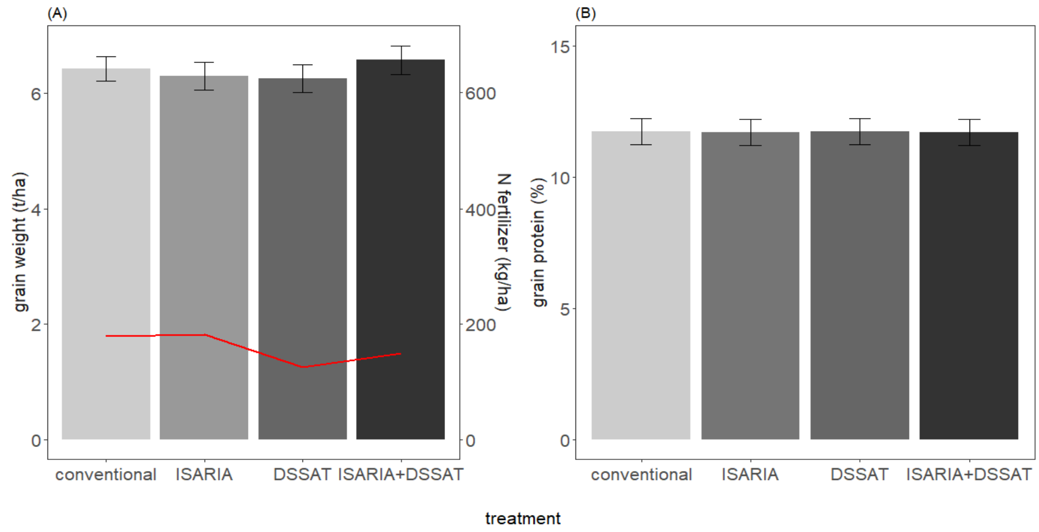
Materials and methods

A field experiment was carried out during the vegetation period of winter wheat in 2021-2022 at the Experimental Station Ihinger Hof (48◦44’ N, 8◦55’ E) of the University of Hohenheim in south Germany. The average annual rainfall and annual temperature were 714 mm and 9.1 °C respectively. The soil type of the experimental field was characterized as heavy calcareous brown soil with high clay content. In October 2021, winter wheat (Triticum aestivum) was sown at a rate of 360 plants per m^2. The field was divided into 120 site-specific units (12 m × 48 m). The amount of in-season plant N demand in each unit was evaluated based on different strategies: sensor-based (ISARIA), crop growth model (DSSAT), a combination of sensor and crop growth model, and common N fertilizer management practice by farmers (conventional method). N fertilizer was applied as KAS (27 % N) at three different times (tillering BBCH 22-25, stem elongation BBCH 30-32, and booting BBCH 44-49), with the amounts based on the prescriptions of each evaluated strategy. The experiment followed a complete randomized block design with five replications (blocks). In each block, the treatments were arranged in a row containing eight units, and the conventional method was represented randomly per row. Data analysis was performed with SAS 9.4 statistical software, using a Generalized Linear Mixed Model with Template Model Builder. Winter wheat grain yield and grain protein concentration were modelled as a response to the fixed effects treatments, amount of applied N fertilizer, and block. The row was included as random effects. Means were then compared using the lsmean test at $\alpha = 0.05$ significance level.

Results

Grain yield ($p=0.85$) and grain protein concentration ($p=0.98$) did not differ significantly between the treatments (Fig. 1). Amount of applied N fertilizer neither significantly affected grain yield ($p=0.46$) nor grain protein concentration ($P=0.50$). Slightly higher and lower grain yield and grain protein concentration were found in plots that were fertilized based on the sensor + crop growth model and the single DSSAT strategy, respectively.

Figure 1 Average (A) grain yield [t ha-1] and (B) grain protein concentration (%) for each treatment. The red line represents the amount of applied N fertilizer (secondary y-axis, Fig A).



Discussion and conclusions

The results showed that site-specific fertilization could reduce total N application without yield loss, which is in line with the findings of Argento et al. (2021) and Stamatiadis et al. (2018). The results did not differ significantly between the strategies and different amounts of N fertilizer for grain yield and grain protein concentration in 2022. The modelling strategy recommended the lowest amount of N fertilizer without significant penalties for grain yield and grain protein concentration compared to the other strategies. However, to decide on a suitable strategy for estimating in-season nitrogen requirements of winter wheat on a site-specific level, an economic evaluation of these strategies should be conducted based on current market grain and N fertilizer prices.

Acknowledgements

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P75 - Optimal input efficiency in cotton using multispectral camera system performing real-time VRA

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Introduction

Contemporary Agriculture is facing a major challenge of balancing sustainable productivity with increased food safety under unprecedented pressure of production cost (Medici et al., 2022). Precision Agriculture has positively contributed to addressing these issues, by providing agricultural fields optimized inputs, such as water, fertilizers, and pesticides based on data-driven decisions. The targeted use of input can be conducted by Variable Rate Applications (VRA) in determined zones throughout the field. Such a regime addresses the actual needs of specific parts of the field rather than the average needs of a whole field.

Objectives

In this study, input use efficiency in cotton fields is examined through the Variable Rate Application realized via a multispectral camera system. The Multispectral camera system operates mounted on top of a tractor or self-propelled sprayer and utilizes data from different channels (Red, InfraRed) to generate a Vegetation Index (NDVI) upon which VRA are performed in real-time, while the farmer is driving on the field without further need for additional calibration The multispectral camera system uses unique algorithms that are dynamic in nature and created to achieve input savings whenever possible.

Materials and methods

Trials were performed on cotton fields in Greece for three consecutive years, where fields have been split into two equivalent parts. Half of the field was VRA treated while flat rate applications were performed to the other half. To ensure the uninterrupted completion of the crop's life cycle and productivity, all common cultivating techniques were used in both areas of the field.For variable rate application two major inputs in cotton were considered; plant growth regulators, boll openers, and defoliants. For the evaluation of the impact of the VRA treatments, data gathered during the VRA operations (Vegetation Index maps, Application maps, environmental conditions, etc.) have been compared to yield data and physical measurements taken before and after each application.

Results

By delivering the optimal amount at the right place on the field, input savings (up to 20%) were achieved coupled with unimpeded productivity, which consequently means increased income for the farmers with a reduced environmental footprint.

Table 1. Statistics regarding the in-season real time Variable Rate Plant Growth Regulators (PGR) and Harvest Aid (HA) applications based on data gathered during operations utilising close-range remote sensing (Augmenta Mantis TM) for three cultivation periods (2020-2022).

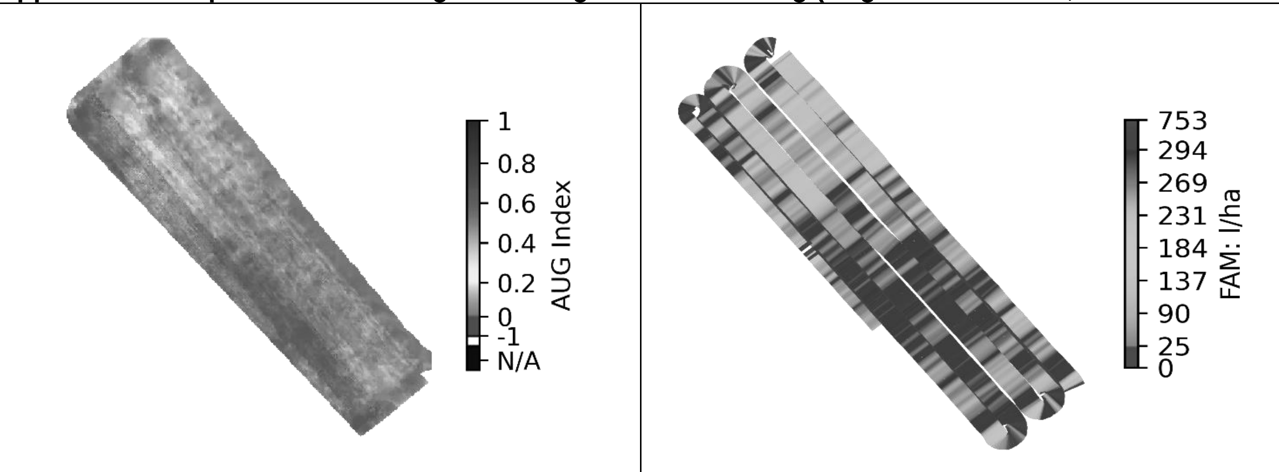
Cultivation period	Field area (ha)*	Savings in PGR (%)	Savings in HA (%)	Yield increase (%)
- 2020	17.67	13.38	-	4.71
- 2021	12.81	12.56	9.03	5.84
- 2022	9.48	5.73	6.97	4.03
Totals	39.96	11.30	8.15	4.91

*Field area of VRA operations (The total field area of both Variable Rate and Fixed Rate Applications was 79.5 ha)

In 2020, savings of 13.38% in PGR inputs were achieved in parts of the the fields that VRA was performed while an average yield increase of 4.71 was reached. Slight decrease in savings was observed in 2021 for PGR Variable Rate applications (12.56%), while the savings for Harvest Aid Variable Rate Applications were calculated at 9.03%. Yield increase of 5.84% was accomplished. During 2022, 5.73% and 6.97% average input savings were realised for PGR and HA Varaible Rate

Applications respectively, while 4.03% was the yield increase for VRA-treated parts of the field, compared to Fixed Rate treates field parts.

Figure 1. (a) AUG Index, Field Application Map of a cotton field in 2021, where Variable Rate Application was performed utilizing close range remote sensing (Augmenta Mantis ™).



(a) (b)

Conclusions

Based on the outcomes of this study multiple benefits can be realised by the integration of Variable Rate Application technologies in cotton fields. The average yield increase was 4.91%, while the PGR and Harvest Aid input savings were 11.3% and 8.15, respectively for three consecutive years. The relationship between VRA and yielding indicates a propensity for higher yields in areas treated with Variable Rate Applications.

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P76 - Application of model-based dynamic prescription maps for optimizing variable rate irrigation

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Introduction

Ensuring a more efficient and sustainable use of water in agriculture is critical to meet the food needs of the rapidly growing world population. Variable rate irrigation (VRI) has been shown to improve water use efficiency and increase crop yields. VRI is usually based on prescription maps delineated according to a static approach. Irrigation rate and timing are optimised by sensor and/or modelling-based methods applied within homogenous zones whose spatial distribution is kept constant during the crop season.

Objectives

. The objective of this study was to develop a procedure based on the combination of the crop-energy-water balance model FEST-EWB-SAFY with remote sensing data of vegetation variables and land surface temperature to generate dynamic irrigation prescription maps.

Materials and methods

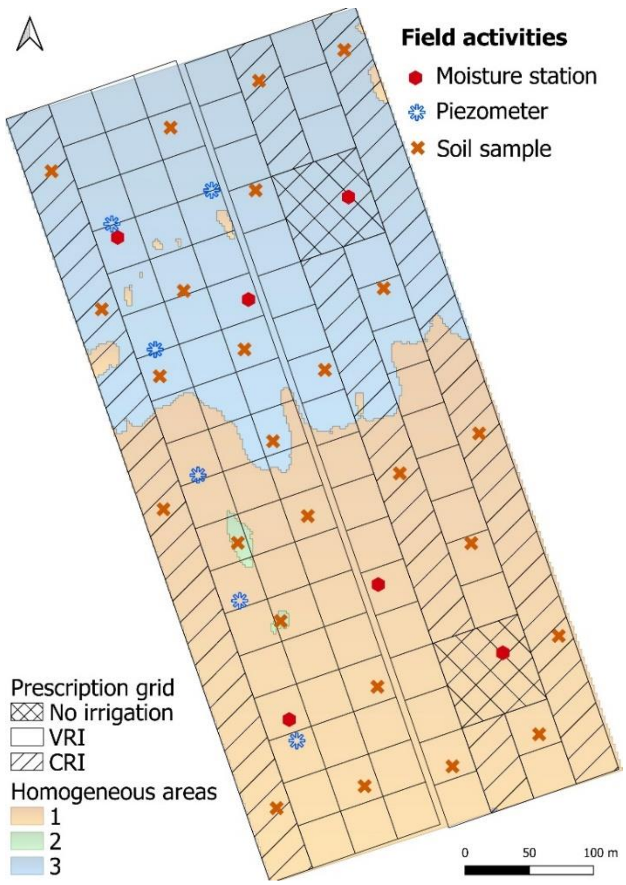

Figure 1. Field activities, homogeneous zones defined by apparent electrical conductivity and prescription map grid

The crop-energy-water balance FEST-EWB-SAFY model couples the distributed energy-water balance FEST-EWB, which allows computing continuously in time and distributed in space both soil moisture and evapotranspiration fluxes, and the SAFY (simple model for yield prediction and plant development).

The model was tested in a 30-ha field cultivated with soybean in 2022 at Ceregnano, in the lower zone of the Po Valley (Italy).

Irrigation was provided by 280m long lateral move irrigation machine, equipped with a precision irrigation system with a lateral resolution of 35 m.

The model was pixelwise calibrated with remotely sensed land surface temperature (LST, RMSE 1.3 °C) and leaf area index (RMSE 0.45) as well as local measured soil moisture at 10cm and 50cm depth (RMSE 0.04). To estimate evapotranspiration, the model required the watertable level measured by eight piezometers as input. (**figure 1**).

Three dynamic prescription maps (e.g **figure 2)** were generated during the season, calculating the pixel-by-pixel difference between the field retention capacity and the daily average of the 50-cm soil moisture profile. A comparison was made between dynamic variable rate irrigation (VRI) and a conventional constant rate irrigation (CRI) system, using an experimental block design with three replicates. The systems were evaluated in terms of crop yield, irrigation volumes, and water use efficiency.

Results

Crop yield (**figure 3**) was significantly affected by the water table depth: a shallow aquifer in the northern area led to an average crop yield of 5 t/ha while the southern area, with a deeper water table, resulted in a crop yield of 3.5 t/ha. Although VRI was applied only in 3 out 5 irrigation events, the results highlighted the positive role of the VRI, which allowed to reduce irrigation volumes and increase the water use efficiency (**table 1**).

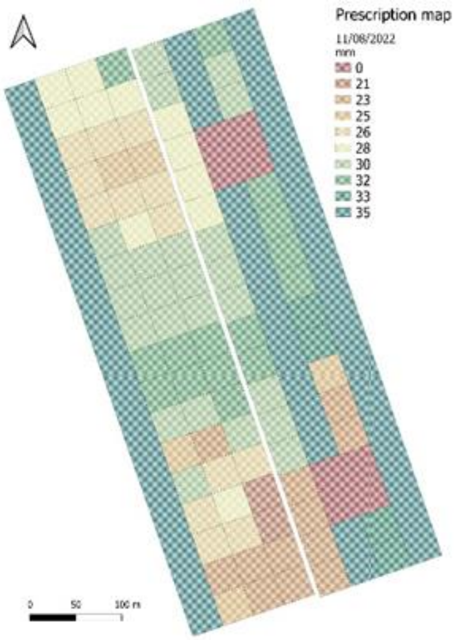

Figure 2. Prescription map applied on 11/08/2022

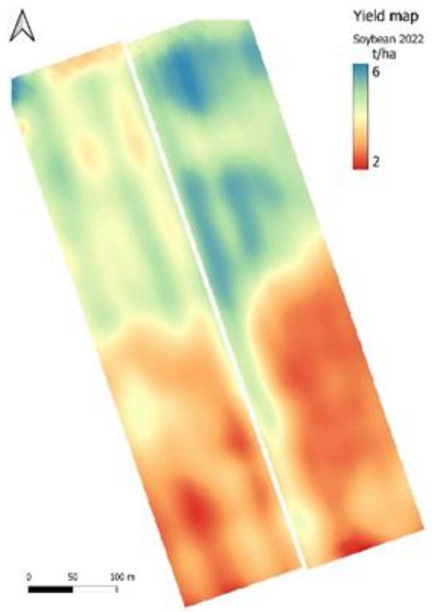

Figure 3. Soybean yield map of season 2022

Table 1. Irrigation volume, crop yield and water use efficiency in VRI and CRI

	VRI	CRI
Irrigation volume (m^3/ha)	**1401 ± 7.6**	**1550**
Crop yield (t/ha)	**4.32 ± 0.1**	**4.36 ± 0.4**
Water use efficiency (kg/ m^3)	**3.08 ± 0.1**	**2.81 ± 0.3**

Discussion and conclusions

This study investigated quantitatively how a pixel-based model and remote sensing method can help to improve irrigation practices. FEST-EWB-SAFY allowed the creation of dynamic prescription maps, capturing variable water requirement resulting from ET losses, soil properties and field management.

Compared with the conventional irrigation system, VRI showed a positive effect on the water use efficiency without causing negative consequences in terms of crop yield.

These findings confirmed that the model-based dynamic prescription maps could be used to optimize variable irrigation in highly spatio-temporal dynamic cropping systems.

Acknowledgements

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P77 – Improving estimates of plant-available phosphorus through sensor data fusion at field scale

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Introduction

On many farms, the smallest management unit is conventionally the field where fertilization is usually performed uniformly. However, within a field, a high spatial variability in soil properties can exist due to geo-pedological setting or land use history of the site. A uniform fertilization can leads to an oversupply of one part of the field, which results in a waste of valuable resources and environmental pollution. In contrast, other parts of the field can be undersupplied and the yield potential is still not exploited. Site-specific fertilization enables the application doses to be specifically adapted to these small-scale differences in nutrient demand and can increase the fertilizer use efficiency at field scale [1]. Therefore, high-resolution data of relevant soil properties is necessary. An efficient way is soil mapping using proximal soil sensors [2].

Objectives

The main objective of the present study was to compare univariate and multivariate modelling of plant-available phosphorus (P_{avl}). For this purpose, a large set of different proximal soil sensing data were used including apparent electrical resistivity (ERa), gamma-ray spectroscopy (γ), ion-selective electrodes (ISE) and X-ray fluorescence spectroscopy (XRF), as well as elevation and yield. They were compared with single-sensor estimates of the phosphorus pentoxide content measured by XRF.

Materials and methods

The data for this study was collected from a 63 ha arable field (PP1392; 52°23'38"N, 14°27'47"E) in the federal state of Brandenburg (Germany). The site is located on a ground moraine plateau formed during the Weichselian glaciation [3]. According to the German Soil Inventory (Bodenschätzung), the soil texture of the test field is dominated by sand and loamy sand fractions.

Sensor data was collected either in-situ (ERa: Geophilus system, Geophilus GmbH, Trebbin, Germany; γ: MS-2000-CsI-MTS, Medusa Radiometrics BV, Groningen, Netherlands) using two mobile multi-sensor platforms or measured on 249 reference soil samples in the laboratory (pH: Hanna Instruments, Vöhringen, Germany; K: van London, Houston, USA; XRF: Vanta, X-Ray Fluorescence Analyser, C-Series, EVIDENT Europe GmbH (Olympus), Hamburg, Germany) (Table 1). Soil sensor data was collected during a field campaign in 2020, except for the Geophilus system, which was acquired in 2017. In addition, elevation data was measured by the Geophilus system using a differential GNSS and crop yield by a combine harvester in 2019.

Table 1. The soil sensors used in this study and their measured parameters

Sensor system	Parameter	Measurements/ha
Geophilus system	Apparent electrical resistivity	246
Medusa Gamma	Total counts, ^{40}K, ^{238}U, ^{232}Th, ^{137}Cs	251
Ion-selective electrodes	K, pH	4
X-ray fluorescence spectroscopy	Al_2O_3, CaO, Fe_2O_3, K_2O, MgO, MnO, Na_2O, P_2O_5, SO_3, SiO_2, TiO_2, ZnO	4

Source: author's data

The 249 reference samples were taken from the topsoil (0 to 30 cm) on a triangular pattern with 50 m distance to the nearest six neighbors. Each soil sample was composed of subsamples taken in a radius of 9 m around the center. The samples were oven-dried at 75°C, sieved to < 2 mm and then analyzed for P_{avl} in a calcium acetate-lactate extraction and measured photometrically [4].

After smoothing the sensors' data with a moving average, they were interpolated using ordinary block kriging. From the resulting grids, the sensor values were extracted at the reference sample locations and fused with the laboratory-measured sensor data and the results of the reference analysis.

Prior to modelling, the entire sensor data was normalised to avoid bias due to different value ranges. The data was split in 70 % training data and 30 % test data. The univariate model was constructed using linear regression. For multivariate modelling, partial least squares regression (PLSR), random forest (RF) and support vector machine with radial kernel (SVM) were used. The algorithms were fitted with a 5-fold cross-validation. The following three data scenarios were performed: a) all available variables (‘all’), b) only those variables with a Pearson correlation coefficient > |0.35| between dependent and independent variables (‘cor’) and c) variables selected by applying recursive feature elimination (‘rfe’). The impact of the variables was determined by the model-based variable importance.

Results

The results of the modelling are shown in Table 2. The SVM using all variables received the best estimation results. Compared to the univariate reference model, the RMSE decreased from 2.15 to 1.49 mg/100 g and R^2 increased from 0.25 to 0.64.

Table 2. Results of univariate and multivariate modelling of plant-available phosphorus (italic = univariate reference model, bold = model with best results)

Modelling algorithm	Data scenario	Calibration RMSE [mg/100 g]	Calibration NSE	Calibration R^2	Validation RMSE [mg/100 g]	Validation NSE	Validation R^2
LM	*P_2O_5 (XRF)*	*1.69*	*0.30*	*0.30*	*2.15*	*0.25*	*0.25*
PLSR	all (n=22)	1.27	0.60	0.60	1.74	0.50	0.51
	cor (n=3)	1.58	0.39	0.39	2.17	0.23	0.25
	rfe (n=18)	1.29	0.59	0.59	1.77	0.49	0.49
RF	all (n=22)	0.56	0.92	0.95	1.79	0.48	0.49
	cor (n=3)	0.93	0.79	0.83	2.15	0.25	0.27
	rfe (n=18)	0.55	0.93	0.96	1.74	0.50	0.52
SVM	**all (n=22)**	**0.67**	**0.89**	**0.90**	**1.49**	**0.64**	**0.64**
	cor (n=3)	1.55	0.41	0.43	2.22	0.19	0.26
	rfe (n=22)	0.39	0.96	0.97	1.57	0.60	0.61

Source: author’s data

For all calculated algorithms and scenarios, the most important variable was P_2O_5 from XRF analysis. SO_3 from XRF is among the five most important variables in the data scenario ‘all’ for all algorithms.

Discussion and conclusions

Sensor data fusion led to a significant improvement in the estimation of P_{avl} at our test field. Besides P_2O_5, other elements from the XRF measurements are also relevant. Even though other sensor variables were not among the most important variables for all algorithms, they were important for certain algorithms, e.g. pH for PLSR, crop yield for RF and Gamma ^{40}K for SVM.

A fusion of geo-physical and chemical data is recommended for estimating P_{avl} as a basis for determining fertiliser requirements.

Acknowledgements

This work was carried out within the framework of the project ‘TONIA – Teilflächendifferenziert-optimiertes Nährstoffmanagement im Ackerbau’ as part of the agricultural European Innovation Partnership program (EIP-AGRI) to improve agricultural productivity and sustainability (funding code: 80259061) as well as by the German Federal Ministry of Education and Research (BMBF), Project: “I4S – Intelligence for Soil: Integrated System for Site-specific Soil Fertility Management” (Project No.: 031B1069A).

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P78 - Investigations of spatial nitrate leaching, the basis of innovative approaches in groundwater protection

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Introduction

Excessive nitrate leaching into groundwater is still a major problem in certain regions of Europe. Therefore, legal fertilization restrictions have been repeatedly amended to improve area-wide groundwater protection. In recharge areas of aquifers groundwater protection zones with further regulations on fertilization and pest management are determined by hydrogeologists. But to decrease nitrate leaching it is not sufficient to regulate fertilization, further agricultural management impacts such as crop rotation, tillage, intercropping, as well as site conditions (soil type, soil texture) affect nitrate leaching. Therefore, in many cases, waterworks collaborate with farmers to promote further nitrate-decreasing measures adapted to the site and farm conditions. Almost all these groundwater protection measures are applied on the field scale. But there is also great variability of nitrate leaching on the sub-field scale [1].

Objectives

This study shows a methodological approach to deviate nitrate-decreasing measures from multi-year satellite maps. The aim is to identify zones with an increased nitrate leaching risk and apply the nitrate-decreasing measures targeted. The digital methods used are newly developed multi-year satellite maps (relBMPmap) [2] that show the relative distribution of the normalized difference vegetation index (NDVI) over 5 years. These maps identify stable zones with better or worse plant growth and are negatively correlated to N surpluses if the fields are fertilized uniformly. Zones with worse plant growth are characterized by higher N surpluses and higher N loss risks. Thus the multi-year satellite maps detect nitrate-leaching zones with worse plant growth and higher N surpluses. Up to now, the relBMPmaps were generated for single arable fields. This study

1) shows multi-year satellite maps related to soil, plant, and nitrate data for single fields
2) scales them to a groundwater recharge area of an aquifer to identify nitrate-sensitive areas

Materials and Methods

1) Soil and plant data were collected from a field in a drinking water recharge area in southern Germany

Ground-truth data:

- Soil properties: SOC, TN in 0-30 cm → 10 georeferenced samples ha^{-1}
- Nitrate concentration in leakage water in 0-2.5 m → 5 georeferenced corings ha^{-1} using a tractor-mounted deep drilling advice

Digital methods:

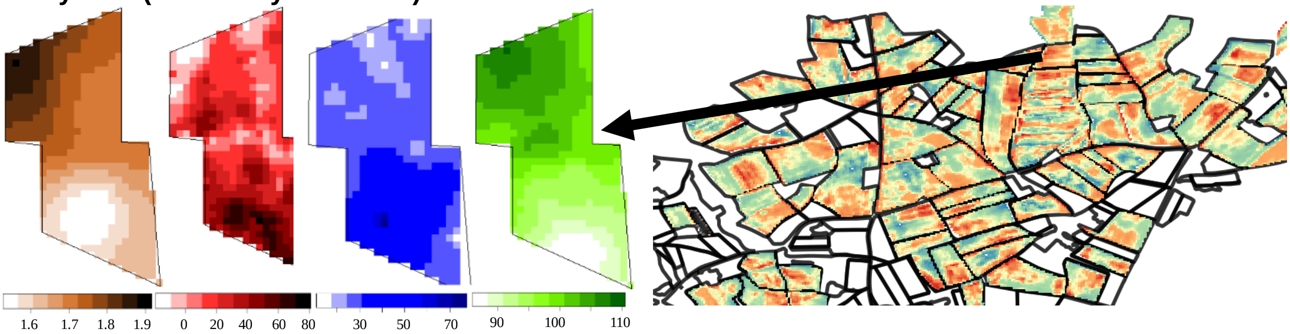
- N uptake + N balancing winter wheat 2021: **Tractor-mounted sensor reflectance measurements** + calculation of vegetation index REIP700 of the winter wheat + calculation of N uptake winter wheat using an algorithm + calculation of site-specific N surplus for each measurement point *(N surplus = total N fertilization – N uptake by the tractor-mounted sensor)* → 235 reflectance measurements ha^{-1}
- Multi-year biomass potential maps (relBMPmaps): Satellite reflectance measurements + calculation of the mean Normalized difference vegetation index (NDVI) of the study field of 5 years (2016-2021) + calculation of the relative NDVI over 5 years for each grid element *(relative NDVI grid = mean NDVI grid over 5 years/mean NDVI field over 5 years x 100)* → 100 grids ha^{-1}).
- The different data sources were transferred into a grid of the same resolution (10 x 10 m) and correlated to each other using geostatistics in R studio (n =523).

2) Calculation relBMPmaps by satellite data for all arable fields in the drinking water recharge area in QGis and generating a map of the whole recharge area.

Results

The study field had a mean SOC content in the topsoil of 1.71 % (1.37 – 2.03 %). The mean N uptake of winter wheat in 2021 determined by the tractor-mounted sensor was 188 kg N ha^{-1} and varied from 147 kg ha^{-1} to 229 kg ha^{-1}. The mean N surplus (uniformly applied mineral N fertilization 200 kg ha^{-1}) of the field was 12 kg ha^{-1} and varied from -29 kg ha^{-1} to 53 kg ha^{-1}. The mean nitrate concentration of the field in 0 to 2.5 m was 46 mg l^{-1} with a variation from 25 mg l^{-1} to 86 mg l^{-1}. Higher nitrate concentrations occurred in zones with lower N uptakes and higher N surpluses. These sub-areas were characterized by higher SOC contents. The relBMPmaps also had higher relative NDVI´s in these zones and showed the strongest correlations to measured nitrate concentrations (r = -0.55; n =523). N surplus by the tractor-mounted sensor was moderately correlated to nitrate concentrations (r = 0.52). The soil property SOC content as an indicator of soil fertility showed strong negative correlations to nitrate concentrations (r =-0.65) and positive correlations to N uptake by the tractor-mounted sensor (r = 0.70) and relBMPmaps (r = 0.86). The digital methods (tractor-mounted sensor and relBMPmaps) were strongly positively correlated to each other (r = 0.78).

Figure 1. left side: Kriged maps of the spatial distribution of SOC in % (brown), N balancing by tractor-mounted sensor in kg ha^{-1} (red), nitrate concentration in 0-2.5m in mg l^{-1} (blue), and relBMPmaps 2016-2021 by satellite in % (green) of the study field (5.5 hectares); right side: RelBMPmaps of the arable fields in the drinking water recharge area (430 hectares including the study field (marked by the arrow)



Source: author’s data

In a further step, the relBMPmaps were applied to all arable fields in the drinking water recharge area (figure 1 right side). The map shows sub-field areas of arable fields with higher (blue-green) or lower (red) relative NDVI´s as indicators of 1) plant growth and 2) yield potential.

Discussion and conclusions

The relBMPmaps showed as well strong negative correlations to calculated N surplus by the tractor-mounted sensor (indicator nitrate leaching risk) as strong positive correlations to SOC contents in topsoil (indicator soil fertility and related to available water capacity). Furthermore, there were moderate negative correlations to measured nitrate concentrations. The method is appropriate to detect sub-field areas of arable fields with less yield potential (lower SOC contents) and increased risk of nitrate leaching (higher N surpluses) caused by lower plant N uptakes in these zones. The measured nitrate concentrations confirm this. The scaling of this method from single fields to whole recharge areas is an innovative approach to identifying nitrate-sensitive zones in drinking water protection. The method by satellite data is more powerful than N balancing by tractor-mounted sensors. The detected zones with increased leaching risk could be fertilized site-specific or managed with different crop rotations. A drastic step would be to take them out of arable cultivation and to sow permanent grasslands with decreased risk of leaching. This could be a way to apply this expensive measure targeted and cost-efficient. The detected zones should be discussed with the farmers.

Acknowledgments

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P79 - Innovative proximal soil moisture sensor for supporting irrigation scheduling in a walnut orchard

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Introduction

Accurate monitoring of soil moisture status is essential for, among others, supporting agricultural water resources management and irrigation scheduling. For this reason, many soil moisture sensors with different characteristics have been tested and applied [1]. More recently, an innovative ground non-invasive method to measure integral soil moisture over relatively large area (hectares) named cosmic-ray neutron sensing (CRNS) has been developed [2]. The enhancement of these detectors for estimating soil moisture has shown good potential also for agro-hydrological applications but the studies are still limited [3,4].

Objectives

The present study aims to develop and test an approach for supporting water management and irrigation scheduling in a walnut orchard based on CRNS sensor. To this end, soil moisture measurements by CRNS are collected and compared with more traditional soil moisture sensors (TDR sensors). Additional accompying data like weather data and irrigation data were gathered, processed and analyzed for the assessment of the water management practicies.

Materials and methods

The experimental field is a irrigated walnut orchard located in Bondeno, Ferrara (FE), Italy, under the Agronoce s.r.l. farm management. The walnut area is divided into separate drip/micro-sprinklers irrigation sectors that can be managed independently. The area of interest for the study is approximately 8 hectares.

Soil moisture measurements were assessed by a CRNS-Finapp sensor FINAPP3 (Montegrotto Terme, Padova, IT) installed on July 2021 in one of the aforementioned irrigation sectors. The sensor was thereafter calibrated as reported in [5]. Within the same sector, soil moisture data were taken for comparison from six TDR sensors installed within the CRNS sensed area at three locations and at two soil depths of 20 cm and 40 cm, respecitively.

Air average daily temperature and precipitation were gathered from the weather station installed in situ by Agronoce s.r.l technicians and from three stations nearby (<5 km?) the experimental field, selected from the network of the regional environmental agency ARPAe (https://simc.arpae.it/dext3r/). The irrigation schedule data for the specific sector have been provided by Agronoce s.r.l. and were used for the present research to assess the soil moisture signal from the sensors.

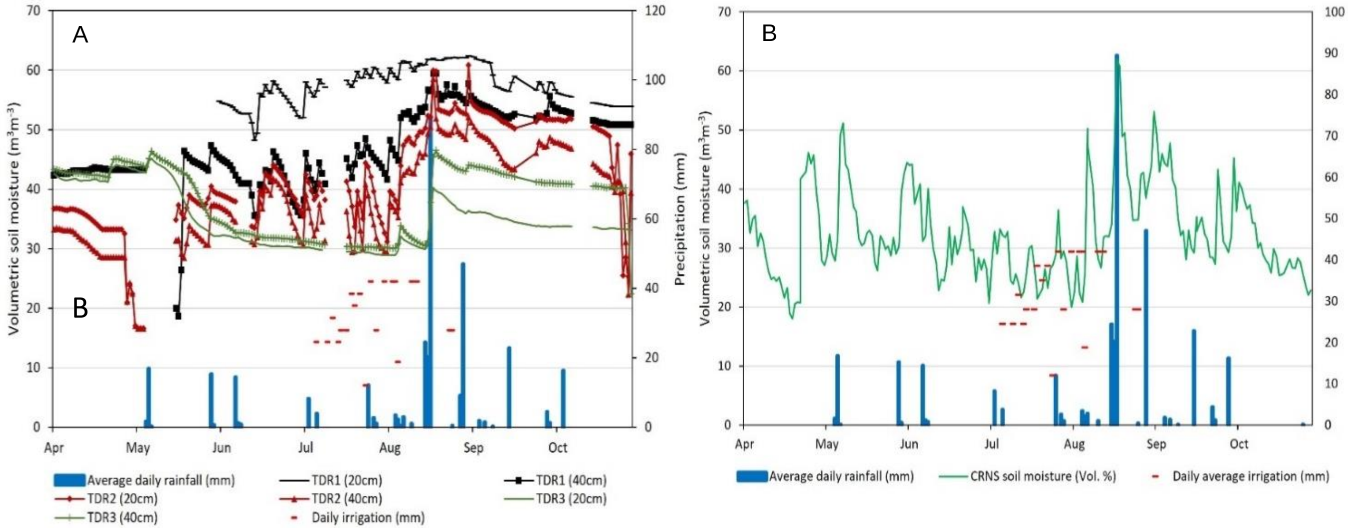
Results

All the data processed and presented in the current research are referred to the growing season period April-October 2022, as it has been considered a crucial time frame for irrigation management and scheduling.

TDR volumetric soil moisture (Figure 1-A) showed a high discrepancy at the beginning of the season, while a better response was moderately visible during rain events and irrigation. Overall, throughout the growing season, TDR sensors were shown to be partially functioning, with more than half of the available probes whose signal appeared hindered. Conversely, CRNS-Finapp volumetric soil moisture pattern showed a consistent signal all along the season. It displayed a very good soil moisture outcome data response to rain events and irrigation (Figure 1-B).

Weather data from the four weather stations exhibited similar patterns for air daily temperature, while some differences were identified concerning daily average precipitation (data not shown). Despite the weather station in situ, it could not be excluded a certain variability in rain events within a large area of cultivation.

Figure 7: A) Volumetric soil moisture from six TDR sensors together with average daily precipitation and daily irrigation. B) Volumetric soil moisture from the CRNS-Finapp sensor, together with average daily precipitation and daily irrigation.



Discussion and conclusions

In this research, several data have been gathered, processed and compared, with the attempt to fulfil the Precision Agriculture goals, as to support management decisions according to estimated variability for improved resource use efficiency and sustainability of agricultural production.

Overall, this study showed the importance to integrate the data collected at the different weather stations to overcome the lack of data that might occur by using a single station. Moreover, it highlighted the difficulties to use point-scale soil moisture measurements to support irrigation management of a large irrigated cultivation area. Besides, TDR sensors were shown to be only partially functioning, being challenging to be considered reliable for irrigation management.

In contrast, CRNS soil moisture sensor was shown to be a reliable tool for soil moisture assessment during the growing season, being shown also suitable for large-scale soil moisture estimation, to enhance future irrigation management and scheduling in an extensive orchard field.

Further activities will be focused on which other parameters would be necessary, such as for assessing the plants' water status as well as the integration of reliable tools to assess soil moisture and plant water available.

Acknowledgements

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P80 - Variable Rate Drip Irrigation in Vineyard: A Case of Study in Franciacorta Area

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Introduction.

Irrigation of vineyards is becoming an increasingly important topic for European viticulture. Indeed, changes in rainfall patterns and rising temperatures have been expected to increase water stress in several wine-growing regions, affecting yield and grape quality [1]. To adapt viticulture to these new climatic conditions, irrigation provides a long-term solution suitable for high levels of water stress [2]. However, the water availability for irrigation is usually limited and contended with other water uses, requiring high efficiency in the water management [3]

Precision irrigation, through a site-specific water management, allows to optimize water usage and reach grape quality goals. However, it has only recently been introduced in many European wine-growing areas and studies are required in order to define optimal design and management protocols

Objectives

The aim of the study is to evaluate the influence on yield and grape quality of a variable rate drip irrigation system (VRDI), managed using Decision Support System (DSS), in a commercial vineyard.

Materials and methods

The experiment took place in 2021, in a 4.5 ha commercial vineyard (cv Chardonnay) located in Adro (Lombardy, Italy), in the Franciacorta DOCG area, known for its sparkling wine.

The vineyard was divided into three sectors: (i) a variable rate drip irrigation system managed using a DSS (**VRT**); (ii) a uniform irrigation system managed by the farmer (spacing between drippers: 0.6 m; flow rate 1 L h^{-1}) (**AZ**); (iii) non irrigated (**NI**).

In order to assess the spatial variability of soil characteristic, an electro-magnetic induction (EMI) sensor was used to measure the electrical resistivity (ER) of the soil. Measured ER values were analyzed to delineate homogeneous zones (HZ) within the field. A pedological profile was opened in each MZ to detect and analyze the main characteristics of the different soil types.

The irrigation was managed using Irriframe, a free source Support Decision System (DSS) performed by the Associazione Nazionale Bonifiche Irrigazione Miglioramenti Fondiari (A.N.B.I.).

At harvest total yield per vine was recorded in six biological repetitions for each thesis and for each water demand area. Furthermore, sugar content (° Brix), Titratable acidity (g L^{-1}) and pH of must were analyzed. All data were analyzed using IBM SPSS Statistics 24.

Results

The vineyard is characterized by five HZs with different textures, depths, and water storage capacities (figure 1). It was possible to define: (i) a High Water Demand Area (HWDA), which includes two HZs characterized by shallow and excessively draining soils, exposing the plants to a greater risk of water stress (VBO.1; VBO.2); (ii) a Low Water Demand Area (LWDA) that includes the remaining HZs (VBO.3, CZO.1, CZO.2).

The design of the variable rate drip irrigation system predicted the creation of two areas, perpendicular to the rows and created through the laying of a single dripline characterized by different spacing between the drippers (flow rate: 2.2 L h^{-1}), higher in LWDA (1.2 m) and lower in HWDA (0.6 m). In this way, each irrigation schedule distributes less water in the first area than in the second, satisfying the different water needs of the plants, due to the different characteristics of the soils.

Results refers to one season management (2021, first year of the experiment). Variable rate management (VRT) allowed a 17% water saving compared to standard farm management (AZ). It is interesting to note how this value is the result of a 28% increase in irrigation volumes in HWDA with a 36% reduction in LWDA, thus better accommodating the plant's needs.

Despite using less water, the yields and quality of grapes in VRT sectors were not significantly different from those in AZ and NI. Moreover, in VRT thesis, there is a general tendency to reduce the differences between areas with different water demand (table 1). This greater homogeneity was evident in the yield, thanks to an increase in productivity in the HWDA (+0.4 kg per plant compared to AZ), but also in the quality of the musts. Indeed, regarding total acidity, a crucial parameter for a sparkling base, in the VRT thesis, the differences between the two WDAs were drastically reduced thanks to higher values in the HWDA (6.48 g/l compared to 5 g/l of AZ), with a gap reduced to less than 2 g/l compared to 5 g/l of the other theses. The same trend was observed for the pH and sugar content of the musts. In this latter case, there weren't significant differences between the two WDAs in VRT, while there were significant differences in the other theses, up to 4.5° Brix.

Figure 1. Soil profile of the HZs and experimental design.

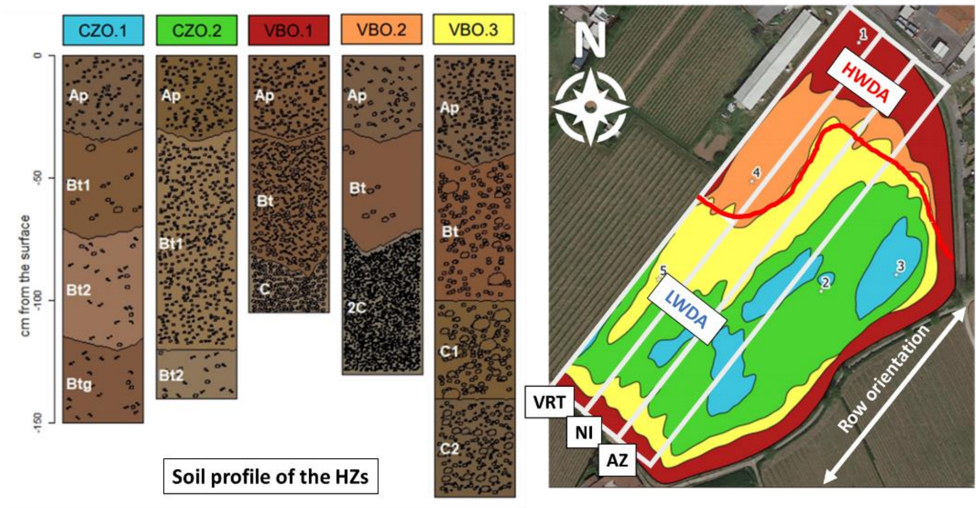

Table 1. Yield and quality of must in different thesis and water demand area, recorded in 2021. * significant at 0.001 level; ns not significant**

	Yield (kg per plant)		Total acidity (g L-)		Sugar content (° brix)		pH	
Thesis	*LWDA*	*HWDA*	*LWDA*	*HWDA*	*LWDA*	*HWDA*	*LWDA*	*HWDA*
Az	3.14	2.70	9.04	5.00	14.33	18.82	2.97	3.38
Sig.	***		***		***		***	
NI	3.05	2.25	8.01	4.95	16.48	18.98	3.06	3.50
Sig.	***		***		***		***	
VRT	3.17	3.10	8.35	6.48	16.14	17.13	3.03	3.28
Sig.	ns		***		ns		***	

Conclusions

In vineyards with spatial variability of the pedological and topographical characteristics, the variable rate irrigation can be a valid tool for homogenizing production, making them converge towards levels consistent with the oenological objectives. In this way it is possible to reach optimal yield levels and fruit quality even in the areas potentially most exposed to water stress, optimizing the use of water.

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P81 - In-season crop model autocalibration for variable rate nitrogen fertilization in winter wheat

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Introduction

Over the last decades, several crop simulation models (CSMs) have been developed the quantify the effect of different management practices on the soil-plant-atmosphere continuum (Jones et al., 2003).

To run each set of simulations, the DSSAT model requires a minimum dataset to run the simulations, including soil weather, crop management, and genetic parameters. Crop parameters are often determined through a time-consuming trial-and-error manual calibration, where they are adjusted to fit the observed phenology and crop growth. However, this optimization approach is highly subjective and strongly depends on the experience of the calibrator (Confalonieri et al., 2016). Therefore, the crop calibration procedure represents a crucial aspect of employing a crop model successfully: poor crop calibration results in poor performance of the simulation model. Moreover, objective mathematical tools are required to provide an unbiased cultivar calibration.

To provide robust and unbiased model calibration, Roll et al. (2020) presented a time-series estimator (TSE) working in the DSSAT environment with multiple in-season observations. In a recent study, Memic et al. (2021) tested the TSE on several soybean cultivars and fertilization treatments included in the DSSAT package with TSE resulting in better nRMSEs than GLUE.

Objectives

The objective of the current study was to evaluate the accuracy of in-season model autocalibration N fertilization recommendations compared to other fertilization treatments.

Materials and methods

The experiment was conducted on an 11.6 ha plot located in Caorle, Italy (45°37'44.3"N 12°57'07.8"E). Soil properties of the experimental area were determined using samples collected in previous studies. The analysis resulted in different management zones. Winter wheat (Triticum aestivum L.) cv. Rebelde (APSOV, Italy) was planted on November 10th, 2020, at a seeding rate of 220 kg ha^{-1}.

The four fertilization treatments were compared over 2020-2021 using a strip trial design with two replicates per treatment. The fertilization treatments included:

1. Uniform fertilization: consisted of the farmer, business-as-usual fertilization rates;
2. Variable rate approach 1 (VRA1): The DSSAT model was run using the manually-calibrated cultivar and historical weather data (1992-2018) to determine N rates for the 1st and 2nd applications;
3. Variable rate approach 2 (VRA2) and 3 (VRA3): The DSSAT model was run with seasonal forecasts and proximal sensing to determine N rates for the 1st and 2nd applications. The model was run using the manually-calibrated cultivar for VRA2 and TSE cultivar for VRA3;

The optimal N fertilization rates for the VRA1, VRA2 and VRA3 approaches were defined using the economic analysis package included in the DSSAT, considering grain price and all production costs.

As previously discussed, the most economically convenient N amounts for the VRA2 and VRA3 approaches were coupled with in-season estimates of crop N status following the methodology presented in Gobbo et al. (2022):

$$N_{RATE} = \frac{OPTIMAL\ N_{up} - ACTUAL\ N_{up} - N_0\ (t_{end} - t_i)}{Eff_C\ (t_{end} - t_i)} \quad (1)$$

Results

On the one hand, the VRA1 approach had the lowest yield (3.1 t DM ha^{-1}) and agronomic efficiency (AE; 16.3 kg grain kg N^{-1}) than all the other fertilization approaches. On the other hand, coupling seasonal forecasts and proximal sensing (VRA2) resulted in the highest grain yield and AE.

The VRA3 approach performed slightly poorer than the VRA2 with an average grain yield of 4.2 t DM ha^{-1} and AE of 22.6 kg grain kg N^{-1}, higher than the uniform and the VRA1 method (Figure 1).

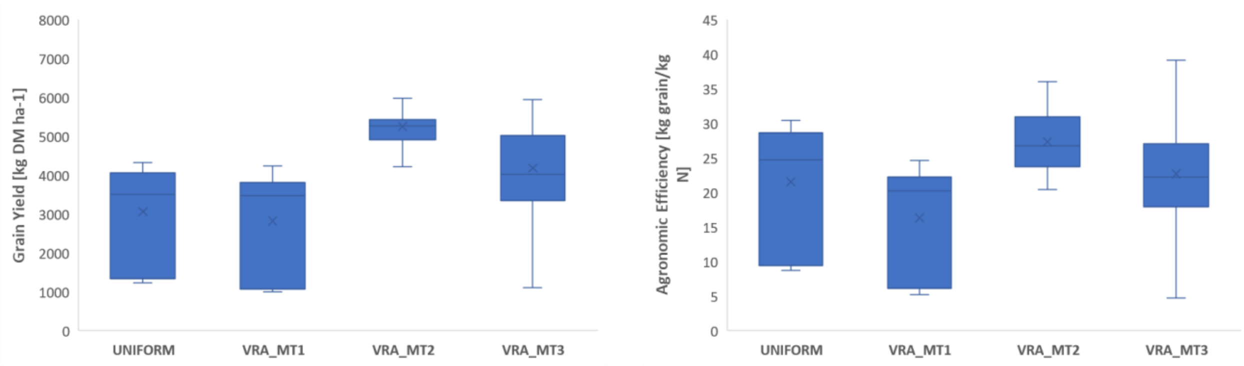

Figure 1. Average grain yield (left) and agronomic efficiency (right) for the different fertilization treatments tested during the 2020-2021 growing season.

Discussion and conclusions

The current study highlighted the sensitivity of crop simulation models to weather variables, especially when outlier conditions are observed. Coupling seasonal forecasts and proximal sensing (VRA2 and VRA3) methodologies resulted in better yields and AE than VRA1 and uniform fertilization. The VRA2 had a 72% higher yield and 37% higher AE than the uniform treatment, whereas similar AE and 27% higher yield than the uniform were observed for the VRA3. The lower-than-expected performance of the TSE-based cultivar could also be related to the limited amount of data points used to run the automatic calibration right before the 2nd application. Remote sensing techniques could be used to increase the number of available data points (i.e. Sentinel 2, one potential observation every 4-5 days).

Acknowledgements

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P82 - High-resolution soil moisture mapping in micro-irrigated orchards by on-the-go microwave radiometry

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Introduction

The Soil Moisture Active Passive (NASA) and Soil Moisture and Ocean Salinity (ESA) satellites offer global measurements of surface (0-5 cm) soil moisture, vegetation thickness, and other hydrologically relevant variables via space-borne L-band (1–2 GHz) microwave radiometry. Unfortunately, their spatial resolution (~35 km) is not suitable for field-scale agricultural management, especially in highly heterogeneous systems, such as micro-irrigated orchards. In this research, a recently invented Portable L-band Radiometer (PoLRa) [1] was used to measure surface soil moisture at very high resolution (<2 m) in micro-irrigated orchards in Southern California. At short scales, microwave radiation can be used to measure soil moisture, but it is also affected by surface roughness and soil and air temperature. Especially in arid and semi-arid environments, micro-irrigated orchards are very heterogenous systems. Soil moisture is typically high near the irrigation emitters and lower in the alleyways and between emitters (when spaced far apart from each other). Additionally, soil roughness may vary from orchard to orchard because of soil tillage and other management practices (e.g., soil beds, crop residue applications). Furthermore, soil temperature may change across an orchard because of local cooling effects due to tree canopies. The nature of the relationship between soil moisture with near-ground on-the-go L-band radiation in such heterogeneous systems is unknown. As similarly reported for other soil sensors to soil property multi-site linear calibrations [2], it may be that soil moisture's effect on the PoLRa measurements (i.e., surface brightness temperatures) remains constant (e.g., same slope) across datasets collected in different orchards and at different times. If this hypothesis is correct, a linear model equivalent to an Analysis of Covariance (ANOCOVA) model could be used to estimate soil moisture from PoLRa measurements. The regression model would include a global (e.g., for a farm, a region) slope coefficient and survey-specific intercept coefficients.

Objectives

This research observes the relationship between surface soil moisture and PoLRa surface brightness temperatures over three different orchards and compares simple linear regression and ANOCOVA modeling to estimate soil moisture from sensor measurements.

Materials and methods

The research was conducted at the Experimental Research Station of the University of California, Riverside (33°58'22.5"N 117°19'07.6"W) on October 22, 2022. The PoLRa was mounted on the side of an all-terrain vehicle at a 45-degree angle with the soil surface. The sensor was paired with a cm-scale geopositioning system. Temperature brightness (in K) retrieved with the horizontal (TBH) and vertical (TBV) L-band orientations were measured every second.

Three orchards were surveyed: a recently established almond (*Prunus dulcis* Mill.) with bare soil and leveled surface; a young olive (*Olea europaea* L.) planted on 30 cm tall beds and with hedge-grow style canopy; and a mature navel orange (*Citrus* × *sinensis* Osbeck) with large canopies planted over leveled soil. A transect along the irrigation line was collected at each orchard with the PoLRa. Along the transect, 9 surface soil sampling locations were sampled just after recording PoLRa measurements. At each location, undisturbed soil cores (0-5cm) were collected at the vertices of an equilateral triangle with sides of about 0.5 m, to capture the average volumetric water content (VWC) for collocated PoLRa measurements. The relationships between BTH and BTV with soil moisture measured at the three orchards were analyzed for general correlation. Simple linear regression and ANOCOVA models were developed.

Results

Descriptive statistics for TBH, TBV, and VWC are reported in Table 1. The Pearson correlation coefficient (*r*) between TBH and TBV was 0.68 ($p<0.05$). The correlation coefficient between VWC and TBV was significant ($r=-0.69$) but was not significant with TBH.

Table 1. Average and standard deviation for the measured temperature brightness in the vertical (TBV) and horizontal (TBH) and ground-truth surface (0-5cm) soil volumetric water content (VWC).

	Overall		Almond Orchard		Olive Orchard		Orange Orchard	
	Average	(St. Dev.)	Average	(St. Dev.)	Average	(St. Dev.)	Average	(St. Dev.)
TBV, K	258.57	4.86	258.02	7.22	258.06	1.78	259.64	3.73
TBH, K	231.71	12.62	219.00	12.28	234.53	2.62	241.60	7.26
VWC, m^3 m^{-3}	0.17	0.09	0.16	0.11	0.14	0.09	0.19	0.07

Source: author's data

The following backward-stepwise multiple regression was developed to estimate VWC:

$$VWC = 3.564 - 0.013 \times TBV \qquad \text{Eq. 1}$$

Equation 1 had a coefficient of determination (R^2) of 0.48 and was significant at the $p < 0.05$ level. The model had an overall Root Mean Square Error (RMSE) of 6.67%. The model coefficients were significant. Notably, the standard error of the slope coefficient was 0.003. Model assumptions were verified.

The data were grouped by orchard to calculate the following ANOCOVA model:

$$VWC = a_i - 0.014 \times TBV \qquad \text{Eq. 2}$$

The model had intercept coefficients (a) specific for each orchard (i). For almond it was 3.811, for olive it was 3.794, and for orange it was 3.870. The model was significant, had R^2= 0.60, and RMSE = 5.82%. The coefficients were significant. The standard error for the slope was 0.003. Model assumptions were verified. In particular, the homogeneity of regression slopes was confirmed.

Discussion and conclusions

The spatial and temporal variability of VWC in micro-irrigated orchard systems is very complex and notoriously hard to characterize. The ANOCOVA model to estimate VWC from PoLRa measurements had encouraging low RMSE. The model was developed for three different orchards with sandy-loam soil texture. The results suggest that the PoLRa may be used for on-the-go VWC mapping in micro-irrigated orchards. Using ANOCOVA calibration models, once a slope coefficient is determined for a region (e.g., a whole farm), limited data may be needed to estimate the survey-specific adjustment (i.e., intercept coefficient). Future research will test the use of in-situ fixed moisture sensors (e.g., capacitance probes) to calculate the survey-specific ANOCOVA adjustment. The surface VWC measurements are useful to confirm water delivery across an orchard yet do not provide sufficient information to calculate rootzone (e.g., 0-1 m) plant available water. Despite its limitations, the PoLRa is easy to mobilize and may allow for rapid orchard-wide estimations of soil moisture which can help growers improve their water management and provide accurate ground truth to broad-scale hydrologic models that study water dynamics using satellite data.

Acknowledgments

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P83 - Use of remote sensing and machine learning techniques to study the impact of climate extremes of crop evapotranspiration

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Introduction

Data-driven technologies are employed in agriculture to optimize the use of limited resources. Crop evapotranspiration (ET) estimates the actual amount of water required by crops at different growth stages, thereby proving to be the essential information needed for precision irrigation. Crop ET is an important variable in regions like the U.S. high plains, where farmers rely on groundwater for irrigation [1]. Since the groundwater levels in the region are dropping [2], owing to over-exploitation, the long-term viability of irrigated agriculture in the area is endangered. Moreover, the increasing frequency of extreme events caused by climate change [3] can significantly affect crop ET rates, leading to water stress which adversely affects crop yields.

Objectives

The objectives of this study, therefore, are: i) to analyze historical weather data to determine which climate extremes most influence crop ET and ii) to quantify the seasonal change in crop ET for future climate change scenarios.

Materials and Methods

Finney County, which is a major maize-producing county in western Kansas was selected as the location of this study. Weather data comprising of daily maximum and minimum temperature, and daily precipitation were extracted for a 30-year historical time period and eleven indices representing agriculturally relevant climate extremes were calculated at a weekly time step. Using the FAO Penman-Monteith equation [4], reference ET was calculated from weather data and multiplied with crop coefficient (k_c) determined from the remotely-sensed Normalized Difference Vegetation Index (NDVI), to estimate crop ET. Based on previous research conducted in our group where NDVI raster images extracted from the Landsat 7 satellite and aerial images from manned aerial vehicles were used to determine kc [5,6], the following relationship was used:

$$K_c \ = \ 1.4571 * NDVI - 0.1725.$$

The random forest (RF) regression model [7] was used to model the association between the climate extremes and crop ET. Using the 70% of the data for the parameter tuning resulted in the optimal RF Model parameters being the number of variables randomly sampled at each split (mtry = 4) and the number of regression trees to build (ntree = 500). Standard staistics were calculated (R-Squared, RMSE, MAE) to assess the model's performance accuracy on both the training and the test data. The influence of each climate extreme index on crop ET was determined using a variable importance plot by a process called feature selection.

For the future, climate data were retrieved from twenty GCMs for a 75-year time period, which was divided into near-term (2025-2049), mid-century (2050-2074), and the end-of-century (2075-2099) periods. The CMIP5 output of daily statistically downscaled data was used for RCP4.5 and RCP8.5 scenarios and was used to calculate the same set of climate extreme indices that were calculated using the historic data. The calculated indices were then used as input data to predict crop ET using the RF model.

Results and Discussion

The estimated Kc curve (Fig. 1) follows a similar trend to the FAO maize crop coefficient curve with an estimated mean Kc value of 0.6 for the initial growing period and 0.9 for mid-season which are different as compared to the FAO values. These differences could be due to specific growing conditions and management practices in Finney County as well as due to the normalization of peak values of Kc, resulting from the averaging of all the Landsat NDVI values from pixels of maize-growing areas to produce a single value of NDVI for each day.

Figure 1. Comparison of crop coefficients (Kc) estimated from Landsat NDVI with the standardized values of FAO.

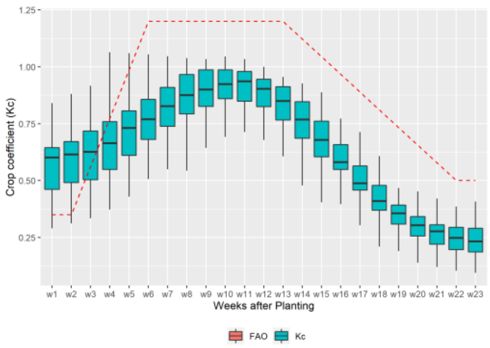
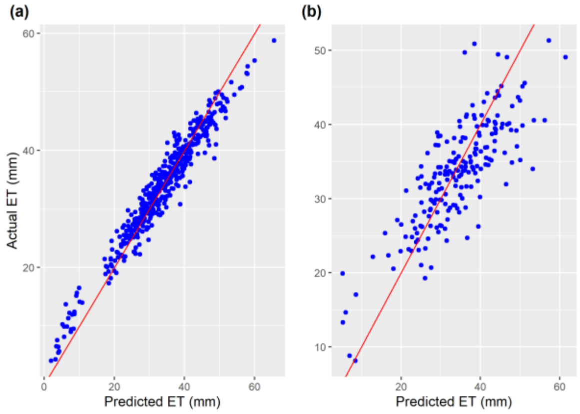


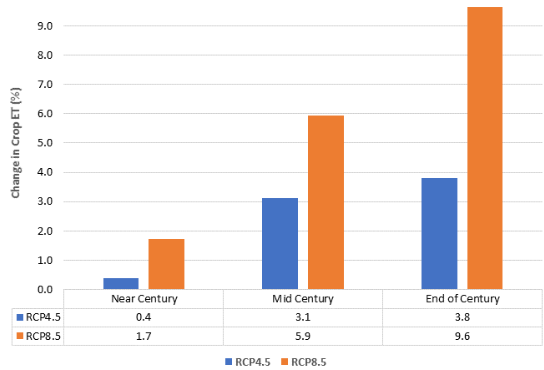
Figure 2: Plot of actual ET against predicted ET: (a) training data; and (b) test data



A comparison between the observed ET from the test data and the predicted ET using the RF model revealed that both very low and large levels of ET were underestimated by the model (Fig. 2). This is most likely due to the fact that RF averages values at each node's end when building decision trees, causing extremely high values to be averaged with low values [8]. Consecutive dry days (CDD) was found to be the most influential climate extreme index in the RF model with most of the other derived indices influencing the model being those related to increasing temperatures.

When compared with historical data (Fig. 3), the results of ET predictions under RCP4.5 showed a 0.4% increase (mean = 22.1mm) in the weekly ET in the Near Century, a 3.1% increase (mean = 22.7mm) in the Mid Century, and a 3.8% increase (mean = 22.8mm) at the End of Century. While under RCP8.5, the results showed a higher increase in crop ET which aligns with similar predictions of ET under global temperature rise [9] due to high emissions, leading to greater loss by evapotranspiration.

Figure 3: Percentage change in Crop ET under RCP4.5 and RCP8.5 future climate scenarios



Conclusions

This study found that crop ET was most influenced by the maximum number of consecutive dry days and days with temperatures greater than 30°C and that climate extremes can have a substantial effect on agricultural crop water demand, which has critical implications for crop yields and ultimately, food security. Furthermore, our study concludes that crop ET would increase significantly under both RCP4.5 and 8.5 scenarios in the near-term, mid-century, and end-of-century timeframes. The extent of these changes was higher under the RCP8.5 scenario, emphasizing the necessity of reducing greenhouse gas emissions to lessen the effects of climate change on agriculture. The results of this study imply a steady potential increase in irrigation water requirement in the future and with the aid of these predicted ET data and anticipated changes in crop ET during the growing season, agricultural producers will be able to develop strategies to optimize their use of the limited water resources.

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P84 - Development of a high-troughput monitoring system for fire blight in fruit orchards

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Introduction

The increasing introduction and spread of phytopathogens, favoured by changing climatic conditions, is a major challenge for European commercial fruit growing and fruit breeding. Fire blight (*Erwinia amylovora*) is one of the most dangerous diseases in fruit growing. Regular monitoring is essential to detect and prevent the introduction and spread of the pathogen at an early stage of infestation. Thus, a digital monitoring system for the detection and localisation of fire blight infections in orchards based on RGB images is being developed in this study.

Objectives

The purpose of the study is to implement a high-throughput monitoring system to detect and locate fire blight symptoms on shoots, flowers and leaves in fruit orchards.

Materials and methods

On five dates in 2021 and 2022, a large image data set with 5,087 RGB images of fire blight symptoms was created. After artificial inoculation, the images were taken in experimental orchards at the Julius Kühn-Institute for Plant Protection in Fruit Growing and Viticulture in Dossenheim, GER, and in the experimental greenhouse at the Julius Kühn-Institute for Resistance Research and Stress Tolerance in Quedlinburg, GER. Various camera systems, including Canon EOS 90D and Samsung Galaxy Tablet, were used to capture the typical symptoms of fire blight infections on shoots, leaves and flowers.

To date, 1.077 collected RGB images were manually annotated by bounding boxes using the Computer Vision Annotation Tool (CVAT) [6] by fruit experts. For this purpose, the classes SHOOT, LEAF and FLOWER were defined. In addition, disease symptoms that could not be clearly regarded as fire blight symptoms were also identified and integrated into the image dataset as a separate class (MAYBE).

The convolutional neural network (CNN) "MobileNetV3-Large" [1] with 4.231.556 parameters was chosen for image classification to detect and locate fire blight symptoms on RGB images. The labelled images were cropped using the bounding box information as a pre-processing step for training, validation and testing, resulting in a total of 8.728 cropped images. This dataset of cropped images was split into the training set of 6.545 images, the validation set of 435 images and the test set of 1.748 images. To prevent overfitting of the model and to estimate the dataset and annotation work in this first model test, the CNN was initially trained 100 epochs. In this first training run, a batch size of 16 and the "Adam" optimization method [3] with a learning rate of 0,0001 were used.

Results

By cropping the images using the bounding box information as a pre-processing step, 8.728 cropped images were generated and used for the first test run with the Convolutional Neural Network (CNN) "MobileNetV3-Large" [1]. The use of different camera devices or image qualities supported the robustness of the detection model, which is an important prerequisite for machine learning-based disease detection [4,5].

The precision of the first test run was 78,13 %, which means that the fire blight symptoms were correctly recognised. At the same time, 68,18 % of the symptoms in the test data set were assigned to the correct class (sensitivity). In the harmonic mean of precision and sensitivity (F1 value), this results in a hit rate of 72,66 %.

The accuracy of the model is lightly higher at 73,46 %, which indicates that the data set is relatively balanced.

Discussion and conclusions

In order to detect and prevent the introduction and spread of Erwinia amylovora at an early stage of infestation, regular controls are necessary. In order to offer fruit producers and growers a fast control, with clear identification and localisation of disease symptoms, a machine detection based on a "MobileNetV3-Large" algorithm will be developed. Large image datasets are highly relevant for successful training of a machine learning algorithm [2]. However, creating a large image dataset for fire blight is challenging. In this project, therefore, fire blight symptoms were photographed after artificial inoculation in the greenhouse of the Julius Kühn-Institute in Quedlinburg and in the experimental orchard of the Julius Kühn-Institute in Dossenheim.

To prevent possible fire blight symptoms from being overlooked in a machine learning-based method, these potential symptoms were integrated into the training and labelled as MAYBE. If, after training, the model detects too many 'false-positive' symptoms (i.e. symptoms that are not fire blight), the MAYBE category can be removed.

With over 78% correct detection of fire blight symptoms, the results of the attempt to train an algorithm are promising. With an expansion of the annotation dataset and refinement of the annotations, it is likely that higher fire blight symptom recognition rates can be achieved in the future. In addition, disease symptoms will be accurately located within the orchard using a novel photogrammetry approach on georeferenced images. Based on this data, a monitoring model will be developed to enable a high-throughput control system for fruit production and breeding.

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P85 - High-efficiency harvesting of jujube by air suction harvester: suction pipe gas MHD acceleration control

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Introduction

With the popularization of the dwarf and dense planting mode of red jujube in Xinjiang, China, the problem of falling fruit harvesting has been paid more attention. Under the background of poor working environment and low picking efficiency of manual picking jujube, as well as narrow row spacing and heavy work congestion in dwarf and dense planting mode, scholars have focused on the research and development optimization of automatic picking machinery, especially air-suction harvester. The air-suction jujube picker uses negative pressure airflow to pick up jujube fruit, which can achieve more than 8 times the efficiency of manual picking [1]. However, the existing air-suction harvesters still have problems such as high loss of airflow consumption, limited suction output of suction pipe, and low efficiency of harvesting [2,3]. In order to improve the above problems and harvest jujube timely, economically and efficiently, great efforts need to be made to control the wind speed and wind pressure of the airflow in the suction pipe. The traditional improvement methods mainly include changing the fan speed, increasing the number of airflow nozzles, optimizing the structure of the conveying pipeline, etc. [4], while the optimization methods for the flow control of the suction pipe gas have not been reported.

In this paper, combined with the planting characteristics of dwarf dense planting and the advantages of air suction jujube harvesters, the magnetohydrodynamic (MHD) acceleration technology is used to accelerate the control of the suction pipe gas to optimize the the suction of harvester [5,6].

Objectives

To complete the coupling simulation analysis of the magnetic field, electric field and flow field in the pipe under electromagnetic field conditions.

To verify the feasibility of MHD acceleration technology in jujube harvester suction pipe.

To study the control law of MHD excitation on the airflow movement of the pipe.

Materials and methods

Based on the MHD acceleration technology, the structure of the jujube harvester suction pipe was optimized. The metal electrodes connected to the circuit were arranged on both sides of the pipette, and a uniform high-strength magnetic field parallel to the electrode plate was deployed. Among them, the metal electrode connected to the circuit created conditions for the ionization of gas in the pipe, so that a considerable amount of plasma was generated in the pipe, and the Lorentz force generated under the action of strong magnetic field was used to control the movement of plasma in the wind tunnel.

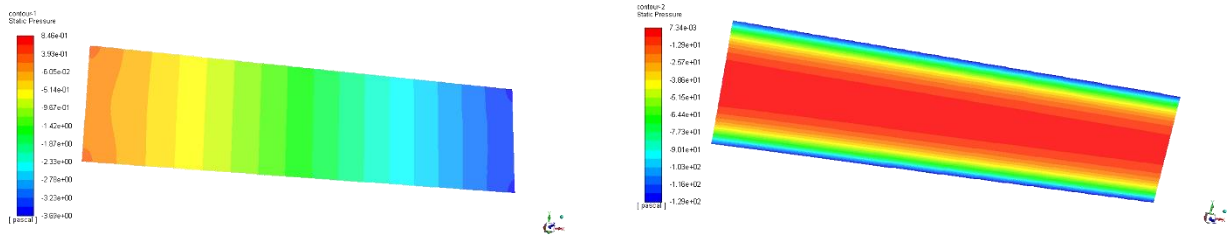
Firstly, the flow field of the pipe without magnetic field was calculated. The SOLIDWORKS software was used to geometrically model the air suction pipe part of the jujube harvester. Import the established geometric model into ANSYS for meshing and applying boundary conditions. The flow field in the pipe was solved by Fluent.

Secondly, the flow field of the pipe under the external electromagnetic field was calculated. In Ansys Maxwell, Maxwell's equations were solved by finite element method to calculate the 3D magnetic field distribution in the pipe, including magnetic induction intensity and electromagnetic force. The magnetic field data were derived from the post-processing of ANSYS Maxwell. The MHD module of ANSYS Fluent was used to load the magnetic field data as an external force. The flow field in the pipe under the external electromagnetic field was solved by Fluent.

Results

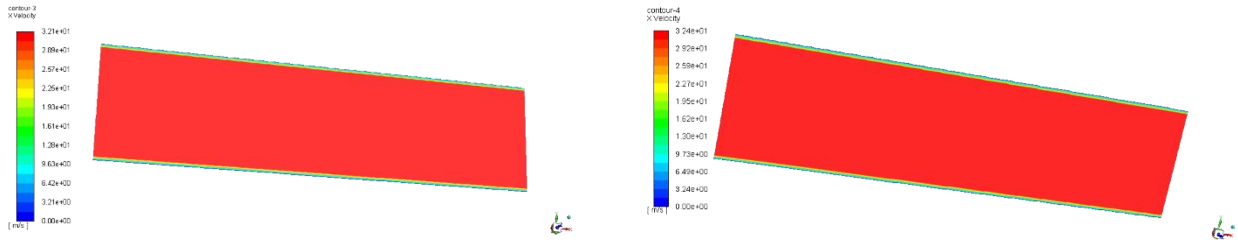
According to the calculation, the wind speed at the entrance was set to 32 m/s. Figure 1 showed the internal pressure cloud diagram of the pipe on the XOY section before and after applying the external electromagnetic field, and in the figure, the left side was the air inlet. It can be seen that the pressure loss in the suction pipe along the flow direction was obvious without electromagnetic field. However, after the introduction of electromagnetic field, the pressure distribution inside the suction pipe was relatively uniform, and there was no obvious pressure loss along the flow direction, only a slight loss near the wall of the pipe. Figure 2 showed the velocity along the X-axis direction inside the pipe (consistent with the direction of airflow inflow) on the XOY section before and after applying the external electromagnetic field. After adding the electromagnetic field, the maximum wind speed in the pipe increases from 32.10 m/s to 33.57 m/s, an increase of 4.6 %.

Figure 1. Pressure comparison inside the pipe



Source: author's data.

Figure 2. Velocity comparison inside the pipe



Source: author's data.

Discussion and conclusions

It can be seen from the experimental results shown above that it is feasible to apply the magnetic fluid flow control to the acceleration control of the suction pipe, and the results provide a theoretical basis for optimizing the suction output of the pipe.

Although this study significantly reduced the pressure loss, the speed increase was not ideal. Subsequent teams will further focus on the optimization of this method, such as exploring the best external magnetic field parameters, to obtain better experimental results.

Acknowledgements

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P86 – Yield prediction in different fruit species using systematic sampling

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Introduction

Chile is one of the largest fruit producers in the world, with approximately 375,000 hectares planted with fruit trees (ODEPA, 2021), with the largest area occupied by cherries (Prunus avium) with 61,559 hectares. Yield estimation for fruit species is a big challenge (Uribeetxebarria, 2019), since it determines several management and operational practices, such as fertilizer rates, people and machinery necessary for harvest, boxes to pack, land and sea freight needs, and, finally, the production budget.

The species chosen for this study were avocado with a planted area, at national level, of 32,387 hectares, European plum with 12,529 hectares, and European pear with 5,878 hectares.

Usually, to estimate yield in fruit trees, counts are made in different phenological stages, which are quite erratic, given the variability among trees, counting systems used, and age of the fruit. Counts are included in a yield components model, where yield is a function of the number of trees per hectare, the number of fruits per tree and the weight of the fruit.

Objectives

The main objective in this study was evaluate the accuracy of systematic sampling for yield estimation in different fruit species.

Materials and methods

The study was performed at the Peumo commune (Rapel Valley, Chile) located at the coordinates 34º20’30.42’’ South and 71º15’52.74’’ West. The study area corresponds to a semi-arid, Mediterranean region, with a temperate climate with temperatures in the range of 5.5 to 27.6 ºC, while precipitation varies between 400 and 420 mm yr^{-1}. The soil belongs to the order Mollisol, which presents a silt loam texture, neutral pH, low organic matter content (~2%), and medium fertility. Avocado, pear, and French prune orchards were evaluated in this study.

Experimental design

A systematic, non-aligned grid with ~ 20 sampling points (trees)/field was established at each field, before harvest, and once the fruit had reached its commercial size. All the fruits were removed from each tree, counted, and individually weighted. Fruits were sorted and classified into size categories.

Yield was estimated, by field, using the yield component approach, as follows:

$$Yield\ \left(\frac{kg}{ha}\right) = \frac{trees}{ha} * \frac{n°fruits}{tree} * \frac{weight\ (g)}{fruit} * \frac{1kg}{1000g}$$

Cross validation was performed by comparing real versus estimated yield. Extracted fruit weight were added to the total weight to calculate the “true” yield.

Statistical analysis

Maps were produced using kriging interpolation. An omnidirectional linear variogram with all data was used in all cases.

Accuracy of the estimation was calculated as follows:

$$accuracy\ (\%) = \frac{(estimated - observed)}{observed} * 100$$

Sampling efficiency was evaluated by dividing the estimated error and the average of the variable:

$$e = \sqrt{\frac{t^2 * s^2}{n}} \quad \text{and} \quad \%e = \frac{e}{\bar{x}} * 100$$

Results

A large spatial variability in terms of number of fruits per tree, fruit weight, and yield per tree was observed in all fields and species studied (Figures1, 2, and 3). Yield was estimated with an overall accuracy varying between 2-7% depending on the species and the statistic used to estimate fruit weight (Table 1,).

Figure 1. Spatial variability of number of fruits (left), fruit weight (center), and yield per tree (right) in avocado.

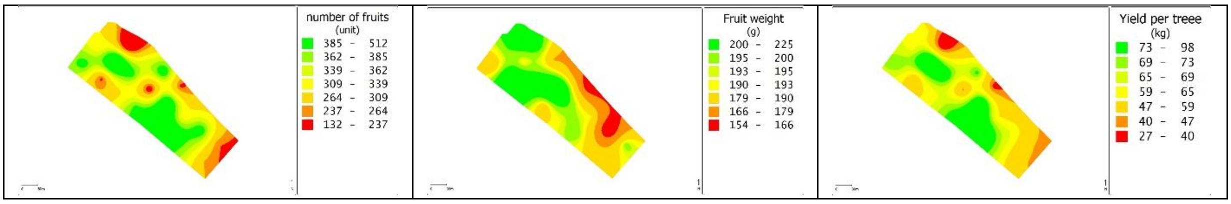

Figure 2. Spatial variability of number of fruits (left), fruit weight (center), and yield per tree (right) in pear.

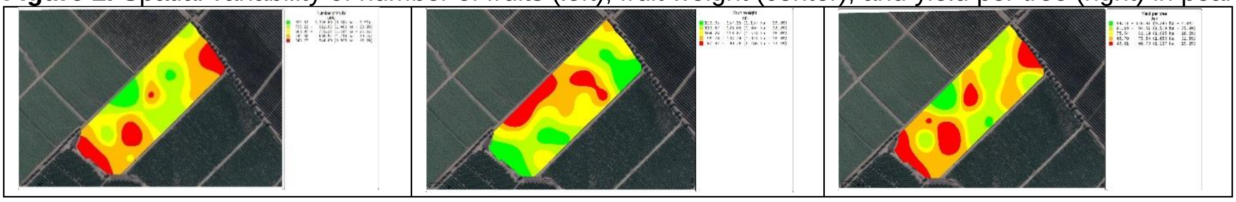

Figure 3. Spatial variability of number of fruits (left), fruit weight (center), and yield per tree (right) in prune.

Table 1. Yield estimation in avocado considering average yield, confidence intervals and accuracy of the estimation.

Field	Statistic	Yield	Lower	Upper	Accuracy
		------------------kg/ha------------			%
Avocado (overall)	Average	28,064	25,354	30,774	7.0
	Real	26,141			
Pear	Average	50,250	43,905	56,595	-2.0
	Real	51,250			
French prunes	Average	41,695	29,956	54,863	2.7
	Real	40,600			

Discussion and conclusions

Systematic sampling with a minimum of twenty samples per field allowed a good estimation for yields of the evaluated fruit species. Predictions were within 95% confidence intervals in all studied fields.

Fruit yields are a function mainly of the number of fruits; therefore, the task is to find simpler ways of counting them.

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P87 - Automated apple orchard blossom mapping from drone image analysis

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Introduction

Precision orchard management (POM) approaches increase tree-level bloom cluster load monitoring. Thinning practices impact on farm profits, and blossom load estimation allow the yield prediction. To maximise profits, the grower must monitor flower load variations and define appropriate thinning strategies, since field conditions require from variable to homogeneous thinning. Farmers manually monitor flower load, according to Teodorescu et al. [1] considering that fast, reliable while automated procedures are rare and expensive. In this study a large-scale orchard blooming was mapped using aerial-image analysis and direct georeferencing.

Objectives

The research work was carried out with the aim of developing a software with the capability to map apple orchard flower load variability at individual tree level. The study also focused on i) computing efficiency, ii) robustness, iii) two-dimensional and three-dimensional tree training systems adaptation, and iv) complete automation of the process.

Materials and methods

A 1.6 ha "Fuji" apple orchard in the Po valley (Italy, 44.7651278 N - 11.7587535 E) was sampled on April 10, 2021, in order to collect flowering data at BBCH stage 60–65. Trees were super-spindle trained, and the planting distance was 3.3 m x 1.0 m. Data were sampled using the Manfrini et al. [2] method, thus the flower cluster load of 100 apple trees was manually sampled and associated with the trees' GNSS coordinates (epsg: 4326). Additionally, high resolution aerial images were collected as proposed by Piani et al. [3].

Python 3.10.1 was used to develop the "Single Photogram Processing" (SPP) software, which first algorithm is designated for airborne images' metadata extraction (GNSS ground-referenced point, elevation, drone/camera yaw, pitch, and roll angles) for the direct georeferencing of the raster.

To save computation time and provide the software with high-resolution flowering information of a constrained and unique area, an algorithm to clip each aerial image ("clipped frame" - CF) according to the tree training systems (2D or 3D) was implemented, making the distinction between the 2D SPP and 3D SPP software. The GNSS coordinates of the centre and four corners of the CF are computed from the raw-image extracted metadata to be used as Ground Control Points (CF-GCPs) in the direct georeferencing of the CF.

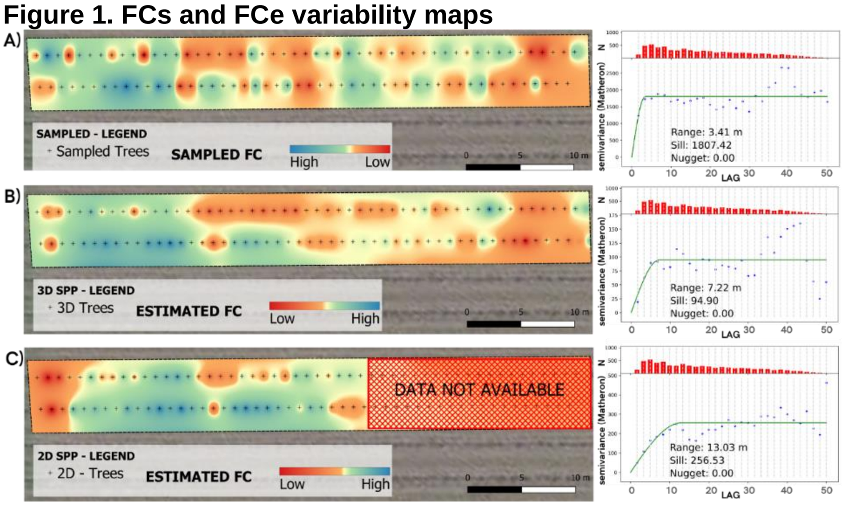
The trees GNSS locations were calculated with the Haversine – *hav(ϑ)* – and saved as point shapefile. The latter was clipped with the orchard boundary vector layer to produce a vector layer called C_{trees} that contains the trees within the field. To identify the trees within the CF (CF_{trees}), C_{trees} was clipped one CF-polygon layer at a time (calculated from the CF-GCPs). Based on the tree-rows bearing angle and planting distance, for each tree point in CF_{trees}, the tree area (TA) shapefile was produced and used to clip the georeferenced CF at tree level (CF_T). A computer vision algorithm then analysed the pixels of the CF_T raster to classify them into either "flower" pixel (F_{pix}) or "not flower" pixel (NF_{pix}). To reduce the environmental noise, the CF_T segmentation was performed into the HSV colour space. The total number of detected F_{pix} into the CF_T was used to calculate the flower cluster load of the tree.

The Euclidean distance between the CF_T estimated and the actual GNSS location (epsg: 32632) was used to calculate the georeferencing RMSE. Through the use of inverse distance weighted (IDW) interpolation of estimated flower cluster loads (FC_e) and sampled cluster loads (FC_s), the effectiveness of 2D SPP and 3D SPP in mapping the field spatial variability was evaluated. To assess the performance of the direct georeferencing algorithm in terms of computation time, a SOTA software (Pix4D mapper) was used as a benchmark.

Results

The software's in-row positioning RMSE was 1.60 m for 2D SPP and 0.19 m for 3D SPP. The assessment of geo-spatial flower load variability was more effective when utilising 3D SPP compared to 2D SPP (Figure 1). Regarding the processing time, the proposed direct georeferencing algorithm resulted in the generation of raster files for the 1.6 ha orchard within 143 s, whereas the stitching process required 6 h. The 3D SPP mapped the trees flower load over 1.6 ha within 34-47 minutes. In comparison, the 2D SPP required 40-47 minutes to complete the same task. In comparison to the methodology suggested by Piani et al. [3], it was observed that both SPP algorithms exhibited a speed enhancement of 89%.

Figure 1. FCs and FCe variability maps



IDW flowering maps and spherical variograms obtained from: A) sampled data, B) 3D SPP estimated flower clusters considering georeferencing error C) 2D SPP estimated flower clusters considering georeferencing error. Source: Authors' elaboration

Discussion and conclusions

A Python software for mapping orchard flowering variability was developed. It resulted fast and adaptable to different tree training systems. It allowed to generated flower load output maps as an input for mechanical, chemical, and manual thinning prescription. The study also showed that consumer-grade drones can map orchard flower load variability. The in-row georeferencing error was ±0.19-1.60 m. However, the system accurately represented the orchard flower load variability while saving 89% of the processing time. To quickly map large orchard, a loss in geo-spatial accuracy is acceptable. The software could handle different training systems providing quick (~21-29 min/ha), flower load distribution information possibly helping growers in improving the orchard production efficiency and sustainability. Future research will examine field application issues like presence of hail-nets, weather and light conditions, as well as reducing the georeferencing errors.

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P88 - Quantifying temperature on apple surface by means of thermal point cloud

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Introduction

In apples (*Malus* x *domestica* Borkh.), excess solar radiation and elevated temperatures can produce several physiological disorders in the exposed surface including sunburn, compromising fruit quality, storability and enhancing food waste. Fruit skin temperature (FST) can be utilised as a reliable indicator to identify types of sunburn symptoms in apples, but three-dimensional (3D) data are requested. While 3D vision systems received attention in horticulture, limited studies reported yet to observe the fruit surface temperature by means of LiDAR (FST_{LiDAR}) 3D sensing.

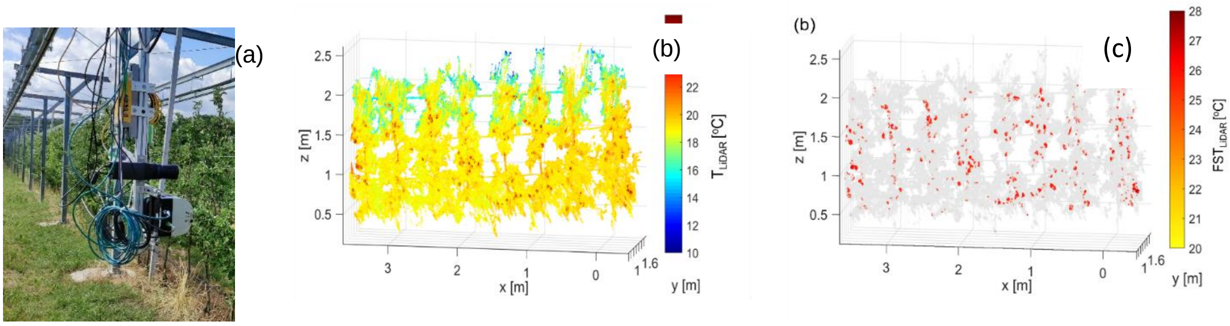
Objectives

This work presents a phenotype sensing system aiming to quantify the distribution of apple surface temperature by means of 3D point cloud.

Materials and methods

A circular conveyor platform was developed at Leibniz Institute for Agricultural Engineering and Bioeconomy (ATB), employing an electrical engine working with 50 Hz (DRN71, SEW Eurodrive, Germany) and stainless steel chain with mechanical suspensions for mounting multiple plant sensors. This phenotyping platform established in ATB experimental apple orchard (Fig.1a), enabling the monitoring of 109 trees (Malus x domestica Borkh. 'Gala' and 'JonaPrince') in one row of 84 m length. A mobile 2D LiDAR sensor (LMS-511, Sick AG, Waldkirch, Germany) was mounted vertically on the metal frame at 0.7 m above the ground level, while it was configured with a 0.1667°angular resolution, 25 Hz scanning frequency. Additionally, a thermal camera (A655sc, FLIR Systems Inc., MA, USA) with a spatial resolution of 640 × 480 pixels at 50 Hz. For segmenting apple surface, the LiDAR's backscattered reflectance and the geometric feature of curvature were used to find the range of apple points in the 3D tree point clouds [1]. The system was extrinsically calibrated [2]. This allowed to extract the FST_{LiDAR} of apples. In 10 trees, the temperature of apple surface (n = 293) (FST_{Manual}) was manually measured and compared with the correspondent averaged FST_{LiDAR}. Measurements were carried out in low (0 -1.8 m) and high (1.8-2.6 m) sections of tree heights at 140 days after full bloom.

Figure 1. Representation of (a) phenotype sensing system mounted on the circular conveyor, (b) 3D thermal point cloud and (c) segmented temperature on fruit surface (FST_{LiDAR}) [ºC] in sampled trees measured at harvest.



Results

Tree organs, found above 2 m, revealed reduced temperature not exceeding 18.2 ºC. Moreover, the T_{LiDAR} on stem points showed a mean value of 20.6 ºC with 0.65 ºC standard deviation (Figure 1b). After the application of fruit detection algorithm, the shape from 282 fruit with an 89.7 % and 90.1 F1 score was segmented in the high and low part, respectively. The FST_{LiDAR} ranged between 20 and 28 ºC (Figure 1c). The fruit located in the low side of tree developed a reduced average

FST_{LiDAR} (26.98 ± 1.81 °C), while a less pronounced value (28.39 ± 1.61 °C) was observed in the upper area (Table 1).

Table 1. Results of LiDAR-derived fruit surface temperature (FST_{LiDAR}) in low and high canopy regions regarding standard deviation (SD), coefficient of determination (R^2), and root mean squared error (RMSE).

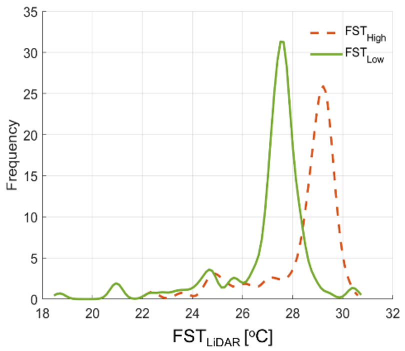
FST_{LiDAR} [°C]	Mean ± SD	R^2	RMSE [%]
Low	26.98 ± 1.81	0.95	0.12
High	28.39 ± 1.61	0.91	0.18

The FST_{Manual} was related with FST_{LiDAR} of apples in the low and high areas of the trees, resulting in an R^2 of 0.95 and 0.92 with an RMSE of 0.12 and 0.18 [%], respectively. However, an enhanced variation was found in the FST_{LiDAR} of low areas, ranging from 18.68 to 30.46 °C (Figure 2). In parallel, FST_{LiDAR} from both areas partly overlapped. However, the most frequent values for apples in high areas appeared between 28.8 and 30.17 °C, while in low ranged from 26.65 to 28.38 °C.

Discussion and conclusions

The phenotypic system was able to detect the temperature on apple surface, a result that can be utilised in the monitoring and prevention of fruit sunburn. It also provided meaningful information about the FST_{LiDAR} on apples, which correlated strongly with the FST_{Manual} in low (R^2 = 0.95) and high (R^2 = 0.92) side of the tree. The values of apples in the upper part of the tree showed enhanced FST_{LiDAR} values compared to the low side, indicating the inner tree spatial distribution of fruit temperature. Estimating the FST in field conditions by mean of LiDAR 3D sensing, can be an essential step for modeling temporally the FST and improve sunburn management strategies.

Figure 2. Histogram of apple fruit skin temperature distribution in low and high areas by means of LiDAR laser scanner.



Acknowledgements

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P89 - Automatic detection of woody crop diseases combining aerial-ground robots and network sensors: An upscaling remote sensing approach

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Introduction

Population increase, climate change, and loss of arable land, along with the increasing appearance of new pests and diseases, threaten the world's food supply [1]. Specifically, the price, quantity, and quality of the agricultural goods are all impacted by the cascading effects of climate change on agro-ecosystems and agriculture, which is the economic sector most vulnerable to changes in climatic patterns [2]. Therefore, the adaptation to new situations is inevitable. The viticulture industry is also impacted and is committed to innovative solutions to reduce the effect of the carbon footprint and adapt to climate change [3]. Out of the agricultural sectors, viticulture has one of the higher profit margins resulting from high-quality wine. Therefore, it has also shown great technological advances when it comes to precision viticulture [4]. At the same time, not only viticulture but also diseases are quite impacted by climate change and varying weather patterns. In this view, the presence of the pathogen, susceptibility of the host, and an environment that supports the pathogen's life cycle are necessary conditions for the development of a disease [5]. The balance of these three factors is affected by climate change, which has an increasingly significant impact on the phenology of the vine, accelerating the ripening of the grapes and the complete phenological cycle, changing the metabolism of the vine [6]. Therefore, to effectively mitigate diseases, an effective monitoring of the crop based on several resources is demanded. Current solutions are expensive not always available during the timeframe that is required to identify the disease's location and apply the corresponding treatment. Therefore, it would be desirable to obtain the most accurate information possible, taking advantage of all the technologies currently available in agriculture, such as sensors, satellites, unmanned aerial vehicles (UAVs) and unmanned ground vehicles (UGVs).

Objectives

This paper aims to present a potentially efficient (e.g., resources, time, and economic) solution for early-stage detection of crop diseases over large agricultural areas by combining spatial layers from heterogeneous sources, such as weather and IoT sensors, satellites, UAVs and UGVs.

Materials and methods

Field tests were conducted in a commercial vineyard property of 'Terras Gauda' (Tomiño, Galicia, Spain), in summer 2021 and 2022 within the framework of H2020 FLEXIGROBOTS project. 'SERESCO' was in charge of sensors, 'Wageningen University' of UAVs and 'CSIC' of UGVs.

Results

The approach presented is an upscaling remote sensing approach (Fig. 1) where the target crop is analyzed in subsequent spatial resolutions - hectares (field-level), meters (row-level), centimeters (plant-level) - over three steps. These spatial layers are obtained by integrating information provided by environmental network sensors, satellites, unmanned aerial vehicles (UAVs), and unmanned ground vehicles (UGVs). The network sensors, combined with the satellite information, provide an initial estimate where the disease could be under development over several fields. This information is sent to the UAVs which survey the fields and generate a risk-based probability map with the potential disease location on the crop rows within the fields [7]. Finally, the UGVs inspect these locations on the rows and determine the disease location and status of the plants. Each platform has a unique sub-system that provides geo-referenced information of the disease location at each level scale. This information is then modeled using machine learning techniques to generate a final map with the best estimate of the disease's location.

Discussion and conclusions

The findings presented on this paper show that the approach proposed could potentially yield better results when compared with current methods: 1) Reduces the time to detect the disease's locations on the crop up to 1 h/ha; 2) Increases diseases localization accuracy in more than 60%; 3)

Reduces the amount of chemical treatment up to 80%, as the pesticide is only applied to the plants with risk of developing the disease; and 4) Has a positive return of investment (ROI) after 6 and 3 seasons when employed respectively by small (<100ha) and medium (<1000ha) scale producers.

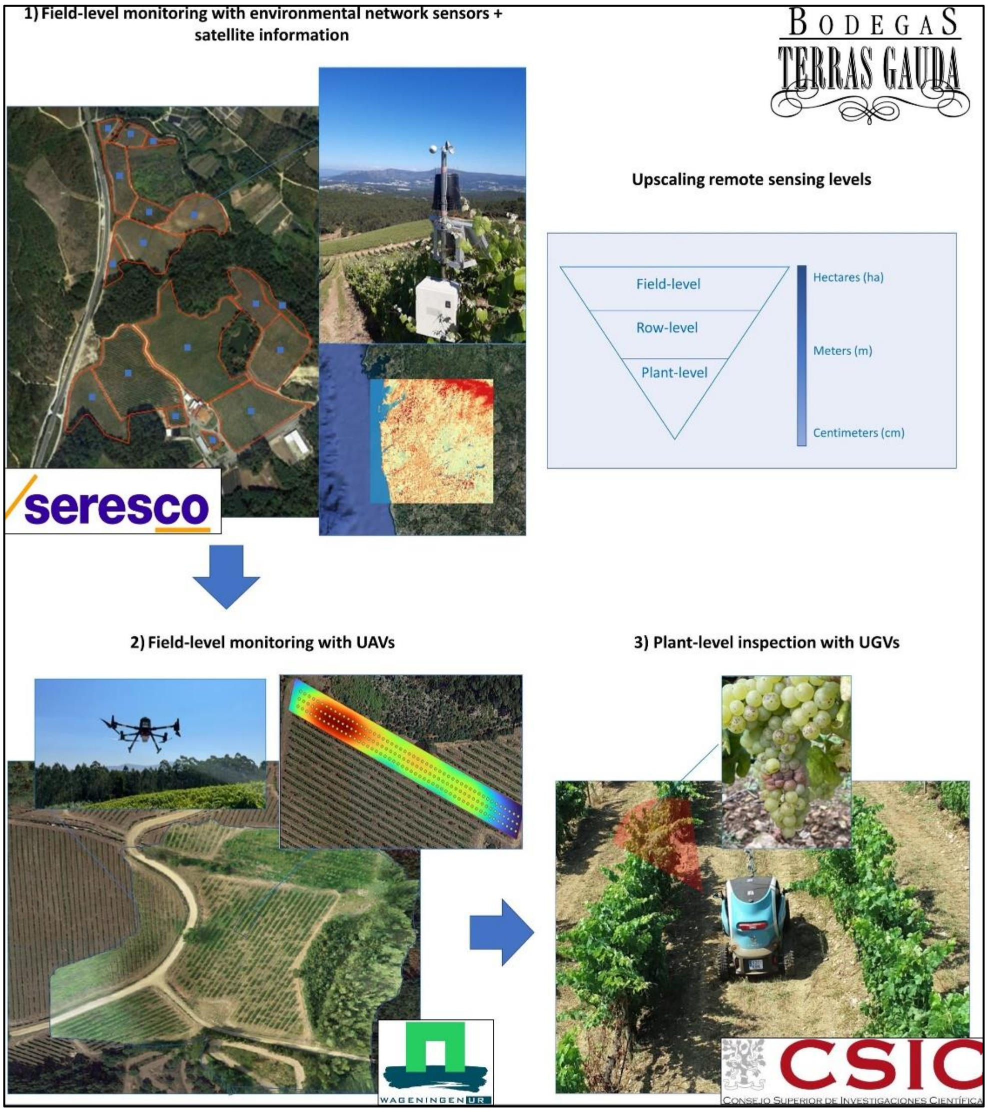

Fig. 1. Workflow combining spatial layers from heterogeneus sources (satellites, sensors, UAVs and UGVs).

Acknowledgments

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P90 - Detection of Citrus bark cracking viroid (CBCVd) on hop (*Humulus lupulus*) using multispectral imaging

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Introduction

The Citrus bark cracking viroid (CBCVd) is considered a mild citrus plant pathogen. But after transmission to a new host, hop (Humulus lupulus), it caused an aggressive disease and high economic loss. Infected plants show developmental inhibitions and die within 3 to 5 years. CBCVd has no known vectors. It is transmitted mechanically, either by infected plants or plant residues. The only available management option is eradication, i.e. uprooting and destruction of infected plants. Timely and spatially accurate management is therefore of utmost importance to prevent CBCVd from spreading.

Objectives

The main objective of this study was to evaluate the use of unmanned aerial vehicle (UAV) based multispectral imaging for detection of hop plants infected with the Citrus bark cracking viroid.

Materials and methods

A hop field in the Savinjska hop growing region of Slovenia was selected for this study. Multispectral images of this field were recorded in August 2020 using a quadcopter-mounted (Skyhero Spyder X4-850 Geo Edition) 5-band multispectral sensor (Micasense RedEdge-MX).

The health status of all plants in the field was determined by visual inspections, following official guidelines for CBCVd field inspections [1]. Each plant was classified either as “Healthy” or “Infected”. The coordinates of all infected plants (n = 85) were recorded with below 10 cm accuracy, using a Stonex S9i N GNSS receiver. The same number of healthy plants was selected randomly, to ensure a balanced data set. Using these point data, a shapefile was built, where each plant was marked with a 40 cm diameter circle. These polygons were then used to extract leaf-area pixels of each plant.

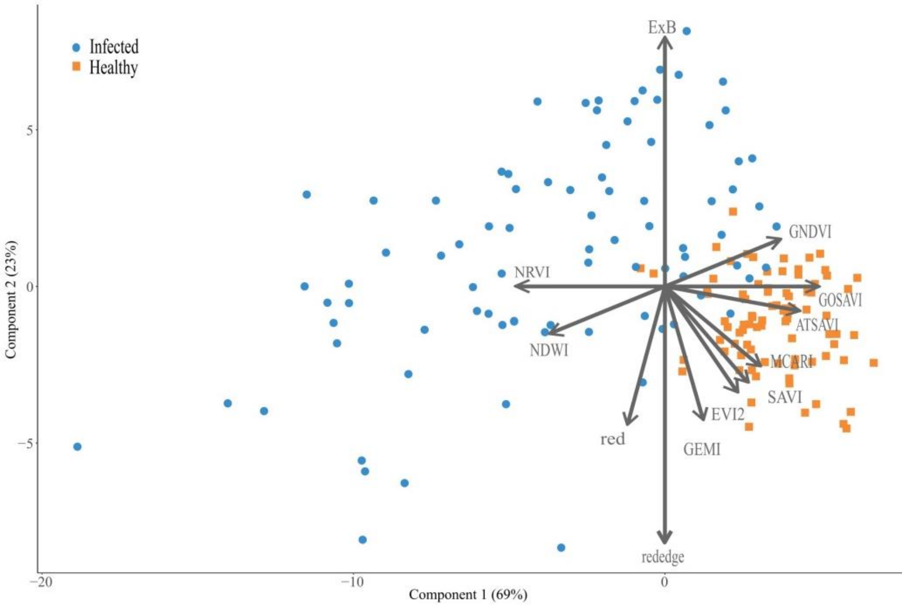
From the 5 spectral bands several indices were calculated, yielding a total of 40 features. For dimensionality reduction, and data exploration and visualization sparse principal component analysis (sPCA) was used. The dimensionality reduced data were then split in training and test sets (70:30 split), and Support vector machine classifications with grid search for hyperparameter tuning were performed on per-pixel and per-plant (i.e. mean spectra) data. The models were validated using 5-times repeated 105-fold cross validation. For per-pixel classification a simple majority vote procedure was implemented. Image preparation and analysis was performed in R.

Results

Sparse PCA selected 12 features of importance, which accounted for most of the observed variability. The first two components together explain approximately 91 % of the variability. The second component was characterized by a strong gradient between the rededge band and ExB (excess blue index); most of the remaining selected indices had a moderate negative correlation with PCA component 2. The division between both groups of plants was observed mostly along Component 1 (Figure 1). Healthy plants were associated with higher values of indices GNDVI, GOSAVI, ATSAVI, MCARI, SAVI, EVI2, GEMI and the rededge band. On the other hand, infected plants had higher values of indices NRVI, NDWI and ExB. Diseased plants also showed a higher variability, i.e. greater spread in the biplot.

In the conducted experiments, the classification success rates were found to be notably high. When per-pixel classifications and majority voting were combined, the best results were achieved, with an accuracy of 94.7%. Classification based on pixel data also yielded acceptable results, with an accuracy of 82.1%. Mean spectra classifications achieved almost the same accuracy as per-pixel and majority voting, at 94%. Moreover, the utilization of majority voting led to a constrained classification process, thereby reducing confidence intervals in comparison to both per-pixel and mean classifications, with confidence intervals ranging from 91.1% - 97.1%, compared to 83.5% - 98.7%, respectively. These findings highlight the effectiveness of combining per-pixel classifications with majority voting in achieving highly accurate results in classification tasks.

Figure 1. Sparse Principal component analysis biplot.



Source: author's data.

Discussion and conclusions

Multispectral imaging can be used to accurately identify hop plants infected with CBCVd. The higher variability observed in diseased plants could be attributed to a number of factors. Both healthy and infected plants were spread throughout the field, so spatial heterogeneity of resources had a limited effect on the variability of spectral responses. The spectral response of diseased plants can exhibit a wider range of values due to the varied severity and progression of the disease. Additionally, plant diseases can affect different parts of the plant in different ways, such as affecting the leaves, stems, or roots. This can also contribute to the higher variability observed in diseased plants. These issues could be further investigated by repeating the plant health assessment step and classifying infected plants into disease severity classes (e.g., low and high severity).

The importance of indices GNDVI, GOSAVI, ATSAVI, MCARI, SAVI, EVI2, GEMI, and their lower values for infected plants indicate a reduction in photosynthetic activity, biomass production, and chlorophyll content. These are expected effects of virus infections, which lead to changes in pigment structure and reduced photosynthetic activity [2].

Time series analysis would enable development of an early detection method, thus further facilitating timely management and limitation of CBCVd spread.

These findings emphasize the potential of combining sPCA and SVM as a tool for the identification hop plants, infected by CBCVd, and the importance of selected indices in characterizing diseased hop plants.

Acknowledgements

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P91 - A novel fruit-zone cooling system to face multiple summer stress in Pignoletto cv.

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Introduction

Pignoletto (*Vitis vinifera* L.) is a white Italian variety cultivated in the Bologna area (Italy) for the production of the Protected Designation of Origin (PDO) Colli Bolognesi Pignoletto wine. In recent decades, many of the most suitable vineyard areas in Italy have been frequently exposed to intense solar radiation, high vapor pressure deficits (VPDs) and high temperatures, especially during the ripening period. As reported by various authors, in conditions of water scarcity and thermo-radiative excess (multiple summer stresses), the Pignoletto shows a slightly conservative use of water which is mainly related to stomatal behavior aimed at limiting water loss. However, the occurrence of multiple summer stress leads to leaf necrosis and photoinhibition and a significant reduction in yield due to sunburn damage that may appear as berry browning and/or necrosis [1]. These effects are striking when the bunches are directly exposed to heat due to a lack of vegetative vigor or for canopy management choices such as late defoliation [2] which is largely applied during the season mainly to reduce cluster rot infections. Some short-term agronomic techniques, such as smart irrigation allow today to mitigate the negative effects of climate change on grapes. Therefore, ultra-fine misting systems have been developed to cool grapevine canopy air evaporatively limiting the negative effects of multiple summer stresses, reducing both water consumption and leaf wetting and consequently plant diseases [3].

Objectives

Starting from these assumptions, a fully automated fruit-zone cooling mist system was implemented in the Pignoletto experimental vineyard of the University of Bologna, characterized by summer heat weaves, to improve the microclimatic conditions of the grapes during the ripening, the yield and to reduce sunburn damage.

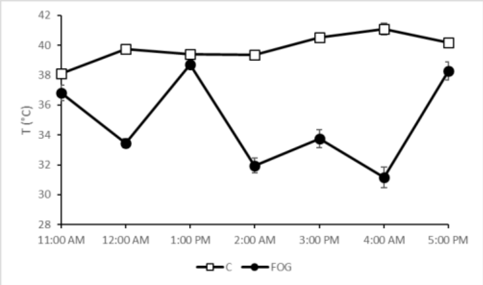
Materials and methods

The trial was carried out in the 2022 season in Bologna (44°32'N, 11°22'E) on Pignoletto (*Vitis vinifera* L.) vines, spaced at 1,20 m within a single row and trained to Guyot system. The treatments compared were: vines subjected to defoliation of the basal leaves before veraison (C) and vines subject to defoliation as C but sprayed with nebulized water (FOG). The leaf removal was applied to increase the effects of sun radiation on cluster. The number of clusters was uniformed at 20 per vine and the vineyard was not irrigated. The cooling system was composed of both a wireless sensor network (WSN), able to acquire the microclimatic data within the canopy and an actuator that triggers the nebulizers when the threshold of 35 °C is exceeded. In detail, the system is composed of a hardware part: (a) a control unit connected to a network of sensors capable of continuously recording the relative humidity and temperature values of the canopy (iFarming srl, Imola, Italy); (b) a pipeline equipped with nebulizers which, at the operating pressure of 3.5 Bar, deliver drops of 50-55 microns in diameter. Each vine was equipped with a 4-way fogger (mod. RIVULIS F.L.F., Rivulis Irrigation, Gvat, Israel) with a flow rate of 5.4 Lh^{-1} per nozzle. The misting system has been located inside the canopy at cluster height. The software part analyzed the microclimatic data collected by the nodes sending the impulses to a solenoid valve that automatically regulated the opening and closing of the misting system. Water was applied from DOY 204 (August 2nd) until DOY 236 (August 24th) with the following cycle: fogger on 5 min, off 15 min. This cycle lasted one hour at the end of which the system carries out another air temperature check. Since fogger spacing along the rows was 1.2 m, each vine received nearly 1.5 mm h^{-1} of water.

Results

During the 2022 season, the fruit zone cooling system was tested for the first time in field conditions, focusing on the impacts on berry temperature and the effects on yield parameters. The season was warm and dry with an amount of 260 mm of rain falling from April to October. Furthermore, the period was characterized by intense heat waves therefore the system was activated during 8 days and, as reported in Figure 1, it successfully reduced the canopy temperature during the hottest hours of the day. Additionally, the berry temperatures registered around midday in FOG were consistently below the thermal value measured in C (Table 1).

Figure 1. The trend of air temperature measured within the canopy during the warmest hours of a typical August day (DOY 217) in defoliated (C) and vines subjected to nebulization (FOG).



Each value is reported as mean ± SE (n = 3 per treatment)

Table 1. Berry temperature (°C) recorded on vines subjected to defoliation of the basal leaves (C) and on vines subjected to defoliation and misted (FOG).

Trt	DOY 217	DOY 223	DOY 235
C	39.0 a	34.4 a	35.8 a
FOG	30.9 c	27.1 c	28.2 c

Different letters indicate significant differences between treatments according to the Tukey test (p ≤ 0.05).

Starting from uniform vines, significant differences between treatments were reported in terms of yield attributes. In particular, FOG showed significant increase in yield and cluster weight compared to C (Table 2). A further notable result was the reduction of necrosis (percentage of damaged berries) which was recorded in FOG compared to C.

Table 2. Yield attributes of Grechetto gentile vines at harvest.

Trt	Yield (kg)	Cluster weight (g)	Berry mass (g)	Necrosis (%)
C	3.9 b	143 b	1.74	11.6 b
FOG	4.3 a	160 a	1.75	3.5 a

Different letters indicate significant differences between treatments according to the Tukey test (p ≤ 0.05).

Discussion and conclusions

The cooling system of the bunches zone tested at the University of Bologna was able to reduce the damage from sunburn on Pignoletto vines during the 2022 season characterized by heat waves conditions. In detail, the system was able to reduce both the air temperature within the canopy and the berry temperature, increasing yield due to the higher cluster weight and lower sunburn damage compared to defoliated vines. The results agree with those reported by Kliewer and Schultz [4] on different varieties with the overhead sprinklers operating continuously beginning at bloom time. This seems to be related to the positive effect exerted by the mist on the fruit-zone microclimate which can reduce berry temperature evaporatively [4].

Acknowledgements

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P92 - Complementarity between manual measurements and image analysis for grape yield estimation.

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Introduction

Yield estimation is a key issue for the whole grape and wine industry. To address it, many studies have focused on sampling yield components (e.g. number of bunches or berries, berry mass, yield per vine, etc.). Among these components, the number of berries is the most challenging to measure because manual measurements are tedious and destructive. Alternatives are therefore to model it from easier and non-destructive manual measurements or to use emerging technologies [1]. In this poster, two estimation methods of the number of berries are considered : i) one estimate relates to the number of berries per bunch, modeled using bunch dimensions manually measured according to a NDVI stratified sampling design (StS), and ii) the other estimate relates to the number of visible berries detected in the whole block thanks to a machine learning analysis of images proximally sensed using an RGB camera (AVis).

Objectives

The objective of this poster is i) to assess the complementarity of AVis and StS and ii) to compare the ability of these two estimates of the number of berries to support a grape yield estimation. Therefore, the estimates obtained using the same yield estimation strategy but integrating one or the other estimate of the number of berries are compared. The yield estimation strategy is based on the empirical equation multiplying yield components [1].

Materials and methods

The study involves 3 blocks from 2 vineyards in the region of Bordeaux, France, for 2 years (2021 and 2022).

The StS method consists in estimating the number of berries per bunch using a nonlinear mixed-effects model based on the length and greatest width of the bunch. The measurements of bunch dimensions have been manually performed using a stratified sampling design based on NDVI maps taken the previous year at a 0.15m resolution and with an inter-rows extraction (Figure 1, 1st row). 3 NDVI classes were considered. The training dataset contained 4 to 8 bunches per NDVI class. To obtain the estimate of the number of berries per bunch, dimensions of 30 to 80 bunches were measured per NDVI class. The number of bunches and the berry mass were also estimated per NDVI class. Grape yield was estimated at the block scale by summing the product of the estimates of number of vines, number of bunches per vine, number of berries per bunch and berry mass for each NDVI class.

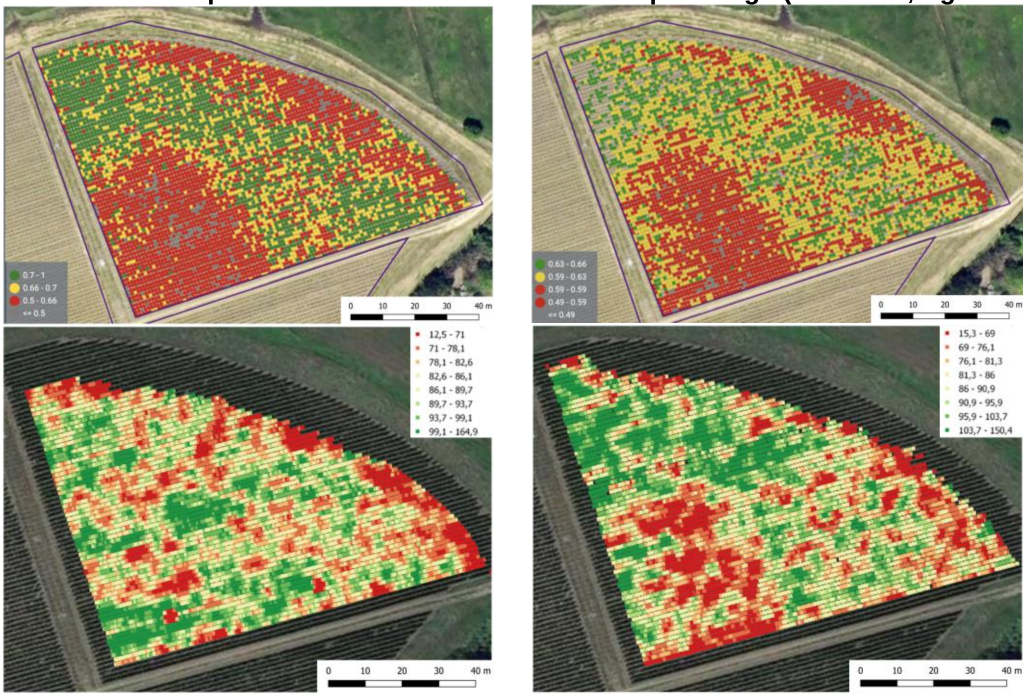
The AVis method uses an automatic camera sensor described in [2]. It is composed of a color camera (5 megapixel) and an industrial flash, associated with a GNSS sensor. The camera is either fixed to a wheelbarrow to acquire images for each vine of the measurement sites, or embedded on a tractor to automatically acquire images of the vines for the entire block. The images are processed in two steps: identification of the candidate berries using a radial Hough transform; final detection and counting using an extended version of LeNet (Deep Neural Network), with 10 convolutional layers. The reliability of the berry detection was checked by comparing the number of visible berries detected by the algorithm with the number of berries counted by hand on the same image. A linear regression using 316 images showed 6% underestimation (r^2 =0.97).

The number of visible berries per image can be mapped to show intrablock variability. An orthogonal projection on the row was carried out to improve the GNSS precision. Grape yield was estimated at the block scale by multiplying, for each NDVI class, the total number of visible berries, the ratio between the number of visible berries and the actual number of berries (computed for a few vines per NDVI class) and an average berry mass.

Results

(Figure 1, 2nd row) shows the maps of the visible berries per image for 2 years. The pattern observed in the NDVI map of the previous year is not visible on the map of the number of visible berries in 2021, but clearly visible in 2022. This difference may be partly explained by the bunch thinning operation that has been carried out in 2021 just before the images acquisition (no bunch thinning in 2022). Similar results have been observed on all the block of the experimentation, showing the relevance of the results from a qualitative point of view.

Figure 1. First row : NDVI Map (left: 2020, right: 2021), Chateau Calon Segur;
Second row: Maps of the number of visible berries per image (left: 2021, right: 2022)



Source: author's data

Table 1. StS and AVis estimation errors in 2021 and 2022 for the 3 blocks of the study.

Year	2021			2022		
Block	1	2	3	1	2	3
Actual yield (tons)	1.1	5.4	3.2	8.2	4.2	2.8
Sts estimation error	64.9%	50%	21.1%	0.2%	- 4.4%	16.4%
AVIs estimation error	-65.4%	745.6%	120.3%	-49.4%	52.6%	-17.8%

Source: author's data

StS estimate errors are between 64.9% and 0.2%, 2022 estimates being much better than 2021 ones. AVis estimate errors are between 745.6% and -17.8%, due to a high instability in the ratio between the number of visible berries and the actual number of berries.

Discussion and conclusions

The StS method has already proved to be more efficient than random sampling. In this work, it showed good results in 2022 and not so good in 2021, the year being characterized by exceptional climatic conditions (frost, precipitations). The AVis method produced relevant yield maps with regard to the cultural operations carried out. However, combined with stratified sampling, it did not improve yield estimates.

Acknowledgements

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P93 – Vinelapse: an autonomous grapevine observation image sensor

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Introduction

Understanding the spatial and temporal variability in a vineyard is a key step towards appropriate and cost-effective management. As illustrated by the abundant scientific literature in precision agriculture [1,2], image sensors provide an efficient way to fetch information on the vineyard at different temporal and/or spatial resolutions. Temporal variability may for instance be extracted from satellite data, such as Sentinel-2 time series [3]. However, the low spatial resolution of these sensors often limits them to a few applications. This excludes other potential areas of interest such as estimating the current development stage and growth speed of the plant. This also makes more precise image analysis tasks such as differentiating foliar symptoms from different diseases more difficult to conduct. In these cases, the individual and precise dynamics of a plant is of paramount interest.

Objectives

There is thus an interest for ground-based image sensors built to monitor a plant with high temporal resolution. Such a sensor needs to be robust (ability to withstand repeated agricultural machinery crossings), energy efficient (ability to monitor the whole vegetative season without any battery replacement) and cost-effective (using multiple sensors in the same vineyard). These objectives motivated the design and testing of Vinelapse, an autonomous static camera sensor designed to monitor a grapevine throughout the vegetative season.

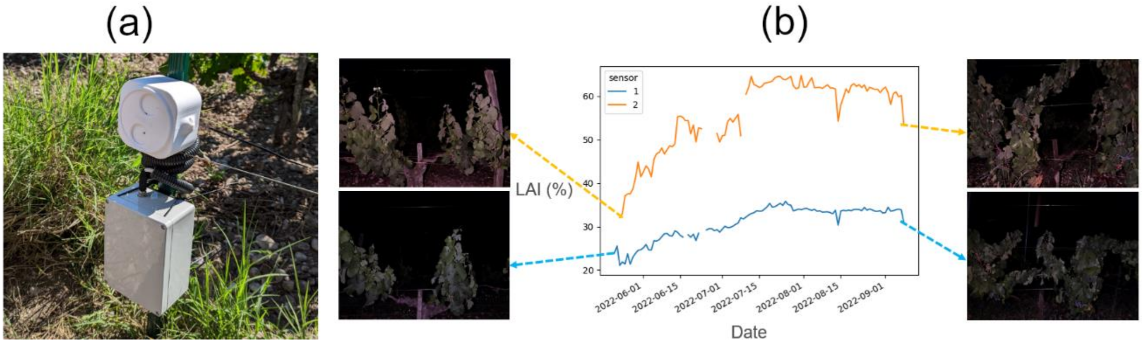
Materials and methods

The sensor (as shown in Figure 1-(a)) revolves around the cooperation between a Raspberry Pi Zero computer and an Arduino MKR WAN 1310 microcontroller connected via a serial link. The sensor is programmed to take a nightly picture with controlled lighting using a combination of visible and infrared LEDs. Leaf Area Index (LAI) and Normalized Difference Vegetation Index (NDVI) are computed on the fly using the Rapsberry Pi. Low energy consumption LoRa communication is then used to send that information as well as other key information such as battery voltage to an online PostgreSQL database. Information about the sensor status and plant growth can be easily visualized on a Grafana dashboard (available at http://212.227.215.54:3000/d/me2z7-X7k/iot_luchey?orgId=1).

Results

The architecture presented in this study was first tested during the 2022 season using 4 sensors installed in a vineyard (Château Luchey-Halde, Mérignac, Bordeaux region). Battery life varied between sensors and was on average roughly equal to 3 months. In total, 493 daily pictures were acquired in 2022. Examples of pictures and LAI time series from a high vigor and a low vigor plant are shown in Figure 1-(b).

Figure 1. (a) Picture of the sensor in a Château Luchey-Halde vineyard. Bottom case contains the 12V battery powering the system. (b) Example of 2022 LAI time series and images obtained from the monitoring of two grapevines, showcasing different vigor levels.



Source: author's data

From these preliminary results, it is apparent the sensor was able to capture the dynamics of the plant growth from mid-May to September. The noisy nature of the LAI time series can be explained by a few factors:

- Variations in the artificial lighting intensity
- Different weather conditions (e.g. rainy nights yield lower LAI estimations)
- Alteration of the camera framing related to agricultural machinery crossings

Discussion and conclusions

While the sensor was successfully tested during the 2022 study period, room for various improvements remains. Notably, possible improvements include energy consumption, stability of the lighting system and accuracy of the vegetation detection algorithm used to compute LAI. Future studies will also cover the whole vegetative season, starting from budbreak. Besides, the sensor was initially designed for a simple vigor application but other potential applications may benefit from the rich temporal information of the obtained dataset:

Berry color changes can be monitored during the veraison period, potentially allowing for a better understanding of the spatial and temporal dynamics of this key grapevine development stage (yield estimation)

Leaf symptom expression can be monitored on diseased plants. This may include, for instance, the visual symptoms during the period preceding esca disease apoplectic form.

Future works will attempt to evaluate the relevance of merging temporal information from the VineLapse sensor with spatial information from image sensors installed on agricultural machinery (covering the whole vineyard at a few key dates during the season). The main objective of these works is to gain a better understanding of joint spatial and temporal dynamics in the vineyard.

Acknowledgements

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P94 - Detection of damaged white grape bunches

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Introduction

Crop pests are the cause of significant yield losses every year [1]. This is one of the reasons why early detection and treatment is crucial to prevent diseases from fully developing. Common pests include *Botrytis cinerea,* a necrotrophic pathogenic fungus that affects more than 200 different plant species including vineyards, one of the crops most vulnerable to this pest. Therefore, monitoring of the vineyard for early detection and treatment of the pest is crucial to maximise crop yield. The most common detection methods involve physical interaction with the fruit [2][3][4] and, although accurate, are very laborious and difficult to apply on a large scale in a commercial wine farm.

The approach to detection with non-invasive strategies can be based on the information provided by a camera, RGB images, on board some kind of vehicle travelling at very low speed. Thus, the processing of each image will require the detection of the grape bunches and its subsequent classification as healthy or damaged.

Objectives

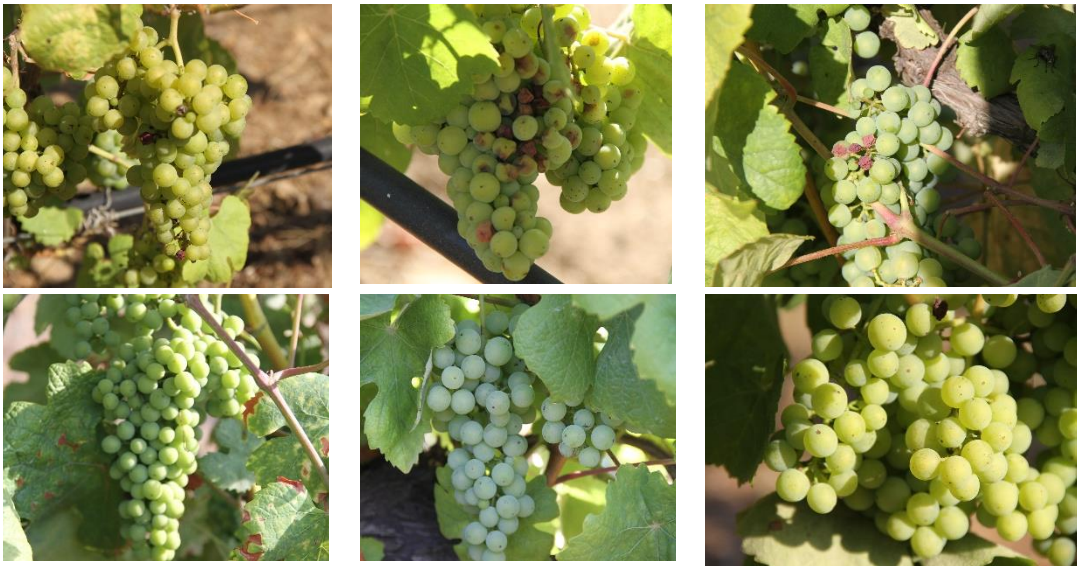
The aim of this work is to build a white grape bunch classifier. For this purpose, a set of more than 10 deep learning models will be trained using images in which only a single bunch of grapes appears, which can be either healthy or damaged. .

Materials and methods

Sampling was carried out in commercial vineyards (Terras Gauda vineyards, Pontevedra, Spain) in the first week of August 2022. Specifically, a month and a half before the harvest, coinciding with the period of Botrytis appearance and when treatment is still possible.

Images of white grape bunches, without lighting control, both healthy and damaged by various causes, including Botrytis, were taken with an RGB camera (an EOS 7D camera, Canon, Tokyo, Japan) with a resolution of 2584x1938 pixels. Figure 1 shows examples of the images taken.

Figure 1. The three images in the first row correspond to damaged grape bunches while the three images in the bottom row correspond to three healthy grape bunches.



A total of 1055 images were collected, ensuring that the proportion of images of damaged bunches was similar to the proportion of healthy bunches. Thus, the dataset consists of 559 images of damaged bunches and 506 of healthy bunches.

The dataset was divided into 80% images (844) for training and testing and 20% images (211) for validation. In addition, the images were also rescaled to 896x512 pixels, as required by the selected models.

The models were implemented with Python, using Tensorflow's Keras library. Training was performed on a supercomputing infrastructure (CESGA) with Tesla T4 and NVIDIA A100-PCIE-40GB GPUs.

As an evaluation metric, accuracy and recall were combined by calculating the number of true positives, false positives, true negatives and false negatives. The harmonic mean was used to combine precision and recall into a single value that we have called "classification accuracy".

Results

The classification accuracy ranged from 0.89 (EfficientNetB0) to 0.95 (EfficientNetB7). EfficientNetB0 was also the network with the lowest number of parameters (5.3M) and EfficientNetB7 had the highest number of parameters (66.7M). These parameters are important as they indicate the complexity of the network and are related to its response time when classifying.

Discussion and conclusions

Botrytis cinerea represents a serious problem in commercial vineyards, which makes early detection of the disease of vital importance. In this work, several models has been used to discriminate between healthy and damaged bunches, both by *Botrytis cinerea* and other problems that produce visually similar damage.

Of all the models trained, the EfficientNetB7 network stands out with a classification accuracy of 95% but with more than 12 times more parameters (66.7M) than the smallest network obtained (5.3M) which shows a classification accuracy of 89%. The complexity of the network is important in determining the classification response time. This is a crucial issue when you want to act by applying treatment at the same time as the problem is detected, as is the case with the treatment system we are developing.

Acknowledgements

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P95 - Early detection of *Botrytis cinerea* infection in plants by pulsed thermography

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Introduction

Active Thermography (AT) is a well-known non-invasive and non-contact technique that represents an outstanding analytic approach in many fields. In recent years it has been gaining great interest in agriculture as it is well suited to the emerging needs of the precision agriculture management strategies [1]. Plants are subjected to a wide range of abiotic and biotic stresses mediated by virus, bacteria, fungi, nematodes and others, which reduces the productivity of agricultural crops. Among these, *Botrytis cinerea* is one of the most economically important plant pathogens that attacks over 200 host crops worldwide [2]. Although fungicides exist for its control, many classes of these have failed due to its genetic variations. In this work, we monitor the effects caused by the necrotrophic fungus *B. cinerea* on both pepper and tomato plant leaves by pulsed thermography (PT) in early pre-symptomatic phase. Pepper and tomato plants were inoculated with different concentrations of *B. cinerea* and monitored by PT for seven days after infection. Our results demonstrate that monitoring based on the active thermographic approach proposed here can be an effective tool to detect the presence of the fungal infection investigated in plant leaves in real time.

Materials and methods

a. *Plant: growth and inoculations*

Pepper (*Capsicum annuum*) and tomato (*Solanum lycopersicum*) plants were grown in pots in natural soil (Triplo Bio Natural) under a 16-h light/8-h dark photoperiod at 23 °C in a controlled growth chamber. Leaves of each plant investigated were infected with three different concentrations 10^4, 10^5 and 10^6 conidia/ml of *Botrytis cinerea* (isolate B05.10) by inoculating 10 µl of the suspensions at 4 different sites. Infection was repeated on 5 plants for each conidial concentration. Control plants were inoculated with distilled water or with spores of the non-pathogenic fungus *Trichorderma harzianum.*

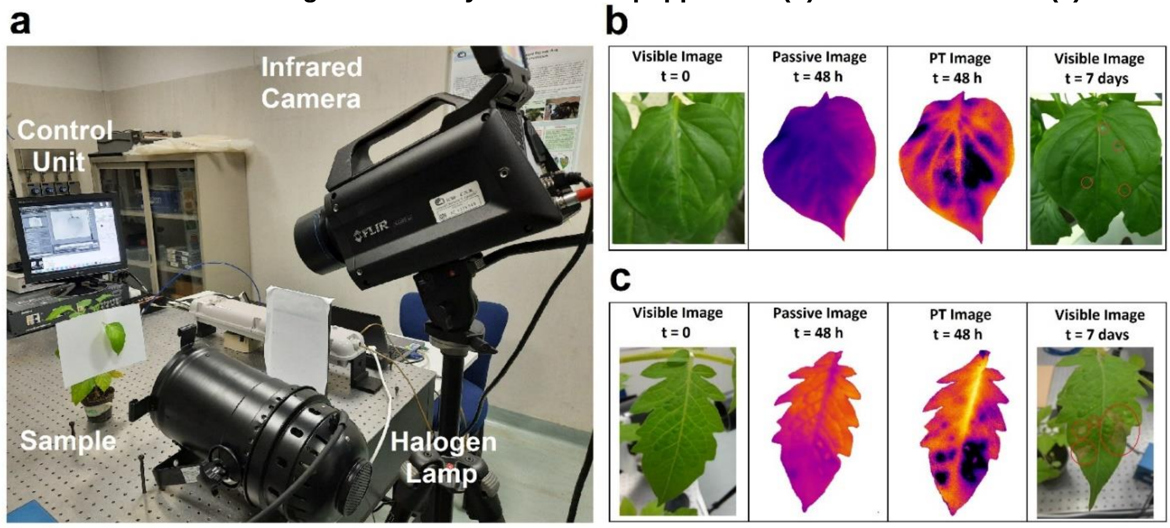
b. Thermal imaging measurements

Pulsed thermography analyses were performed on pepper and tomato plants inoculated with the conidia or with sterile distilled water. MWIR camera FLIR X6580 with a cooled indium antimonide (InSb) detector with FPA 640 × 512 pixels and mounting a 50 mm focal lens (spectral band 3.5–5 µm, IFOV 0.3 mrad) was used for the thermal analysis. Treated leaves were heated individually through a 10 s pulse of a halogen lamp and their thermal images were acquired with a frame rate of 10 Hz before, during and for 60 s after heating. Thermal measurements were performed for a time of seven days after inoculation. ResearchIR software (FLIR Systems) was used for image recording and management of the infrared camera. All experiments were conducted in laboratory at a temperature of 22 °C and air humidity in the range 52- 56%. A picture of the experimental set-up is shown in Fig. 1a.

Results

Thermographic monitoring was conducted on 60 leaves inoculated with *B. cinerea* and on 30 leaves with distilled water (control leaves) of both pepper and tomato plants. Representative images of the analysis carried out for both types of leaves studied are shown in Fig. 1. In the figure, the visible images at t=0 of the inoculations and t=7 days, the passive thermographic images at t=48 h and the PT images at t=48 h are shown for both a pepper leaf (b) and a tomato leaf (c). The passive images were recorded before the lamp irradiation while the PT images 30 s after the lamp was switched off. As visible in the figure, PT images showed a thermal distribution characterised by the presence of one or more cold spots that might represent leaf areas with a higher thermal inertia. Moreover, these cold areas have characteristic asymmetric patterns with respect to the leaf axis, and, more interestingly, were not detectable either in the passive thermographic images or in the investigated control leaves. The data collected on the investigated leaves show that the active thermography approach employed is more sensitive than passive analysis in identifying the changes triggered by the plant-*B. cinerea* interaction that are captured just 6 hours after inoculation as cold thermographic zones. Interesting, as shown in Figure 1b and 1c, typic necrotic lesions triggered by *B. cinerea* were visible only after 5-10 days post-inoculation and localized in proximity of the cold areas revealed by PT. The quantity $\Delta T_{inoc}=T_L-T_{CS}$ where T_L and T_{CS} represents the mean temperatures respectively of a reference area on the leaf and of the cold spot observed in the PT images was estimated for all leaves after 48 h from *B. cinerea* inoculations considering frames extrapolated 30 s after lamp irradiation. These values were compared with the maximum temperature variation observed on control leaves ΔT_{cont} evaluated in the same condition. A t-test for mean comparison was conducted on the data set showing a strong and significant difference between ΔT_{inoc} and ΔT_{con} ($p < 0.001$) for both pepper and tomato plants.

Figure 1. Examples of thermographic analysis of leaves infected with the fungus *B. cinerea*: the experimental setup (a), visible images at t=0 of the inoculations, passive images at t=48 h, PT images at t=48 h and visible images at t=7 days for both a pepper leaf (b) and a tomato leaf (c).



Conclusions

Precision agriculture aims to optimize yield and minimize environmental impact. The lack of visible symptoms quickly after a pathogen attack cause substantial hurdles to an its efficient early identification and management. Our results demonstrate that active PT can be an effective tool, also engineerable for remote use, to detect in real-time the presence in plant leaves of the fungus infection, allowing a more sustainable control of this plant disease [3]. PT revealed specific thermal patterns in the infected leaves after a few hours (within 48 h) and, in any case, many days before than the visible appearance of the lesions caused by *B. cinerea*. Statistical parameters based on diagnostic criteria confirmed a good reliability of the active approach used in the early detection of infections of the fungus investigated. Our findings indicate that active thermographic investigations could be used as a valid and robust diagnostic tool for the early detection of one of the most invasive pathogens for different kind of crops.

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P96 - LIDAR and Multispectral 3D data fusion for identifying fungal disease traits in vineyards

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Introduction

Agriculture is responsible for a significant portion of greenhouse gas emissions and freshwater consumption, and conventional farming practices using pesticides have negative impacts on farm profitability, human health, and ecosystems [1]. Precision Agriculture (PA) and Precision Viticulture (PV) can help reduce the use of chemical products in farming by using remote sensing technology to detect diseases and pests accurately [2]. Remote sensing is an accessible way to acquire data from agricultural fields, and optical spectroscopy, which allows the calculation of vegetation indices, is the most common non-destructive data acquisition method [3]. Artificial intelligence, mainly through machine learning and deep learning techniques, is leading to the highest accuracy for disease detection. 3D point clouds in agriculture, specifically in viticulture and vineyard management, have shown their potential for many applications [4,5], although no work for Botrytis disease assessment using point clouds was made.

Objectives

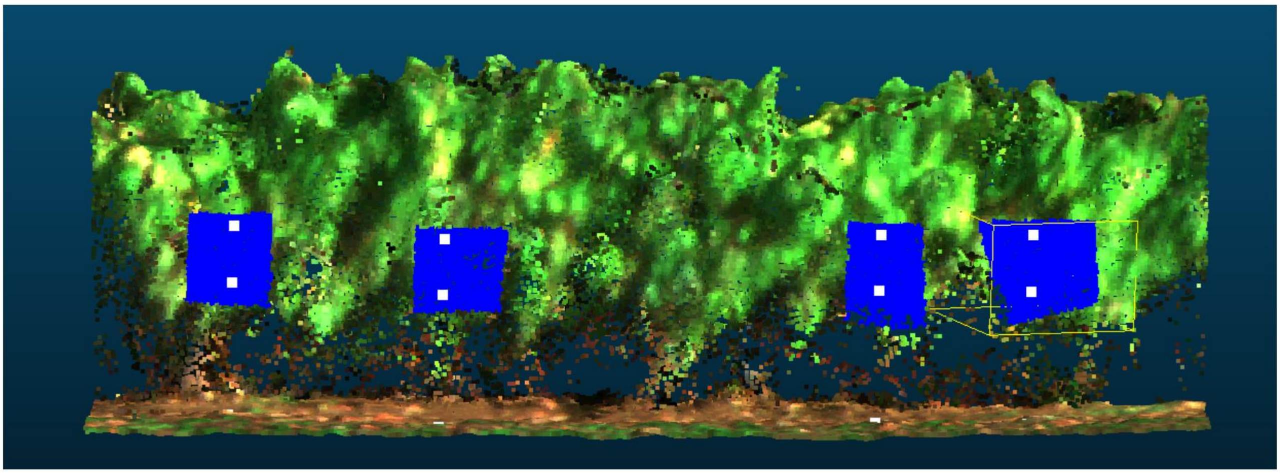
Structure from Motion (SfM) and Multi-View Stereo (MVS) algorithms are used to generate a 3D MS representation of the vineyard, with the resulting point cloud cropped to focus on the region of interest. Then, data fusion between SfM and LiDAR clouds was made, aligning them using a manual pre-alignment and the Iterative-Closest-Point (ICP) algorithm. Two different outputs are explored, including unsupervised vineyard segmentation and disease detection (Botrytis) using 3D point clouds and vegetation indices.

Materials and methods

This article uses 3D point clouds obtained from MS and LiDAR data sources for vineyard analysis. The process involves generating a 3D MS representation using SfM and MVS algorithms, followed by cropping the ROI and aligning the SfM and LiDAR clouds using manual pre-alignment and the ICP algorithm. The project explores two different outputs: unsupervised vineyard segmentation into three classes and disease detection (Botrytis Bunch Rot) using vegetation indices.

In order to label the 3D MS point cloud with corresponding class clusters for disease and healthy regions, the volume of the projected wall region from a height above ground between around 65 to 105 cm was labeled, because the clusters were located in that region. Then, the exact location of Botrytis-affected clusters was employed as an input (ground truth) and, moreover, other positions were randomly assigned as healthy locations (Fig. 1).

Fig. 1. Four labeled clusters.



Results

The east side of the vineyard canopy had a significantly low reflection intensity for all three bands due to the shadows. To address this issue, normalization was done, however, the results indicated that even with this methodology, it was not possible to recover the spectral information. Given the behavior of the shadow side, only the sunny side of the vineyard was employed for the analysis.

Fig. 2 presents the boxplots for some VIs, depicting both cluster distributions, with each distribution's mean represented as a white dot. Boxplots are a convenient way to compare data, with 50% of the data inside each distribution box (between the 1st and 3rd quartile) and the median represented by a black line inside. This allows for a fair comparison of the different VIs between the Botrytis and healthy sample distributions. NDVI, RGI, NGRDI, RGBVI, BGVI, BRVI, VARIg, GLI, MNGRDI, G%, ExG, 2G RGI, RVI, DVI, and TGI showed significant differences for the healthy and Botrytis-affected clusters, with little or no overlap in the 50% corresponding to the interquartile data (1st and 3rd quartile). Out of the 21 selected VIs for this study, only two of them (GRVI and GNDVI) failed to reject the null hypothesis for at least one of the employed tests (Mann-Whitney U test and permutation test). GRVI is the only vegetation index not showing statistical significance.

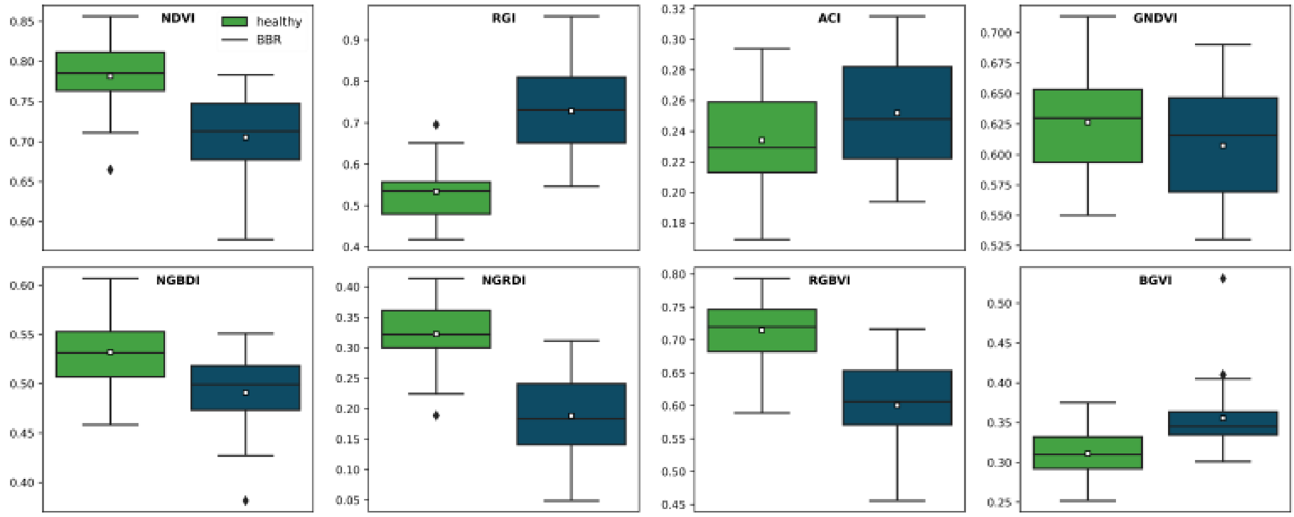


Fig. 2. Boxplots of some of the Vegetation indices.

Discussion and conclusions

The study demonstrates that 3D models can enhance disease detection precision through point clouds, which allow for a more accurate location of disease incidence in the vineyard canopy walls. The use of vegetation indices (VIs) has proven valuable in assessing disease, but they only allow for the detection of vegetative stress spots, and multi-temporal analysis is needed to determine the causes of stress. Almost all vegetation indices showed significant differences between diseased and non-diseased clusters.

Further research is needed to improve the accuracy of the proposed methodology for vineyard segmentation and individualization in 3D

Acknowledgments

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P97 - Machine learning based prediction of soil total nitrogen by using hyper-spectral data in laboratory

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Introduction

Nitrogen (N) is a vital nutrient for crop growth, playing a significant role in agricultural productivity and food security [1]. Accurate estimation of soil N content is crucial for optimizing fertilizer management and enhancing crop yields. However, conventional laboratory chemical analysis techniques are destructive, laborious, complicated, lengthy, and costly to operate. The Analytical Spectral Device (ASD) Field Spec 4 spectroradiometer (350-2500 nm) combined with machine learning models (MLs) considered as a proximal sensing technique for rapid, nondestructive, and cost-effective soil analysis in the laboratory or field [2].

Recent advancements in machine learning and deep learning algorithms, such as Partial Least Square Regression (PLSR) and convolutional neural networks (CNN), have surpassed chemometric approaches in various tasks. The successful application of CNN for soil property prediction has been demonstrated in multiple studies [3]. This introduction lays the groundwork for investigating the potential of advanced machine learning and deep learning techniques in soil property analysis and fertilizer management optimization.

Objectives

Consequently, this research seeks to explore the potential of hyperspectral data combined with machine learning and deep learning techniques for predicting soil N content. The specific objectives of this study include: 1) investigating the influence of particle size on soil spectral signatures, 2) examining whether nitrogen effects can be distinctly identified in the spectral signature when accounting for moisture, and 3) evaluating the performance of machine learning and deep learning models in predicting soil N content.

Materials and methods

Forty-four soil samples were collected from small plots in Freising, Bavaria, Germany, at a depth of 0-30 cm. Each sample's total N content (% of dry matter) was analyzed using standard laboratory methods. Samples were categorized by particle size (2mm to 5mm and above 5mm), moisture levels (0%, 10%, and 20%), and nitrogen treatments (0 kg/ha, 180 kg/ha, 220 kg/ha). A nitrogenous fertilizer solution was applied to the samples in a standard petri dish, and the samples were scanned with an ASD FieldSpec.

The raw soil reflectance data underwent pre-processing including Standard Normal Variate (SNV), Multiplicative Signal Correction (MSC), First Derivative (FD), Second Derivative (SD), and Continuum removal (CR) before modeling [4]. To train and test the PLSR and CNN models, 70% of the samples were randomly selected as the calibration set and the remaining 30% as the validation set [5]. For PLSR, the input variables included soil particle size, soil moisture, and spectral data, while the CNN utilized only spectral data. The output for both models was the total N content of the soil.

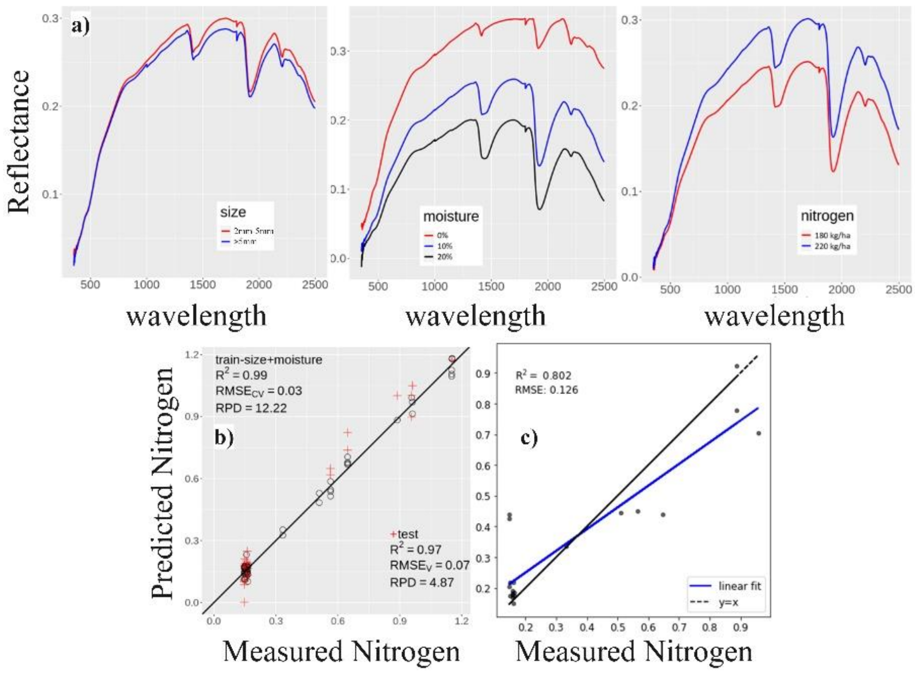
Results

Upon visual inspection, mean reflectance across particle size categories exhibits analogous spectral patterns, with minor deviations for sizes >5 mm within 800-1300 nm, 1400-1800 nm, and 1900-2500 nm bands. Increased moisture content results in greater absorption in the range of shortwave infrared due to water's inherent absorption properties. Interestingly, nitrogen treatment curves reveal notable absorption with increasing input, especially in the 600-1800 nm and 1900-2500 nm ranges, while maintaining constant particle size and moisture. Therefore, integrating particle size, moisture, and nitrogen effects may improve model performance (Figure 1a).

Among pre-processing methods, SNV and MSC considerably improved prediction accuracy and were further enhanced by including particle size and moisture variables. PLSR with the combination of SNV pre-processing dataset and with the inclusion of particle size and moisture treatment with R^2 of 0.97 and RMSE of 0.07 variables outperformed the other models (Figure 1b).

The CNN model yielded promising results, with R2 = 0.802 and RMSE = 0.126, suggesting room for further improvement (Figure 1c). It is too early to assert that PLSR outperformed CNN, since, as achieving optimal results typically requires several thousand data points.

Figure 1. a) Spectral curves differenting particle size, moisture, and nitrogen treatment. b) Scater plot of PLSR model with best prediction metrics. c) Scater plot of CNN model using spectral data as a prediction metric



Discussion and conclusions

Particle size differentiation has a minor impact on soil spectral signatures, corroborating prior research [6]. However, moisture and nitrogen content variations significantly influence reflectance. The PLSR model achieved optimal performance using SNV pre-processed data combined with size and moisture, with our study uniquely integrating these variables to improve prediction accuracy. While the CNN model yielded promising results compared to the result of [7], further refinement is needed.

Acknowledgements

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P98 - Development of an On-line Object Detection Neural Network for weed detection in Tomato Crops

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Introduction

Tomato (*Solanum lycopersicum* L.) is one of the most important crops in the world since it is a primary ingredient in a large variety of foods. Weed management plays one of the most critical roles in tomato crops. However, the standard method for weed management reduces its potential yield, so it is necessary to develop a more effective method. Nowadays, the conventional approach in weed management is herbicides sprayed over the entire crop area, even in free weed areas. Nevertheless, the density and composition of weeds are not uniform throughout the field, with spatial and temporal variation. Integrating site-specific weed management (SSWM) and multi-species weed detection could effectively control tomato crops' most problematic weed species [1]. New techniques such as deep learning (DL) are currently assisting in achieving the aforementioned sustainable aims. This approach has demonstrated excellent and potential outcomes in many study fields [2]. Therefore, a novel procedure based on an object detection neural network, RetinaNet performance, was analysed due to the current developments and the need for fast and efficient detection. The results showed high values of mAP (up to 0.98) depending on the weed species. This research demonstrates the potential of the RetinaNet to detect the most important weed species in tomato crops with a one-step neural network.

Objectives

The current study proposes a one-step detection and classification system of tomato crops' most aggressive weed species, such as monocotyledonous weeds (*Cyperus rotundus* L., *Echinochloa crus galli* L.) and dicotyledonous weeds (*Portulaca oleracea* L., *Solanum nigrum* L.) under real and commercial production fields.

Materials and methods

RGB images were collected using a Canon PowerShot SX540 HS with a spatial resolution of 5184 pixels × 3886 pixels in commercial tomato fields in the province of Badajoz. Images were captured under varying lighting conditions and different backgrounds. The images were acquired in the early stages of growth, the optimal time frame for herbicide weed control. The fields were naturally infested by monocotyledonous (*Cyperus rotundus* L., *Echinochloa crus galli* L., *Setaria verticillata* L.) and dicotyledonous (*Portulaca oleracea* L., *Solanum nigrum* L.). Experts in weed science identified and manually labelled the plant species in each of the 1,713 recorded images. The quality of test prediction was assessed using mAP. Following the scanning process, 10,607 bounding boxes were retrieved. Among the object Detection networks, RetinaNet was adopted because of its excellent performance, which combines the accuracy of two-step networks with the performance of single-step networks [3].

Results

Six species of weeds and crop in actual field conditions were automatically categorised: monocotyledonous (*Cyperus rotundus* L., *Echinochloa crus galli* L., *Setaria verticillata* L.), dicotyledonous (*Portulaca oleracea* L., *Solanum nigrum* L.), and tomato (*Solanum lycopersicum* L.). Not recognised plant (NR) classes have the lowest AP value (0.8234), while the tomato crop class (LYPES) has the highest (0.9744). These test results are presented with the value of intersection over the union (IoU) set to 0.5 (see Table 1). Data augmentation provides data for DL models, decreases the model's dependency on training data, and improves its performance for DL. Deep learning models frequently perform better when trained with additional data obtained via data augmentation [4]. Moreover, augmentation techniques counteract overfitting while enhancing the CNN test's precision [5]. RetinaNet's performance increased from 0.90354 to 0.92755 to decrease detection and classification errors caused by varying image conditions in the dataset. Data augmentation provides data for DL models, decreases the model's dependency on training data, and improves its performance for DL. Deep learning models frequently perform better when trained with additional data obtained via data augmentation [4]. Moreover, augmentation techniques counteract overfitting while enhancing the CNN test's precision [5]. RetinaNet's performance increased from 0.90354 to 0.92755 to decrease detection and classification errors caused by varying image conditions in the dataset.

Table 1. RetinaNet prediction mAP values on the test set per species identified by EPPO code in tomato.

Label	RetinaNet
SOLNI	0.9209
CYPRO	0.9322
ECHCG	0.9502
SETIT	0.9044
POROL	0.9776
LYPES	0.9842
NR	0.8234

Discussion and conclusions

RetinaNet was able to differentiate between monocotyledonous and dicotyledonous weeds with an accuracy of 94% and 95%, allowing for more targeted and efficient spraying. Moreover, the classification procedure is more challenging when the crop resembles weeds; hence, a large number of parameters and a high amount of processing capacity are required to train NNs [6]. Furthermore, RetinaNet's prediction performance for images with dimensions of 3886 by 1926 pixels was 0.2354 seconds per picture, which is too slow for real-time applications. Therefore, pre-processing of the data prior to implementing the system in the field is required. Despite the rapid evolution of computers' data processing capabilities, real-time prediction is not yet possible. However, implementing RetinaNet as a one-step model may become viable due to hardware and software progress in the following years. RetinaNet has accomplished detection and classification in a single step, with mAP values ranging from 0.900 to 0.977. The achieved accuracy is sufficient for conducting adequate selective controls. Moreover, RetinaNet has proven excellent efficiency in classifying two significant categories of weeds: monocotyledonous and dicotyledonous. The presented results for discriminating between species within the same family have enormous promise for identifying herbicide-resistant species.

Acknowledgements

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P100 - Sub-field Scale Soil Salinity Prediction using Machine Learning Algorithms with Remotely Sensed Data in the Prairie Area of Saskatchewan, Canada.

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Introduction

Soil salinity is recognized to be a major threat to agriculture in the Prairies Region of Canada. Salinization not only reduces the yield of agricultural crops but also limits the range of crops that can be grown, thereby reducing the potential economic returns to farmers. Despite decades of soil surveying and soil mapping research, field-scale soil salinity maps are not available.

Objectives

The main objective of this study was (1) to explore the potential use of a remote sensing cloud-based data analysis platform (GEE), (2) to assess the performances of Machine Learning regression models in soil salinity prediction, and (3) to identify the most important variables for soil salinity map prediction.

Materials and methods

Field data collection was conducted in 2020 with a total area of 3241 ha (8008 acres) in an agricultural area of Rose Valley and Nut Mountain regions near Quill Lake (Saskatchewan, Canada). According to the current soil map[1], the study area is in the weakly saline region (2 - 4 dS/m). The field data includes the apparent electrical conductivity (ECa) and the salt estimation in the soil samples (ECe). A total of 680 soil samples were collected (depths of 0 to 20 cm) on 30 sites by stratified random sampling approach. In each file, a zoning map named Swat Zone was used as the stratified zones (5 zones per field). In each zone, 5 soil samples were collected (5 locations per zone, 3 probes at each location), resulting in 25 soil samples per field. From soil samples, the electrical conductivity of soil saturation extract (ECe) or estimated soluble salts was quantified in a lab. Soil samples were collected by a truck-mount soil sampler. Additionally, electrical conductivity (EC) in the soil was measured using truck-mount EM38. Predictors were extracted from multiple source satellite imagery, including Sentinel-1, Sentinel-2, Landsat-5, Landsat-8, OpenLandMap, and Alos Palsar (DEM) with 41 predictors being used. These included some directed sources, such as Digital Elevation Model (DEM) from Also Palsar. However, the majority of variables were extracted from Sentinel 2, Sentinel 1, and Landsat 8. Several vegetation indices (VIs), such as the Normalized Vegetation Index (NDVI), Normalized Difference Yellow Index (NDYI), Soil-Adjusted Vegetation Index (SAVI), Optimized Soil Adjusted Vegetation Index (OSAVI), Normalized Difference Wetness Index (NDWI), Normalized Burn Ratio (NBR), and Modified Soil-Adjusted Vegetation Index (MSAVI), were used to map soil salinity. A Stratified Random Sampling approach was used to collect data points. Classification and Regression Tree - CART, Random Forest - RF, and Gradient Boosted Regression Tree – GBRT, which are available in GEE, were used for the prediction. Leave-one-field-out cross-validation was used for evaluation. The accuracy evaluation metrics include Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2).

Results

Descriptive statistics of soil salinity from 8107 random sample points show that the average EC value of the study area is relatively low (1.14 ds/m) and classified as weakly saline according to the province soil salinity rating. The standard deviation, max, and min values show moderate within-field as well as whole study area variation of soil salinity. Generally, higher soil EC occurred in a relatively small area within the fields and located surrounding sloughs or water bodies. This is more obvious from the soil EC survey map, where high soil EC presents surrounding sloughs.

Our preliminary evaluation of model performance using data from field code 30 (figure not showing). The major reason for selecting this field to explore model performance was that the field has a relatively low EC range value (0.3 to 2.2 dS/m). It was evident that RF performs better in soil EC prediction compared to GB and CART models. RF offers the highest Coefficient of Determination (R^2 = 0.51) with the lowest Root Mean Squared Error (RMSE = 0.56) and Mean Absolute Error (MAE = 0.38). For this reason, RF was used for soil EC map prediction. A full comparison of model performance will be included.

Overall RF performs well with a Coefficient of determination of 0.55. Extended graphs from random fields show that the predicted model performs better on field with higher EC range (> 2.0 dS/m).

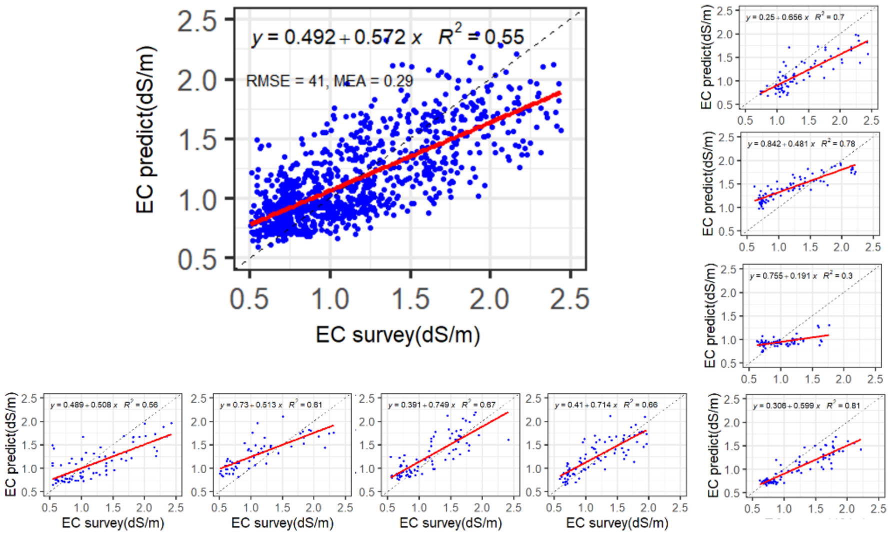

Figure 1: Linear relationship between the predicted and measured EC for the leave-one-out site (small graph) and cross-validation

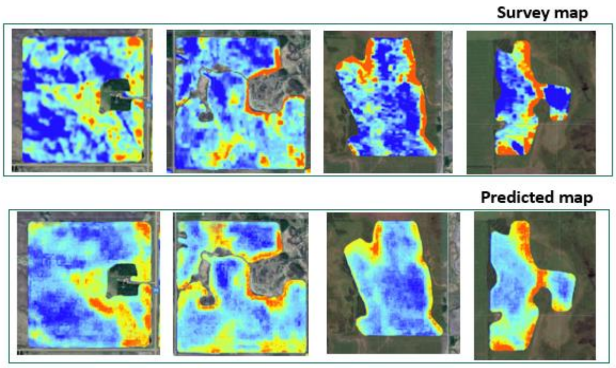

Figure 2: Survey and predicted maps of some sites for visualized comparison

The top 5 important variables include (1) StdDev of Landsat 8 RBR index, (2) mean Normalized Difference Yellow Index (NDYI) from Sentinel 2, (3) stdDev Tasseled cap wetness (TCW) from Landsat 8, (4) median Salinity Index (SI3) from Sentinel 2, and (5) mean Green band (B3) from Landsat 8.

Discussion and conclusions

We explored the potential use of environmental covariates and remote sensing imagery to map sub-field soil salinity in the GEE platform. Soil EC was collected from a field survey in 2020. All input variables were extracted from GEE. Random Forest outperformed the others. NRB, NDYI,TCW, SI3, B3 from multispectral satellite imagery are the top five important variables in soil EC prediction. Future research will focus on collecting more field data and expanding the predicted area into a broader spatial scale.

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P101- Development of a prototype mobile app for crop weight estimation using AI techniques

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Introduction

Recent advances in computer vision and deep learning technologies have led to many crop monitoring studies using cameras to monitor crop growth, etc. These studies use fixed-position cameras, which are limited in their ability to be carried in the field. Therefore, this study aims to develop techniques based on computer vision and deep learning technologies that can estimate crop weight, one of the main factors in crop monitoring, in real-time by using images taken by a built-in camera on a mobile device such as a tablet in the field.

Objectives

The objectives of this research are to develop a crop weight estimation technique that can be used in crop fields using computer vision and deep learning techniques, and to demonstrate the feasibility of the developed technique by developing a prototype mobile app based on Android operating system (OS).

Materials and methods

The crop weight estimation technique using computer vision and deep learning techniques was developed through the process of building a crop dataset, developing an image processing algorithm, developing an image segmentation model, and performing simple linear regression analysis. Cassava, a major crop in Vanuatu, was selected as the experimental crop, and the crop dataset was constructed by collecting crop images and weight data measured by electronic scales using two tablets. Also, we resized the crop images to 256 by 256 to test a trained deep learning model on a low-performance mobile device. Image processing algorithms such as lens calibration, automatic marker detection and geometric correction were used to calculate area from crop images. A crop measurement board was developed to perform geometric correction automatically. To estimate the area of crops from the geometrically corrected images, we designed an image segmentation model using the tensorflow framework based on the U-NET architecture and developed an image segmentation model using the built dataset. The insufficient data for training the deep learning model was augmented using data augmentation techniques. The correlation equation between crop area and weight was calculated using linear regression analysis using the built dataset. The prototype mobile app was then developed using the image processing algorithms, the image segmentation model, and the simple linear regression.

Results

The deep learning model was trained using learning rate 0.001, batch size 16, and adam optimizer to build an image segmentation model of cassava crop using geometrically corrected images and weight data. The results of segmenting a cassava crop using the trained image segmentation model are shown in Figure 1. The R^2 between crop area and weight for the entire dataset was about 0.87. There was a somewhat high correlation between crop area and weight. The image processing algorithm, the crop image segmentation model, and the simple linear regression between crop area and weight were used to develop the prototype mobile app. The app is shown in Figure 2.

Figure 1. Example of the result of segmenting a cassava crop by using the trained image segmentation model

Figure 2. Screenshot of the prototype mobile app developed in this study

Discussion and conclusions

Computer vision and deep learning techniques were used to segment cassava, a major crop in Vanuatu, from images taken with a tablet camera. A simple linear regression was developed through regression analysis between the area and weight of the segmented crop images, and the R^2 was greater than 0.87. The correlation between crop area and weight was significant. It is similar to the results of previous studies[1,2] on crop weight estimation. Using the method developed in this study, we developed a prototype mobile app based on Android. The app was implemented to automatically estimate the weight of crops from images taken by a camera on a tablet. The developed technique can be useful as a key technology to monitor the weight of different crops using computer vision. We also confirmed the applicability of the developed techniques by developing the prototype mobile app.

Acknowledgements

This study was supported by the APEC Climate Center, and a grant from Vanuatu Klaemet blong Redy, Adapt mo Protekt (Van-KIRAP) funded by the Green Climate Fund (GCF).

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P102- A Non-invasive Method of Monitoring the Growth of Individual Melons using UAVs and Machine Learning

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Introduction

Climate warming changes adversely affect agriculture and horticulture conducted under field conditions [1]. Increased CO2 concentration and temperature encourage the search for plant species and varieties adapted to changing habitat conditions and more extended periods of sunny operations. In horticulture, the suitability for cultivating thermophilic species of both orchards and vegetables is being assessed [2]. Melon (Cucumis melo L.) is a valuable vegetable species cultivated on a large scale, mainly in China, Turkey, and India. In Poland, melon is grown on a small scale under covers. Cost reductions can be achieved by growing it in the field on mulches.

Objectives

The main objective of this research was to propose a non-invasive and automated monitoring method to support field studies of mulch-grown melon plants.

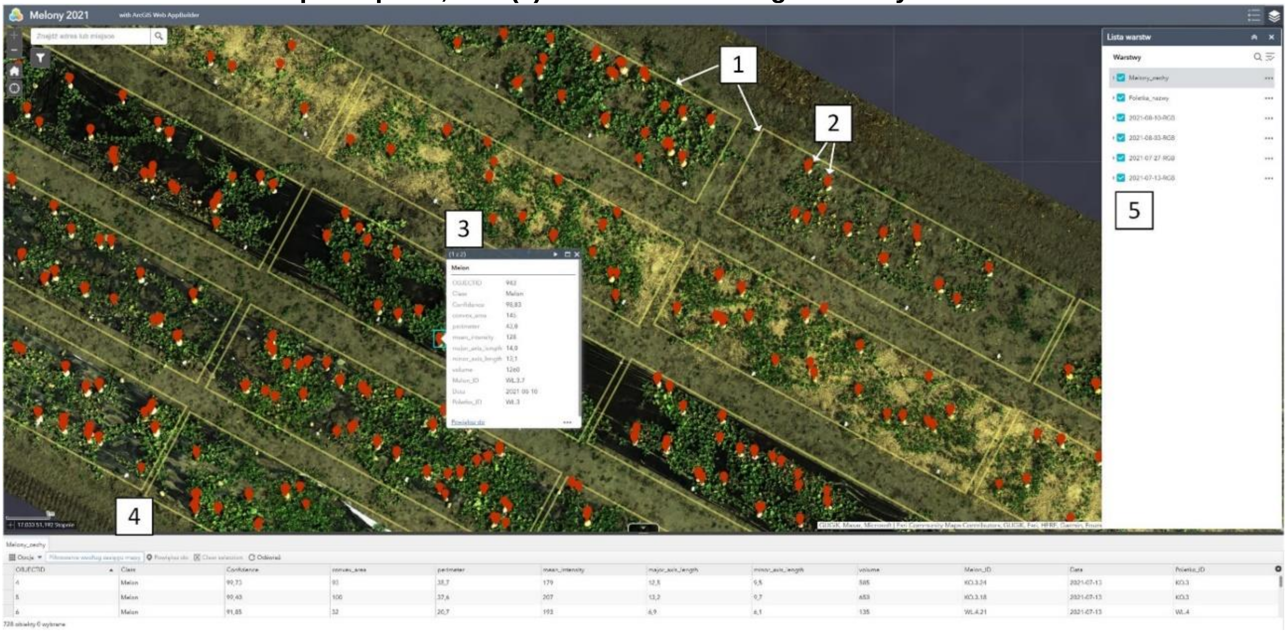
Materials and methods

A method consisting of 4 main stages was proposed, namely: (1) data acquisition and data pre-processing, (2) segmentation of leaves, (3) segmentation of melon fruit, and (4) dimensioning of melon fruit. The collected data came from a field experiment conducted in 2019 and 2021 involving the analysis of the growth and yield of 3 melon varieties cultivated with different soil mulching materials, giving a total of 20 study stations. The experimental field was located in Psary, Poland (52º21'10" N 19º2'33" E). A total of 3 UAV image acquisitions were performed each year. Images were acquired using a Sentera AGX710 camera transported by a DJI M210 RTK drone. The acquired individual shots were combined into an orthomosaic. Three sets of labelled data were prepared for the selected acquisition dates to train deep learning models for melon fruit segmentation. In order to extend the dataset, additional synthetic images were generated using leaf and melon fruit extracted from the images. Details of the method used to generate the 2D synthetic images can be found in [3]. The degree of overlapping by leaves was determined for each labelled melon fruit. Semantic segmentation of leaves was performed using RGB vegetation indices (e.g. ExGR, CIVE) [4] maps and Otsu automatic thresholding. Based on the binary masks obtained after thresholding, leaf area was calculated. For melon fruit extraction from images, instance segmentation was performed using the Mask R-CNN [5] model with the ResNet101 backbone. Model training was performed for the 'only real' and 'real_with_syn' options, determining whether synthetic images are included when constructing the training set. The dataset with real samples was divided 70:30 into training and test parts. The models after training were then used to segment the melon fruit on selected orthomosaics. In order to adapt the size of the input image with the recommended size for Mask R-CNN, the orthomosaics were divided into tiles of size 256x256. A slight overlap between neighbouring tiles was applied during inference to reduce prediction errors from observing only the fruit fragment at the tile boundary. The performed registration of orthomosaics allows the link of single melon fruit from consecutive orthomosaics and, in the case of a lack of linking, to identify the undetected melon fruit. The user manually marked the melon fruit area if no detection was identified. The melon fruit was dimensioned based on the binary masks obtained after instance segmentation. In the lack of overlapping, the visible part of the melon fruit has an approximate ellipse shape. The lengths of the major and minor axis of the ellipse were calculated. The volume of the melon fruit was estimated using the formula for the volume of an ellipsoid. Standard object detection (AP50) and segmentation (F1-score) metrics were used to evaluate the proposed methods. In order to check the robustness of the melon fruit segmentation model to variation among the analysed images, evaluation was performed for the out-domain inference case, when the training and test sets came from different datasets (different acquisition dates for the training and test set). The evaluation was also carried out for the in-domain inference case when the training and test sets came from the same dataset (the same acquisition date for the training and test set).

Results and discussion

The best results for the semantic segmentation of leaves were achieved by ExGR (+ Otsu) (F1-score=0.864), significantly better than the other vegetation indices. For evaluating the melon segmentation model, AP50=98.2 was obtained for the in-domain inference case and AP50=89.9 for the out-domain inference case, indicating that changing the domain significantly affects the model's accuracy. The use of additional synthetic images in the training set positively affected model accuracy, resulting in an increase in AP50 from 97.3 to 98.2 for the in-domain inference case and from 86.7 to 89.9 for the out-domain inference case. The identified detection and segmentation errors in melons were mainly associated with the fruits with the highest cover by leaves. In this group of fruit, the improvement in model accuracy after adding synthetic data was the greatest. The melon fruit detection, dimensioning, and leaf segmentation results were finally summarised in the form of a Web application and made available remotely, presented in Figure 1, detailing its most essential elements.

Figure 1. Web application for visualising results: (1) boundaries of the study areas, (2) detected melon fruit, (3) calculated characteristics for a single melon fruit, (4) attribute table for detected melon fruit with data export option, and (5) menu for selecting the analysed date.



Conclusions

The proposed method proved the potential of non-invasive and automatic phenotyping of melon plants and their fruits in the context of enabling monitoring of their growth by UAV. The use of additional synthetic data in the training set reduced errors in fruit detection, especially in the case of high leaf cover, and increased the robustness of the detection model to variation among the images. Future work should focus on more detailed phenotyping of melon fruit to assess its maturity and the occurrence of anomalies (e.g. damages, diseases).

Acknowledgements

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P103 – Detection of *Conyza* spp in a hedgerow olive orchard by deep learning convolutional neural networks

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Introduction

Olive groves are an important agro-ecological, cultural, and economic resource in the Mediterranean Basin. Among all cultivation systems, the super-high-density hedgerow olive system (1500-2500 trees.ha-^{1}) has become the most popular in recent years mainly due to its earlier beering and higher production than traditional olive orchards (50-160 trees.ha^{1}), and also the fully mechanization of operations, which means shorter harvest periods and lower costs [1]. These new plantations have generally a drip irrigation to provide water and nutrients and are under no-tillage. These circunstances favor the presence of *Conyza* spp, a herbicide resistant (glyphosate and others) and cosequently hard to control weed, which emergence is mostly located within crop-rows close to pipes and drippers.

Early weed detection in crops using imagery is a challenging problem that has significantly advanced with new sensors on board manned or unmanned vehicles (ground or aerial) and the application of both classical image processing and deep learning (DL) techniques [2]. DL has enabled the detection, localization, and recognition of weeds that were not previously possible, and as a result, it is being used in many agricultural applications [3].

Objectives

To detect *Conyza* spp. (hairy fleabane) infestations in a hedgerow olive field using on-ground RGB videos and the open-source convolutional neuronal network "You Only Look Once" (YOLO).

Materials and methods

A set of eight RGB videos were acquired in a hedgerow olive grove located at Córdoba (Spain) (37º48'17''N, 4º45'55''O, WGS84), cv `Arbosana´, planted at a distance of 3.75 x 1.35 m. Videos were recorded along the central axis ot the crop-rows in horizontal orientation to analyze crop lines on both sides using a Iphone 12 in Full High Definition (FHD), with 60 frames.sec^{-1} and H.264-MPEG-AVC compression. The smarthphone was installed on a 3-axis hand gyro-stabilized platform to eliminate vibrations during recording. *Conyza* was at very early growth development (the stage for a potential succcefull control) and individual plants ocupped approximately 10x20 pixels or more. To avoid repetitive data for each video, 3 frames.sec^{-1} were extracted to be labelled, resulting in 2880 images. Each image was cropped into 12 sub-images of 416 x 416 pixels to maintain spatial resolution for the neural network, providing a total of 34560 images, of which 5640 showed the presence of *Conyza*. As a result, a dataset of 19650 *Conyza* labels was generated, randomly distributed in a 70%, 20%, and 10% split for the training, validation, and test datasets, respectively. Based on our previous experiences [3], the YOLO neural network was used in its -5n, -5s, -5m, -5l, -5X, -R, and -7Tiny versions. To evaluate the *Conyza* object detection for each YOLO model, true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN) were counted to calculate precision, recall, and mean average precision (mAP). In addition, Generalized Intersection over Union (GIoU) was taken into account for each metric to evaluate how closely the predicted bounding box matched to the ground truth.

Results

As an example, Figure 1 presents a comparison between manually labeled bounding boxes of *Conyza* plants (red line) and those detected by the generated DL model (green line). It shows a good match in both the number of plants and the occupied space by them.

Table 1 shows the results obtained in the testing phases for each of the individual models. YOLO-v5m and YOLO-v5l achieved the highest accuracy values, 87.6% and 82.2%, respectively. In contrast, YOLO-R offered the lowest value, equal to 62.3%. However, this version of YOLO showed the highest true positive rate, reaching a recall value of 75.2%, followed by YOLO-v5m (67.1%). On the opposite end, YOLO-v5l showed the lowest recall value, 59.1%. Based on these results and evaluating mAP, the best performing model was YOLO-v5m version (74.1%), due to its good balance between precision and recall.

Table 1. Results in testing phase for each individual YOLO model.

YOLO model	Precision	Recall	mAP
V5n	72,4	65,0	70,9
V5s	72,5	65,0	73,3
V5m	87,6	67,1	74,1
V5l	82,2	59,1	70,8
R	62,3	72,8	71,9
X	76,0	65,7	71,6
V7 Tiny	63,5	75,2	73,9

Source: Author's data

Figure 1. Example of *Conyza* spp detection using DL model.

Source: Author's data.

Discussion and conclusions

Weed detection using low-cost, gyro-stabilized on-ground sensors with low resolution is possible by applying DL models. In this study, a model for detecting early-stage *Conyza* spp. based on YOLO DL models was developed using proximal RGB videos taken in a commercial hedgerow olive field naturally infested by the weed and under uncontrolled situations (*i.e*., natural light conditions), which reinforces the robustness of the model. Our results showed that the quality of the detection model varied depending on the YOLO version used, with YOLO V5m providing the best results. Therefore, the developed DL model can be integrated into a more complex system that would allow the generation of infestation maps or the real-time application of herbicides.

Acknowledgements

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P104 - Cognitive computing for classification of six weed species in tomato and maize crops

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Introduction and objectives

Deep learning models based on supervised learning require a large amount of labeled data for training, which is a common challenge affecting the success of image-based weed detection and classification tasks. In the case of using aerial images acquired from drones, spatial resolution is also another variable to consider. The data augmentation technique provides a good solution to alleviate both insufficient dataset and image resolution.

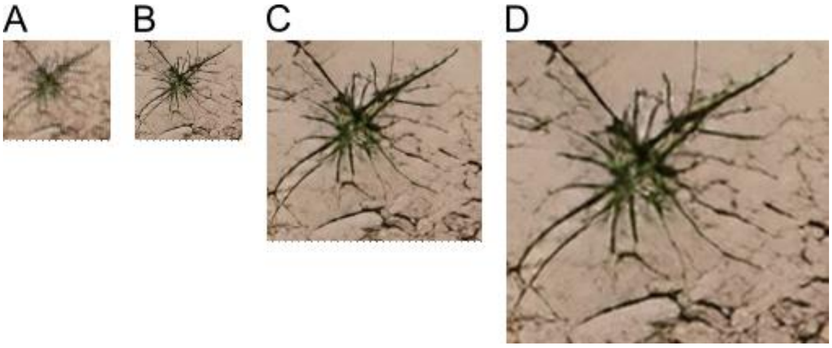
In this study, we investigated the capability of a cognitive computational system for data generation applied to drone-based images collected in commercial tomato and maize fields, with the main objective of identifying six different weed species in an early stage of crop development. Specific objetives were: 1) evaluate the pre-trained Generative Face Priority (GFP) model, based on on Generative Adversarial Neural Networks (GAN), for in blind face restoration by means of spatial feature transform layers, and 2) testing two Convolutional Neural Networks (CNN) classifiers, namely VGG16 and ResNet152, for weed species classification in an early stage of crop development. CNN classifiers can learn relevant image features automatically and have been shown to be very efficient in solving computer vision problems.

Materials and methods

Drone-based images of maize and tomato fields were obtained in a 7,400 m^2 experimental field located in La Poveda farm (Madrid, Spain) and in a 11,685 m^2 commercial field located in Santa Amalia (Badajoz, Spain), respecfively. The weed species found in the fields were *Cyperus rotundus*, *Lolium rigidum*, *Atriplex patula*, *Convolvulus arvensis*, *Salsola kali* and *Solanum nigrum*. RGB aerial images were collected at an altitude of 12 m, which resulted to a ground sample distance (GSD) of 0.17cm per pixel. Next, orthomosaics of each field crop was created using the structure from motion technique, which were subsequently partitioned in fractions of 1,000 $\times$ 1,000 pixels to facilitate the identification and labelling of the weed species. A balanced data set of 1,000 labels per weed species was used to avoid population bias during the training stage of the models. This dataset was then distributed in a ratio of 70%, 15% and 15% for training, validation and testing, respectively.

The GFPGAN model was used on the training images with different scaling factors (Figure 1) to generate high-resolution images that retain the details of the original image, and the CNN-based VGG16 and ResNet152 classifiers were used for the classification task. These models are widely used in image analysis as well as in crop protection applications [1]. For the implementation of the models and the different test experiments, Keras-Tensorflow deep learning framework was used. The model parameters were: 1) image size of 224 $\times$ 224 pixel, 2) batch size = 32, 3) epochs = 100, 4) adaptive moment estimation (Adam) like as optimizer with learning rate = 10^{-5}, and 5) categorical cross-entropy as the loss function. No transfer learning technique was employed.

Figure 1. Example of an aerial image of the weed *Salsola kali*. Original size (A), original size applied GFPGAN (B), increased size x2 applied GFPGAN (C), and increased size x3 applied GFPGAN (D)



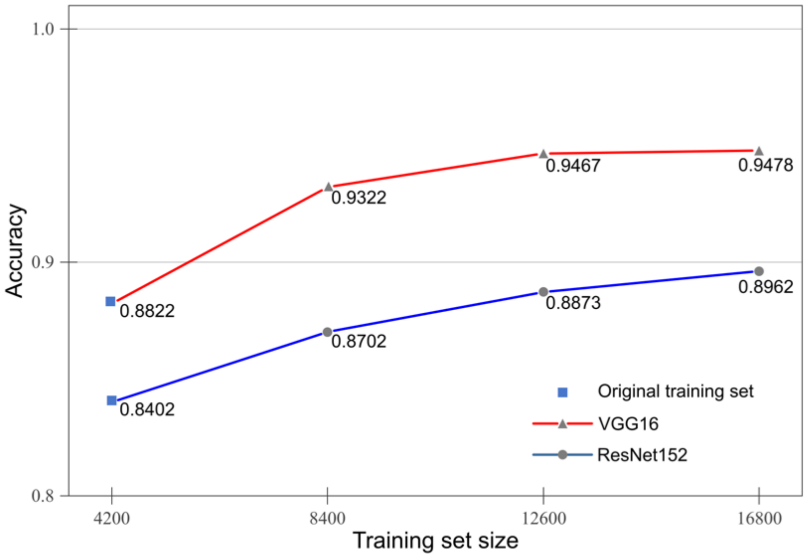
Source: author's data

Results

The models presented high values of precision, recall and f1-score in the classification by species on the test set (>80%), with the VGG16 model standing out (Figure 2), due to the fact that the configuration of the training hyperparameters were the same for both models.

The images generated with the GFPGAN model were added to the original training images, producing augmented datasets of different sizes, the real and augmented datasets were systematically evaluated. The classification results were significantly improved after data augmentation for the two models studied. Specifically, increasing the train set by four times resulted to improve 0.066 and 0.056 the accuracy metric on the test set for the VGG16 and ResNet152 model, respectively.

Figure 2. Training set size vs. model accuracy



Source: author's data

Discussion and conclusions

The use of the GFPGAN model improved the characteristics of the aerial images, as well as their spatial resolution by expanding the image size. The maximum amplification value with which an optimal result was obtained was up to three times in our study. A distortion in the form of interaction between the weeds and the soil was observed in subsequent increases.

Implementation of the data augmentation technique allowed the creation of new images that reflect greater variability for the training data set, improving the performance of the model in its ability to generalize new data, as well as preventing over training.

The developed tool based on cognitive computing would allow implementing timely and effective site-specific weed management (SSWM) following precision agriculture strategies, and thus to control the weed emegences before they cause significant damage to crops, reduce costs by optimizing herbicide applications, and enhance crop productivity, food quality and environment.

Acknowledgements

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P105 - A mobile phone-based tomato maturity monitoring system using identification markers

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Introduction

For efficient crop cultivation in horticultural facilities, it is important to optimize the usage of water, fertilizer, and other inputs, as well as the settings of temperature, humidity, and other parameters. Until now, optimization has relied on the experience and intuition of farmers. Nonetheless, as sensors have made it easier to collect data on the environmental parameters in greenhouses, optimization through analyzing these data has accelerated in recent years. To exclude influences other than input settings, it is important to use direct observation of plant growth as the output data.

Due to the variability in plant growth, data analysis requires information from a wide range of locations within a greenhouse as opposed to a single location. In addition, in order to capture changes in plant growth more precisely, it is preferable to observe the same plant over time.

Research on direct observation of plant growth has been conducted. Methods have been developed to detect tomatoes and assess their maturity from pictures using multinomial logistic regression [1], Mask R-CNN [2], or deep instance segmentation [3]. However, frequently photographing a large facility is labor-intensive. Experimentally, robots have been installed for the automation of monitoring [4], but installation is costly.

Objectives

This study proposed a system that allows farmers to monitor the maturity of identical plants in a wide range of locations by simply filming them with their mobile phones.

Materials and methods

Identification markers and video filming

The camera on a mobile phone cannot adapt to the varying lighting conditions within a facility. Moreover, it is difficult to determine which locations and plants are recorded in the videos, making it impossible to track the same plant. In order to address these issues, identification markers were installed in a facility, which functioned as both color markers and position markers. Markers make it possible to calibrate the color under various lighting conditions and identify the location simultaneously.

The experiment was carried out in a greenhouse in Japan where cherry tomatoes were planted for commercial purposes (Figure 1). The upper and lower black-and-white graphics of identification markers served as position indicators. The middle image, including five colors (red, green, blue, yellow, and orange), is used for color calibration. Markers were positioned every 50 cm along plant rows. The videos were recorded when the recorder walked along a path. A mobile phone (iPhone 12 mini, Apple Inc., California, USA) with a 4K screen resolution and 60 frames per second (fps) was used for filming.

Figure 1. Identification markers installed in a greenhouse.

Fruit detection

From videos, frames that contained identification markers were extracted and saved as image files. Then, the tomato fruits in each image were identified using Laboro Tomato [5].

Since the images were captured when the markers appeared, it was possible to obtain images of the same location from different videos.

Maturity assessments

The evaluation of the maturity of each fruit was based on the color criterion, which classifies tomatoes into ten maturity classes, on a scale ranging from 1 (green, unripe) to 10 (red, fully ripe) [6].

Calibration of color is required to capture the color of each tomato fruit under various lighting conditions. To achieve this, the color of images was transformed using a calibration against the reference color values of identification markers.

For each detected fruit, the mean color value was calculated in the HSV color space. Subsequently, fruit maturity values (1-10) were determined by comparing their hue value to the hue values of the color criterion and determining which hue value was the closest.

Same fruit identification

Using identification markers, images of the same location were captured in different videos. By comparing images, the closest fruits were determined to be identical.

Results

The system detected 96.8% of all tomato fruits in the video. For 82.1% of detected fruits, the same maturity was determined as the ground truth value. For 96.9% of detected fruits, the difference between the estimated maturity and the ground truth maturity was less than one.

Also, the system accurately identified 90.7% of the identical fruits across videos (Table 1).

Table 1. Results of fruit identification.

	Case	Fruit counted	Percentage (%)
Correct	Determined to be identical to a fruit in another video and actually correct	360	74.1
	Determined to be detected only once throughout all videos and actually detected only once	81	16.6
Incorrect	Determined to be identical to a tomato in another video, but the determination was incorrect	9	1.9
	Determined to be detected only once throughout all videos, but were actually identical to a tomato in another video	36	7.4

Source: author's data

Discussion and conclusions

In this study, identification markers were installed, which functioned as both color markers and position markers. Using these markers, from the videos recorded in a facility, the location and the identical fruit were detected with high accuracy, and the maturity prediction error was low. Therefore, the maturity of the same fruit could be monitored over time by simply filming with a mobile phone.

However, in order to monitor the fruits for a longer duration, it would be necessary to track the same fruit regardless of its changing condition. The condition of the tomato truss can be changed on a regular basis by harvesting, removing leaves, or lowering the plant. Future research would be required for more robust tracking.

Acknowledgements

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106 - Transfer and zero-shot learning for weed species detection with small datasets and unseen classes

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Introduction

Weed mapping is an essential step to apply site-specific weed control strategies in the context of precision agriculture. Current machine learning models for this purpose utilize various vision network architectures, are trained using specifically tailored weed datasets (with low generalization beyond the specific conditions of the training set), and with high associated labeling and computational costs, all of which precludes broader uptake of this technology and its use for building more sustainable pipelines. To ensure the reproducibility of methods in real cropfield scenarios, it is crucial to build algorithms that can recognize weeds in the most accurate and cost/time-effective manner. This means detecting and classifying weeds seen or unseen at training, at early plant growth stages (to optimize the application of control measurement), but also leveraging multiple low-cost scalable datasets to ensure broad generalization.

Objectives

This study aimed to explore methods that make weed detection models more reproducible, effective and climate resilient. More precisely, we propose high performing models trained on an early stage weed dataset, and evaluate how transfer learning may help weed detection task in an effort to reduce computation and labeling cost for future models. Thus, peformance of zero-shot learning was analysed in order to be further integrated into weed detection algorithms capable of detecting new weeds not previously seen in the target scenario.

Materials and methods

Transfer learning and zero-shot learning (ZSL) configurations were evaluated using various open-source datasets along with our novel TomatoWeed dataset. This dataset was generated with a small number of drone-based weed images obtained of a commercial tomato field naturally infested with three different species: *Cyperus rotundus*, *Solanum nigrum*, and *Portulaca perenne*. Residual networks of variable depth [1], pretrained on the Imagenet and/or Deepweeds datasets [2] were tested on our novel dataset.

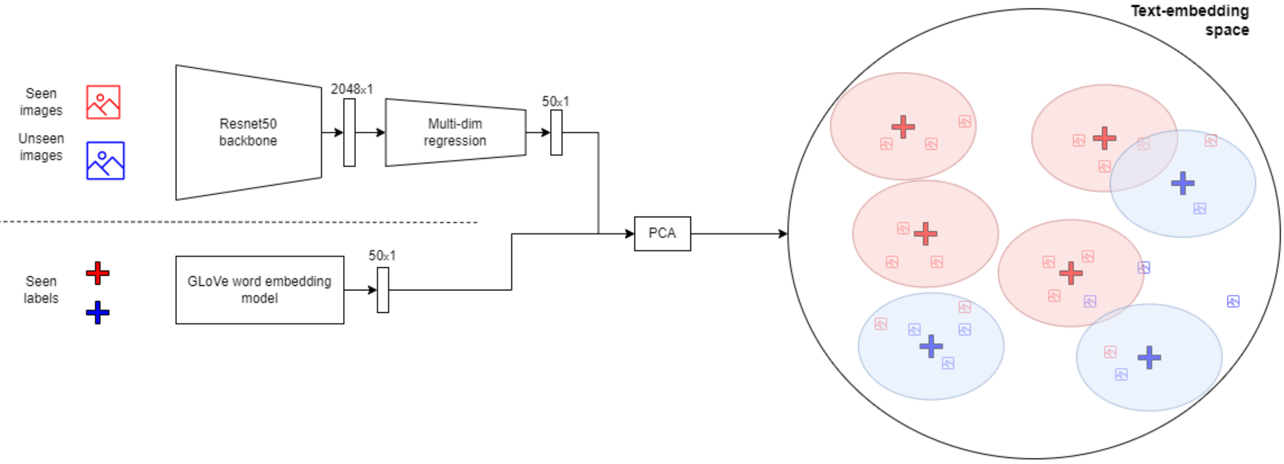
ZSL experiments were led to build more robust weed detection models that can detect weed species unseen at training. This involved using the DeepWeeds dataset to test different projection methods, dimensions, and feature spaces in future scenarios with unseen weed species. Generally, a neural network backbone is trained to project weed images into a class discriminative image feature space. However, using an image feature space becomes trickier when weeds are unseen. Weeds from different classes that present small visual differences may be projected to similar locations, hence unseen weeds are more likely to be misclassified. In text- embedding feature space, classes can appear more distinct as they can be more precisely described in writing. In this study, we have tested the use of a text-embedding space constructed using morphological and habitat descriptions of both seen and unseen weeds from the DeepWeeds dataset. Images are projected in image feature space using Resnet50 backbone. A multi-dimensional regression was trained to project from the image feature space to this text- embedding feature space. Once in text-embedding space, different novelty detection algorithms were tested to determine which weed instances were seen or unseen at training. The schematic in Fig 1 illustrates the proposed architecture.

Results

Transfer learning using a Resnet50 model pre-trained on Imagenet [3] and DeepWeeds [2], and fine-tuned on TomatoWeed dataset resulted in an accuracy of 77.8% on holdout set, outperforming a model trained only on TomatoWeed dataset that obtained an accuracy of 73.7%. This demonstrates the usefulness of transfer learning in weed classification tasks and highlights the benefits of pre-training on relevant datasets for improved model generalization and performance.

Our proposed ZSL architecture was evaluated using the nearest centroid (NC) and Label Propagation (LPA) algorithms, both of which resulted in overall accuracies of 0.55. Given the multi-class nature of this task, this result didn't seem as bad. However, the poor performance for unseen classes suggested that the classifier wasn't able to leverage the text-embedding to flag new classes. Hence we were prompted to conduct a projection test, where we classified unseen projections based on their closest nearest unseen centroid. As such we were trying to declutter the projection space to better understand how unseen images were projected. This approach yielded an accuracy of 0.648, showing promise as it performed better than random for unseen classes.

Figure 1. Representation of our ZSL architecture at testing. The Resnet50 backbone and multidimensional regression are trained prior solely on a set of seen images and labels. The models are expected to transfer knowledge from seen to unseen images. Known labels of seen and unseen classes are used to create a text-embedding space. At testing, seen and unseen images are projected onto this space. Images are then classified using label propagation and nearest centroid algorithms.



Discussion and conclusions

This study demonstrates the effectiveness of transfer learning for weed classification. Using additional external datasets for pretraining improved model performance. Applying a zero-shot learning approach to weed classification allowed models to classify weeds unseen at training. Despite performing poorly, the models showed promise, paving the way for future research.

Acknowledgements

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P107 - Development of multimodal machine learning model for wheat traits assessment under climate change

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Introduction

Humanity faced food insecurity challenges in the past, however today we are facing much bigger challenges regarding food security, which origins heavily lay in global climate change, political instabilities, and growing population [1,2].

Wheat (*T. aestivum*) is the most widely grown grain crop worldwide, with annual production of ~770 million tons, providing about one-fifth of the calories and protein consumed by humans. It is largely grown in water-limited environments with low precipitation, short growing seasons and high temperatures during the reproductive stage, all of which affect plant performance and productivity. [3,4,5]. The ability to develop new genotypes in a short period of time is essential while striving for food security [6]. As a part of the breeding process, phenotyping at scale is one of the leading solutions. High throughput phenotyping often requires data acquisition from a large number of plots in a short time. Remote sensing tools, such as RGB, hyperspectral and thermal unmanned aerial vehicle (UAV) borne imagery, are more frequently used to estimate plants' traits.

The technological development of recent decades led to a higher amount of valuable multimodal data for analysis and further improvement of breeding process. Although the high success of machine learning (ML) in many disciplines, the usage of ML in agriculture is still on its rise, and state-of-the-art techniques are not present and evaluated enough. Thus, the potential of using ML in agriculture in general and specifically in breeding projects is far from being fulfilled.

This research will focus on modern ML models, that will be applied on a combination of spectral, spatial, and temporal UAV-borne imagery as well as ancillary data to improved wheat traits estimation accuracy compared to classical ML techniques.

Objectives

The main aim of the proposed study was to explore the ability of modern ML technique to estimate wheat traits. This aim will be achieved by striving for threefold specific objectives:

1. To estimate a simple wheat trait with a modern ML model.
2. To combine multimodal data into a modern trait estimation ML model.
3. To compare the results from objectives 1 and 2 with results of classical ML approach.

Materials and methods

WheatMax project is a multi-season experiment located close to the Robert H. Smith Faculty of Agriculture facility in Rehovot. Almost 300 wheat genotypes from different sources were included in the study, and over 1700 plots. Based on the project's 2021-2022 growing season, two types of data were sampled, raster and tabular data. The raster data included unmanned aerial vehicle (UAV) borne imagery: RGB (DJI Mavic Mini standard UAV) as well as hyperspectral (Pika L mounted on a DJI M600 UAV) images, over twenty sampling dates (combined). The tabular data included plant traits such as days to heading (DTH), leaf area index (LAI), grain yield, thousand kernel weight (TKW) as well as meteorological data acquired by a portable station. The plots raster data were extracted from the orthomosaic image using a shape files (polygon layer) to create separate raster files for each plot and date.

As the data contains not only multiple types of data but also temporal information which complicates the analysis, although it may provide additional explainable variance to the desired models. Feedforward neural network (FNN) method was used as a classical approach and for the modern modeling approach, a transformer was selected including hyper parameters optimization with Optuna.

Preliminary results

The preliminary results show an advantage in predicting simple traits, like LAI, over previous project's season data (2020-2021), including reduction in complexity of the input data, achieving same results (R^2 ~0.7, mean absolute error ~0.3) with only RGB input instead of hyperspectral alone, using simple FNN model against partial least squares regression (PLSR). It is expected that using hyperspectral data with similar model structure will improve the LAI estimation quality. Using transformer model with a combination of RGB, hyperspectral and meteorological data, is still in progress.

Discussion and conclusions

The error related to the prediction of a complex trait (i.e., yield) might be insufficient, due to complicated process of combination and requirement for high quality data, thanks to relatively large ML model and multimodality. We suggest that further work required to increase the quality of the input data, particularly RGB, including changes in preprocessing algorithms and complexity of the modern ML model.

Acknowledgements

Special acknowledgment to the staff and coordinators of WheatMax Project.

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P108 – Seed Spacing Estimation using CNNs and Seed Localization Sensing System

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Introduction

Planting is one of the most crucial stages while growing plants. Studies [1,2,3] Have shown seed placement plays an important role in increasing yield.

The metric by which planting systems are evaluated is by seed placement metric. Measuring this metric is usualy done by manual methods of using a pogo stick or a ruler. This is very time consuming and human error prone. As climate change accelerates the need for faster development cycles of planting systems, there is a growing demand for automated systems that can accurately measure seed spacing information.

Objectives

This study aimed to develop an algorithm that utilizes cameras and computer vision techniques to quantify seed placement information, reducing human effort and time.

Materials and methods

A 12-row planter was retrofitted with cameras and a GPS. Fig. 1 shows the setup of the camera and LED light The cameras were used to capture approximately 400,000 images, which were then filtered using the ResNet-50 algorithm to select 40,000 images. 8,700 were randomly selected and labeled as corn seeds from this smaller set of images. These images were then augmented to create a larger dataset of 30,000 images.

Image detectors were then trained on this dataset(YOLOR-P6, YOLOX-tiny, YOLOX-s, YOLOX-m, YOLOX-L, YOLOR-CSPX, and YOLOV5). These detectors were designed to identify corn seeds in the images captured by the cameras.

Four additional datasets using the same planter, but with different seed populations and speeds. The seed populations for these datasets were 74,131 and 86,486 seeds per hectare, and the planter was driven at speeds of 9.66 kmph and 12.87 kmph.

An algorithm was developed using GPS information and seed detectors to estimate the distance between individual seeds. This algorithm was then evaluated using several different metrics, including Jensen-Shannon Divergence, mean, standard deviation, difference of counts, and RMS.

Results

Each of the detectors was evaluated with the algorithm on JSD distances and RMS values best models with highest FPS for the 4 runs are shown in the table below

Table 1. Results of the detector with highest FPS

Speed	Seed Population	Detector	Count Error	JSD	RMS Error	FPS
9.66	74,131	YOLOR-CSPX	6	0.223	0.012	23.719
12.87	74,131	YOLOR-CSPX	2	0.298	0.018	25.405
9.66	86,486	YOLOR-CSPX	2	0.244	0.015	24.271
12.87	86,486	YOLOR-CSPX	-3	0.258	0.017	25.431

Source: Authors data

Figure 1. Seed Localization System

Source: [5]

Discussion and conclusions

- This study can be adapted to other types of seeds, such as soybeans, sunflower, cotton and others, by retraining the detector on those specific types of seeds. The detector and tracker are two separate modules in this study, and the retraining process would involve specifically targeting the detector module to recognize and distinguish the new type of seed. This would allow the study to be applied to a wider range of crops and could potentially have useful applications in various agricultural settings.
- The Results indicated that models performed better at 9.66 kmph.
- By using SLS system and YOLOR-CSPX as seed detector algorithm, the total time taken to detect and quantify spacing for all dataset was reduced by a factor of 96 (74.91 seconds), compared to manual method (2 hours).

Acknowledgments

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P109 - Optimization algorithms for plant segmentation of point clouds onboard agricultural robots

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Introduction

Light detection and ranging (LiDAR) sensors are widely used in autonomous vehicles for navigation and obstacle detection, including agricultural robotics. Point clouds generated by this technology are being used to characterize crops. Although different methodologies have been used for the analysis of this type of 3D data, many of them apply standard procedures for the segmentation of field objects, like the widely used Otsu's threshold [1] or the RANSAC methodology [2], which are not suitable for all environments.

Objectives

In this work a different procedure is proposed combining geometrical information from the three-dimensional point cloud with parameters extracted form a histogram analysis and a local comparison of neighbouring points. Therefore, on-the-go positioning for real time navigation and plant identification is feasible based on local data compared with modelled data, and no GNSS signal is needed. The final objective was to find the optimal algorithm for segmenting crop plants from soil and weeds.

Materials and methods

This methodology has been applied on point clouds acquired with two Sick LMS-11 LiDARs onboard a robotic platform moving on rows of cabbages and cauliflowers, along several weeks of crop growth, as explained in [3]. Simultaneous data were registered with the two sensors -one placed in zenith orientation, the second facing the crop form a lateral view - then merged and analysed. Different procedures for selecting the cut-off value between points belonging to the crop and soil points were calculated and compared, including: direct use of the point height in a 3D space, Otsu's threshold on the histogram, a cost function (J) of weighed sum for each point, a linear segmentation after the weighed sum, and several combination of them such as applying an additional factor to the weighed sum related to point height and/or averaging each value over the amount of point present within a given radius. Also, as the histogram was bimodal (crop – soil) another method for finding the most suitable cut-off value was compared based on finding the local minimum.

Results

Different cut-off values were tested on the point clouds denoted as c_F (highest value of weighted sum), c_L (lowest value), c_O (Otsu's methods), and c_P (most prominent local minimum). Figure 1 shows an example of possible issues on data acquired over a row of cabbages. In this example, the ideal cut-off point would have been between c_L and c_O. Note the large prominence of the local minimum in that range, seen in the 4th graph. In Figure 2 the real point clouds after applying such thresholds can be seen: top left the values using the weighed sum J_2 that form the histogram, top right the height-based division using h_{ground} as defined in [2]. Middle and bottom: the divisions corresponding to the proposed cut-off values c_F, c_L, c_O, and c_P as listed in Figure 1

Discussion and conclusions

The developed algorithms for removing soil from point clouds build upon the Otsu threshold method [1] and the height-based histogram manipulation proposed in [2]. This in contrast to the commonly employed RANSAC [4,5] that fits a straight plane with an error margin such that it encompasses the most possible points. This was attempted in the beginning, but failed due to the soil profile and irregularity of the soil height, as explained in the experiment chapters. Alternatively, other algorithms have been proposed, such as cloth simulation on the inverted measurement: turning the 3D world map upside down and "draping" a cloth with a specified stiffness over the result [6]. A comparison with the soil identification [2] has already been done, where the proposed method outperforms this height-based method, by incorporating knowledge of the surroundings of each point for the distinction. Results indicate that none of the proposed weighted sums correctly separated soil from vegetation across all weeks and crop types. However, the cut-off calculation procedure that seems to outperform the rest was based on averaging over the number of points within a given radius, which improves the contrast between soil and plants. These findings are promising both for off-line and real time cloud analysis onboard agricultural robotics.

Figure 1. Example of cut-off methods applied to a row of cabbages.

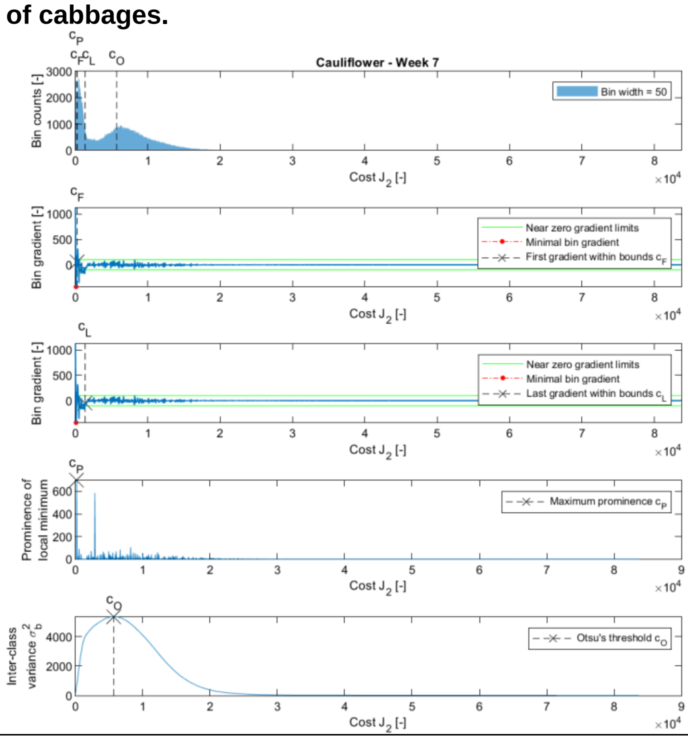
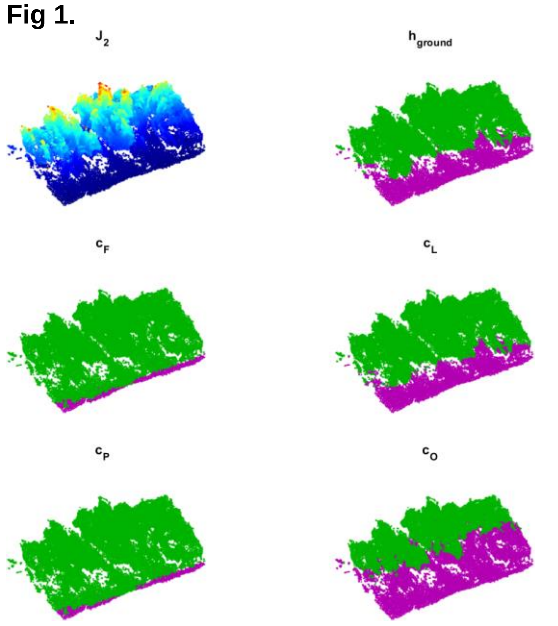


Figure 2. Point clouds corresponding to Fig 1.



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P110 - Active vision and multi-view perception to efficiently tomato target part in high clutter scenario

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Introduction

To deal with labor scarcity and to reduce production costs, there is a growing need for robots to autonomously perform tasks in greenhouses, such as fruit harvesting, de-leafing, and monitoring[1]. To do so, a robot needs to acquire three-dimensional (3D) information about relevant plant parts. However, plants have a complex structure creating many occlusions[2]. This makes it is very difficult to efficiently gather the relevant spatial information[3]. Most current systems collect camera images from multiple viewpoints following a predefined path. Such an approach neither guarantees that all target objects are found, nor is efficient. Instead, methods for next-best-view (NBV) planning reason about the observed and unobserved parts of space to propose viewpoints that have the highest expected information gain. This allows a robot to explore the environment more effectively and efficiently. However, traditional NBV planning attempts to reconstruct the whole plant, while for many tasks, it is sufficient to gather 3D information only of specific plant parts. Active-vision methods therefore need to include semantic information to become aware of the relevant objects in the environment.

Objectives

The objective of this paper is to evaluate the efficiency of robotic active vision perception integration system. Based on the experimental results of the evaluation, each integrated module will be analyzed separately to determine its contribution to accuracy and efficiency. This analysis will help system developers in improving the various algorithm of this system.

Materials and methods

Our work integrates attention-driven active vision with a multi-view reconstruction method to build a semantic object-based model of tomato plants. As a first step, the camera image is processed by a deep neural network to detect the tomatoes, peduncles, and petioles. Combined with the depth map, this results in 3D information about these plant parts. In the second step, this is input to a multi-object tracker, which associates the new observations with already existing objects in the plant model. The plant model integrates multi-view information and represents the class, ID, and 3D pose of the detected objects as well as the size of tomatoes. In the next step, the task manager reasons about the required information to provide objects-of-interest (OOI) to the attention-driven active-vision module, to quickly locate the relevant plant parts. If more information is needed at the current location, the OOI is set to promote local view planning. Finally, the active-vision module uses the OOIs to plan the next-best viewpoint with the highest expected information gain. All steps are continuously repeated to improve the tomato-plant model.

Different settings of the method were compared in a simulation test to evaluate the efficiency and effectiveness of our approach. Settings with/without NBV were compared in Gazebo (simulation test enviornment) to evaluate the efficiency of the system. During the simulation experiment, we expect to compare the pre-defined trajectory planner (“Zigzag” and “Semicircular”) with the NBV planner to obtain the results of detection efficiency. For generating candidates, NBV also uses "Zigzag" and "Semicircular" (Table 1). A total of 60 experiments were conducted with 5 plants 12 times using Gazebo simulators and 3D mesh models of tomato plants.

Table 1. Parameters for Simulation Experiment

Planner	**Predefined** - Trajectory		**NBV** - Surface	
	Zigzag	Semi-cylindrical	Zigzag	Semi-cylindrical
Number of candidates	1	1	20	20
Number of views	10	10	10	10
Hight	0.5	0	0.5	0
Size of Zoom out RoI	xyz: 0.03m, 0.03m, 0.03m			
Size of Zoom in RoI	xyz: 0.05m, 0.05m, 0.05m			

Our evaluation of the planners' performance was based on the number of correct detections. This metric is called the percentage of correctly detected objects (PCO).

$$PCO = \frac{Correctly\ detected\ objects}{Total\ number\ of\ objects} \times 100 \quad (1)$$

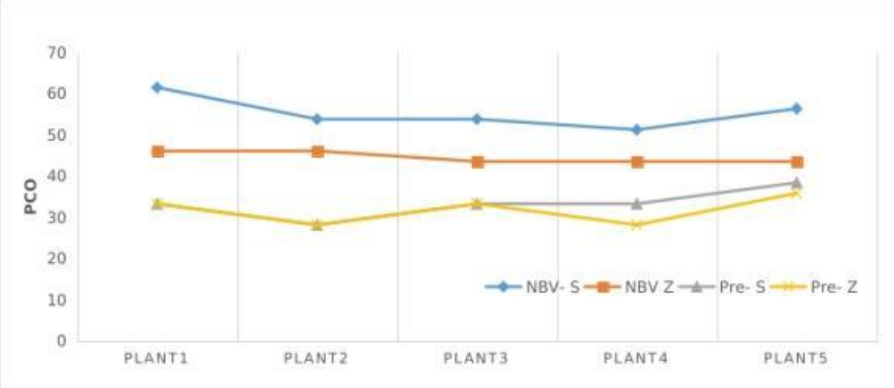
After one cycle detection, system will output the message of detected object class, ID and 3D pose information. From these information, the number of correctly detected objects can be obtained.

Main steps involved in the simulation experiment are as follows: (1) Launch the simulation environment (2) Launch the robot control program (Pre-defined or NBV planner), start the integration system (3) Evaluate the PCO results.

From Figure 1, it can be seen that using the NBV method can enable the integration system to better find the observation position and observe more key parts (tomato, peduncle, petiole).

Results

Figure 1. Performance of the planners on the detection of all key part of tomato plant



Source: author’s data

Based on the PCO values in table II, it can be seen that the predefined planner is limited in its ability to detect key parts because of the fixed number of steps and intervals. Quantitatively, due to the low number of detected objects, the two different trajectory detections don't show much difference.NBV-S planner detected 35.00 - 45.84% more than Pre-S and Pre-Z planners. Despite the slightly inferior performance, the NBV-Z planner is still better than the Pre-defined planner by 11.77 - 30.87%. In comparison with Semi-cylindrical surface, NBV-Z is closer to a plane, which leads to fewer objects being detected from the camera's view point.

Table 2. PCO results for simulation experiments

	PLANT1	PLANT2	PLANT3	PLANT4
Pre-S	33.33	28.21	33.33	33.33
Pre-Z	33.33	28.21	33.33	28.21
NBV-S	61.54	53.85	53.85	51.28
NBV-Z	46.15	46.15	43.59	43.59

Source: author’s data

Conclusions

This paper describes how to integrate the active vision algorithm with the 3D object tracking algorithm to address to deal with object detection issue in high clutter scenario. A Gazebo simulation experiment is used to verify the efficiency of NBV active vision. According to the results, NBV planner is able to find more target objects in the same detection surface.

Acknowledgements

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SIDE EVENT by AgriTech
CN AgriTech RESEARCH ACTIVITIES ON PRECISION AGRICULTURE AND SMART FARMING

AgriTech01: Enabling variable rate sprinkler irrigation of open field crops

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Introduction

Climate change and the need to prevent yield losses due to drought periods are driving an increasing use of irrigation in agriculture. Meanwhile, agriculture is required to become more efficient in its water footprint, given the competing and equally relevant civil and industrial uses. In water demanding open field crops (e.g., tomato, corn, etc.) Precision Irrigation (PI) [1] has shown the potential to significantly decrease the amount of water required by the crop across the growth season, if driven by a suitable Decision Support System (DSS) incorporating adequate soil, crop, weather, and agronomic knowledge. The potential for water saving ranges from a few % to 50%, in a number of case studies investigated worldwide [1] as well as in Northern Italy [2], and is typically assumed to be above 20%.

When within-field soil spatial variability is significant, or spatially varied management operations are adopted, Variable Rate Irrigation (VRI) can provide further benefit [3] in terms of yield and water use efficiency. The added value of VRI vs. PI in terms of input water reduction is less well quantified, but it is typically estimated in the range 5-10% [4]. Clearly, even small benefits in individual farms would accrue into large and significant water saving or reduced irrigation infrastructure investment by water reclamation consortia and local admnistrations. Unfortunately, the higher cost and operational complexity of equipment suitable for VRI are deterring farmers from their broad adoption. Indeed, sprinkler irrigation covers a significant fraction of irrigated land worldwide (above 60% in Europe and above 40% in Northern America) [5]. Techniques enabling automatic monitoring, planning and control of machines equipped with VRI capabilities, including sprinkler-based machines, can have therefore a significant impact toward water use efficiency and sustainability.

Objectives

Site-specific VRI sprinkler irrigation systems are classified into speed control systems and zone or nozzle control systems [4,6]. In speed control systems, water application depth is changed by varying the speed of the self-propelled sprinkler. Hence, these systems enable differential irrigation in rectangular segments or triangular pie-shaped areas, with linear move or center pivot sprinkler systems, respectively. In zone control systems, the irrigator is equipped with controlled valves or nozzles enabling also different amount of water applied along the length of the irrigation bar. Even though zone control systems offer a higher potential for water and energy optimization, their adoption has been very limited [4,6].

The purpose of this contribution is to highlight the obstacles hindering deployment of VRI in many farms and some current trends toward VRI in Northern Italy, with a special focus on Emilia-Romagna, where in the last few years we have contributed to the design of system solutions enabling PI and VRI across the whole irrigated area of the region. Being Emilia-Romagna one of the Italian regions at the forefront of agricultural production and innovation in irrigation, as well as a leading district of sprinkler irrigation equipment manufacturers, we assume that this contribution can be relevant to other areas and countries.

Materials and methods

Several interviews, focus groups, meetings and polls with stakeholders (including farmers, agronomists and consultant experts, public administrators, water reclamation consortia, equipment manufacturers) have been conducted in the course of project POSITIVE (www.progettopositive.it) in order to understand the priorities and the obstacles toward a full exploitation of PI and VRI in Emilia-Romagna agriculture. To our knowledge (including private communications with equipment manufacturers), virtually all sprinkler irrigation equipment deployed at farms in Northern Italy do not include controllable nozzles, and thus are not suitable for zone-based operation. However, since 2020 many new or revamped sprinkler systems (mostly hose reels equipped with spray booms or sprinklers and a few pivot systems) installed in the same area are equipped with control units enabling VRI via speed control.

A key strategy to reap the potential benefits of VRI is (1) to provide farmers for all plots with a tailored, optimized DSS advice integrated in a dynamic VRI prescription taking into account all the peculiarities of the crop and plot, and (2) to automatically program (if feasible) the VRI equipment available on site so as to apply the prescription according to the offered variability features, thereby minimizing the effort required to the farmer to directly program the machine for each irrigation.

Developing an appropriate VRI prescription requires assessment of the actual variability in the field. In order to enable VRI across the whole Emilia-Romagna region, a protocol has been developed to include vegetation information in the IRRIFRAME DSS based on remote sensing data [8]. The protocol relies on the products (multispectral images) provided by Sentinel-2 satellites at 10m x 10m resolution. Moreover, a procedure has been designed to directly feed with the VRI prescription both linear move and center pivot machines equipped which offer suitable web APIs. Further ongoing work deals with rain gun sprinklers mounted on a towed trolley, a type of equipment largely used thanks to its relatively low cost and easy deployment in multiple sites.

Results

At each satellite transit (every 5-3 days based on locations of registered fields) products are retrieved for large areas via the Copernicus Hub API, and the area of interest for each plot segmented. Data are verified for correctness and update. Cleaning operations are applied for outlier removal and to cope with presence of artifacts nearby or within the plot and edge effects. Moreover, a coordinate system transformation is applied to align satellite data with the reference frame adopted by the DSS. Plot-specific NDVI and EVI maps at 10m x 10m resolution are then computed from the cleaned images, formatted, and uploaded in the IRRIFRAME DSS.

To enable machine-to-machine operation, the VRI prescription map must be transformed into an irrigation plan suitable for the available equipment, which - as discussed above - implements VRI using speed control. In the designed VRI advisory service [8], the DSS knows the type of irrigation machine associated by the farmer to each plot, and the abstract *VRI prescription map* (defined in terms of water depth to be delivered in each 10 m x 10 m cell) is automatically transformed into a *VRI application map* articulated in rectangular stripes [9] or triangular pie slices whose size is determined by minimum and step values dictated by the machine. The VRI application map is eventually sent to the irrigation equipment for each registered plot according to a time schedule determined by the irrigation advisory service. The ensuing application map therefore incorporates all the agronomic knowledge required for a valid PI prescription as well as the remote or local sensing information needed for VRI, to the extent allowed by the available equipment.

Acknowledgements

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AgriTech02 - Hyperspectral proximal sensing and machine learning techniques to estimate wheat nutritional status for digital agriculture application

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Introduction

Global megatrends (climate change, population growth, technological change) have gradually caused the supply-demand balance to shift towards a not sufficient and unsustainable food production, with a potentially dramatic consequence for environmental and humanitarian aspects [1]. We are forced to “produce more with less” protecting the most important production factors (i.e. soil and water) and reducing impact to environment (e.g. pollution and greenhouse gases emission) (FAO 2016). For this reason, the development of diagnostic tools able to support farmer towards rational nitrogen (N) management, based on the actual crop requirements, is among the most challenging issues to target European Policy Frameworks and it is a central topic of the National Center for the Development of New Technologies in Agriculture (Agritech). In this context, geo-information products from Remote sensing (RS), able to quantify within-field crop status variability, are fundamental solution to support site-specific N management [1,2]. In particular, a new era of hyperspectral RS (HRS) system, on ground, from UAV platform or satellite (e.g. ASI-PRISMA mission) is opening new opportunity for quantitative crop traits monitoring (LAI, chlorophyll and Nitrogen content) [3]. Appropriate methods must be developed to fully exploit the HRS data information content to generate information useful to smart agricultural management.

Objectives

The overall objective of this research is to develop a processing chain solution based on state-of-the-art machine learning and hybrid methods to generate quantitative information on wheat nutritional status from hyperspectral data. To achieve this, several steps have to be accomplished: STEP 0) “HYPER-CROP system development”, design and deploy an automatic measuring station to perform continuous seasonal acquisition of hyperspectral measurements; STEP 1) “Dataset development” , generate a robust multi-site multi-year data set by exploiting also existing experimental data; STEP 2) “Model development”, set-up machine learning retrieval schema and test model exportability and STEP 3) “Map demonstration”, generate crop traits maps by scaling up model solution with aerial and satellite data. The target crop of the study is the winter wheat due to its relevance as staple food worldwide.

Materials and methods

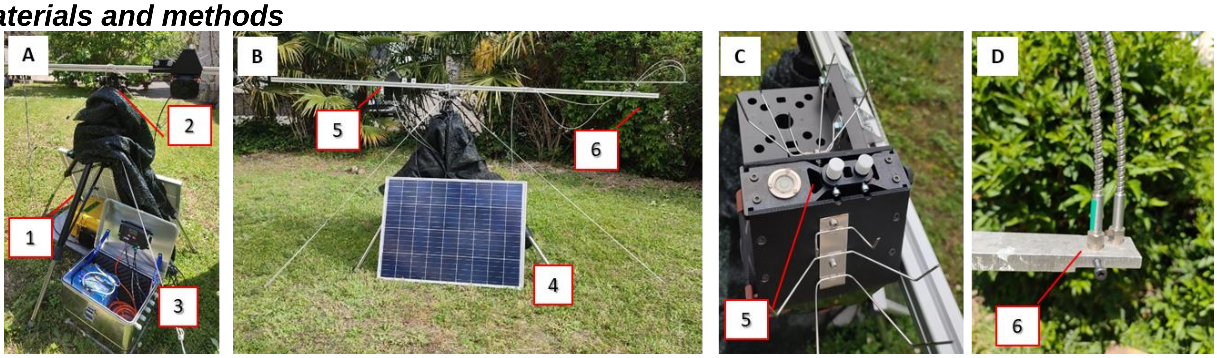

Figure 1. [A & B] HYPER-CROP station composed by the NOX instrument (1), tripod (2), battery charging component (3) and solar panel (4). [C & D] Details of the probes for the incoming solar irradiance (cosine receptors) (5) and upwelling target radiance (fiber optics) for VIS-NIR & SWIR (6).

Figure 1- [A & B] show the prototype of the HYPER-CROP station to acquire continuous hyperspectral data. The system is composed by *i)* the NOX spectroradiometer from JB Hyperspectral Devices GmbH (https://www.jb-hyperspectral.com/), operating in the VIS-NIR and SWIR range (350 – 1700 nm); *ii)* the energy station (solar panel and battery) and *iii)* the tripod (static or rotating to perform experimental measurements). A system for automatic acquisition with a robotic arm is under

development to make it operative in 2024 on a field experiment with different fertilisation levels. The acquired data will be added to previously measured data, increasing the robustness of a multi-site-year dataset for model development and testing (Table 1).

Table 1. Available (2022) and in acquisition (2023) data set of wheat traits and hyperspectral data

Dataset	ARB[1] (2022)	PAR[2] (2023)	BOL[3] (2023)	JDS[4] (2023)	Totals
- Tillering	46*	-	-	40	86
- Booting	96	24**	4	40	164
- Flowering	96	32	4	40	172
Tot	238	56	8	120	422

Crop traits: LAI, Biomass, Leaf Chlorophyll and Nitrogen content

Field phenotyping experiment: ARB (Arborea) one 4 variety - 4 fert. Level – 2 soils 3 replicates; Real farm condition: [PAR] (Parma): 4 site - 4 variety - 4 fer. Level – 2 plots; [BOL] (Bologna) 1 sites - 1 variety - 2 fert. Level - 2 plots; [JDS] (Jolanda di Savoia) 1 site – 2 variety – 2 fer level - 10 plots. In * and ** some data acquisition failed.

Crop traits retrieval will be performed using state-of-the-art methods based on Machine Learning Regression Algorithms (MLRAs) (e.g. Partial least squares regression PLSR) and physically-based approaches (i.e. Radiative Transfer Models - RTMs). This hybrid framework will be tested as it is considered the most promising solution [4]

Results

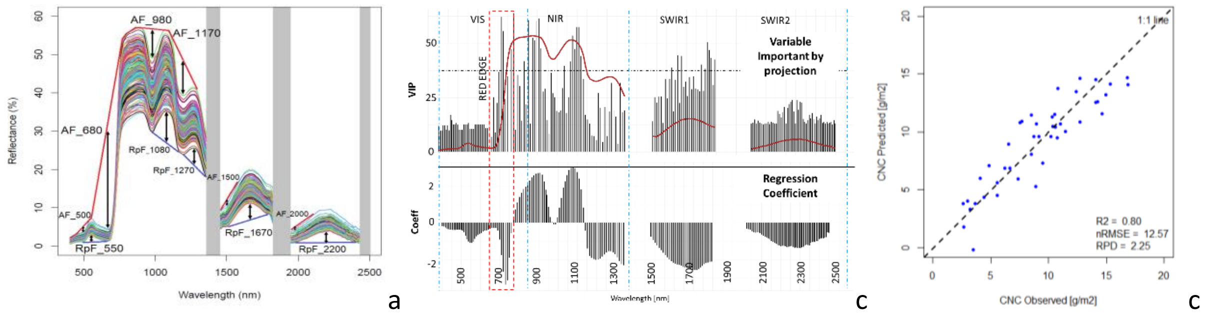

Figure 2. Wheat hyperspectral data (a), PLSR bands importance for CNC estimation (b) and cross validation metrics

Figure 2a provides examples of full range spectra (350 -2500 nm) from ARB data set. Panel b shows preliminary results for PLSR in estimating Canopy Nitrogen Content (CNC) together with important features (VIP and regression coefficient) of continuous HRS data: RED-EDGE (~750 nm), SWIR (~1600 - 1700 nm) and NIR (~850-900 & ~1050 -1100 nm) for Nitrogen estimation. Panel c reports model performance calculated with a leave-one-out (LOO) cross-validation procedure.

Discussion and conclusions

Preliminary results show that full-range HRS data in combination with MLRAs can provide accurate estimates of wheat crop traits at canopy level. Our results suggest that such hyperspectral-based MLRA approaches could be a powerful tool to accurately monitor crop status throughout the cropping season, to further aid precision agricultural practices such as N management. To fully investigate HRS capacity and develop predictive models in relation to crop physiology and management, continuous data for a season are needed. The development of the HYPER-CROP station will allow to complete the dataset needed and to investigate crop physiological responses. related to nutritional status.

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AgriTech03 - Analysis of consumers and famers' behaviour related to the newly developed technologies

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Introduction

The rapid advancement of technology has significantly impacted various industries, including the agricultural sector. Emerging technologies, such as precision agriculture, remote sensing, biotechnology, and digital platforms, have transformed the way consumers and farmers engage with each other and the agricultural ecosystem.

Farmers are faced with growing challenges worldwide and meet changing production requirements [1]. Many agricultural entrepreneurs see the adoption of new technologies as a driving force to reverse the course and transform their businesses, adapting them to market expectations. On the other hand, different consumer segments may show distinctive levels of interest and acceptance of agricultural technologies. Understanding the preferences and motivations of different consumer segments can help target marketing efforts and effectively communicate the benefits of agricultural technology.

Several studies have focused on technology adoption, which represents a crucial issue in the scientific literature [2,3]. In line with this, predicting agricultural innovations' extent and the adoption rate is crucial to measure adaptive capacity and evaluate their future benefits [4,5].

Technology adoption is a complex non-linear process influenced by multiple factors. Several works in the literature have identified specific determinants and models, which consistently explain stakeholders' decisions to adopt innovation: some studies have been developed in the field of social psychology and describe adoption as a function of behavioural intentions and other individual characteristics [6,7].

While the adoption of new technologies presents numerous benefits, it also poses challenges for both consumers and farmers. In this context, studying and understanding the behaviour of consumers and farmers towards newly developed technologies is crucial for businesses to effectively introduce and market their innovations, for policymakers to create supportive frameworks, and for researchers to explore the implications and potential challenges associated with these technologies.

Objectives

This study aims to investigate the behaviour of consumers and farmers in relation to the new technologies developed, their acceptance, attitude, intention and absorption mechanisms according to concepts of adoption and diffusion of innovation, as well as its perceived value, measured through willingness to pay (WTP).

In interactions with other Spokes of Agritech project, this research will contribute to achieve the objectives of Spoke 3, which aims to investigate the economic analysis for the evaluation, uptake and supply chain valorization.

Materials and methods

In order to respond to the research objectives, a preliminary literature review on drivers and barriers in the adoption of the new technologies developed has been conducted. Furthermore, a focus group with stakeholder will be conducted to identify understanding, awareness and knowledge of current adoption and barriers. Finally, a survey on farmers' and consumer adoption and acceptance of an innovative technology will be carried out. In particular:

(1) Farmers' opinions are explored through focus groups, in order to identify a conceptual framework of the relevant issues. We will use semi-structured interviews to key informants, and a questionnaire-based survey with farmers. Then, we will develop a choice experiment on farmers' preference for laser weeding technique with the objectives to identify farmers' preferences for different features of laser weeding machine (e.g., autonomy, energy sources, etc.), examining determinants of farmers' preference for the laser technique.

(2) Consumer attitudes, perceptions and awareness of new technologies will be analysed, as well as the drivers of consumer preferences. The study includes a survey on consumers' valuation for products produced under innovative traceability systems, such as blockchain solutions,

identifying the main sociocultural aspects which determine consumers' choices towards these products.

Results, discussion and conclusions

The result will explain the (potential) acceptance, attitude, intention and absorption mechanisms according to cutting-edge concepts of innovation adoption and diffusion, as well as its perceived value, measured through willingness to pay (WTP).

The analysis of the behavior of consumers and farmers in relation to the new technologies developed in agriculture is essential for understanding the transformation-taking place in the sector. By examining the factors influencing behaviour, the impact on interaction and communication, and the challenges and opportunities that arise, policy makers, researchers and industry stakeholders can make informed decisions to shape the future of agriculture and ensure its sustainability and productivity in the face of advanced technology.

The results of this study could be translated into solutions for the diffusion and exploitation of innovation along the value chain.

Acknowledgements

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AgriTech04 - Improving water quality and availability for a sustainable agricultural management within the AGRITECH project

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Introduction

Climate change is causing unpredictable water availability, exacerbating water scarcity. In addition, water resources often do not have a satisfying quality [1]. The agricultural sector is extremely vulnerable to climate change, and at the same time it is also the largest water user and a major polluter of water [2].

In this context, optimised water management can help in developing efficient agricultural practices and sustainable agricultural production.

Furthermore, strategic planning and definition of technologies for water, wastewater and nutrients reuse and recovery can have a key role to cope with climate change and consequent water scarcity, as well as pollution of water bodies [3,4]. In the case of treated wastewater reuse in agricultural irrigation, methods to assess the potential and the safety of this practice at larger level are necessary, based on structuring water resources balance paying special attention to water quality and actual on-site irrigation infrastructures.

Nature-based solutions are sustainable and low-cost technologies and practices that can contribute to a better protection of ecosystems, with a huge potential to be exploited in agricultural context.

Objectives

In addition to the other Spokes within the AGRITECH project, the University of Bologna (UNIBO) will contribute to achieve the research goals of Spoke 3, which aims at enabling technologies and sustainable strategies for the smart management of agricultural system and their environmental impact. This poster reports the main research activities that will be performed by the research group of agricultural hydraulics of UNIBO within the tasks 3.2.4 and 3.2.5 of the Spoke 3, in detail:

- development of new methods to assess the potential and safety of wastewater reuse at district/basin/regional level for a sustainable planning of this practice, based on water resource balance (available resources/irrigation water needs), available infrastructures, quality and quantity of treated wastewater, risk assessment;
- evaluation of the effects that the application of treated wastewater can have on soil, groundwater, crops and irrigation equipment;
- investigation of the removal efficiency of constructed wetlands when treating wastewater, and evaluation of their capacity to produce suitable effluents to be safely reused in agricultural irrigation, also in accordance with the Italian and the EU guidelines on treated wastewater reuse;
- test of tailored and integrated constructed wetlands at farm level with multiple purposes, such as water availability (e.g. retention, storage, infiltration) and water quality (e.g. pollutant removal) improvement.

Materials and methods

For research activity 1), the potential of treated wastewater reuse in agricultural irrigation [5] will be evaluated for specific areas of the Emilia-Romagna region, considering all the components that have been mentioned above. The wastewater reuse system will include different wastewater treatment plants managed by the HERA Group Spa, the irrigation distribution network of the Renana Reclamation Consortium and the farms within the study area.

For research activity 2), a smart experimental site (Figure 1 a), which has been installed within the wastewater treatment plant of Cesena, will be used to test the effects of treated wastewater on irrigated horticultural crops and orchards (e.g., detection of contaminants) as well as on soil (e.g., detection of contaminants) and irrigation materials (e.g. occlusion, distribution uniformity, etc.), the latter provided by the project partner IRRITEC, but also to evaluate fertilizer saving when treated wastewater is used for irrigation.

For research activity 3), a pilot plant (Figure 1 b), consisting of 6 horizontal sub-surface and 6 vertical constructed wetlands, will be used for the treatment of urban wastewater, in order to investigate the capability of this natural system to produce effluents that satisfies the limits foreseen for agricultural irrigation reuse;

For research activity 4), a surface constructed wetland (Figure 1 c) located within a 12.5 ha experimental agricultural farm of Canale Emiliano Romagnolo land reclamation consortium (CER) in the Emilia-Romagna region will be used for a better reduction and control of non-point sources of pollution from agriculture (e.g. nutrient removal from agricultural drainage water), contributing to the overall environmental protection, especially in rural areas.

Figure 1. a) Reuse of treated wastewater for the irrigation of horticultural crops and orchards; b) Wastewater treatment with constructed wetlands; c) agricultural drainage water management and treatment with constructed wetlands.

a) b) c)

Results, discussion and conclusions

This research will focus on the improvement of water quality (nature-based solution for treatment of domestic wastewater and agricultural drainage water) and water availability (reuse of treated wastewater) in order to achieve improved and sustainable agricultural production. The first results obtained are related to planning, designing, adapting and optimising/calibrating the research infrastructures and pilot systems to be used within the AGRITECH project.

Acknowledgements

This study was carried out within the Agritech National Research Center and received funding from the European Union Next-GenerationEU (PIANO NAZIONALE DI RIPRESA E RESILIENZA (PNRR) – MISSIONE 4 COMPONENTE 2, INVESTIMENTO 1.4 – D.D. 1032 17/06/2022, CN00000022). This poster reflects only the authors' views and opinions, neither the European Union nor the European Commission can be considered responsible for them.

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AgriTech05 - Effect of land preparation on border irrigation performance

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Introduction

The impact of climate change on the future availability and quality of freshwater resources requires a paradigm shift towards the use of new climate-adaptive agricultural water management strategies aided with digital technologies, automated operations and best practices to increase the resource-efficiency, adequacy, productivity, cost-effectiveness, and environmental sustainability of irrigation methods [1]. In this context, traditional irrigation methods (such as border irrigation) need to be supported by best practices that can be implemented to improve irrigation management to pursue water conservation while maintaining crop yields and production quality [2]. In particular, accurate land preparation and levelling practices performed just before the beginning of the agricultural season could help improve the efficiency and adequacy of border irrigation, increasing the uniformity of water distribution on the field while reducing water consumption [3].

Objective

In this work, we will examine the impact of the soil surface microtopography induced by the land preparation on the performance of border irrigation interventions, with the aim of quantifying the benefits of a correct land preparation on the efficiency and adequacy of the watering events.

Materials and methods

The IrriSurf2D model was applied to estimate irrigation performance on a real case study consisting of a closed-end border irrigated sector of about 3,500 m^2 (18 m wide and 190 m long) with an average longitudinal slope of about 6.9 ‰. The model combines microtopography, infiltration and hydrodynamic information and takes advantage of direct on-field measurements (when available) for improving the description of surface water dynamics on borders [4]. The model was calibrated and validated on a case study by comparing the simulated waterfront advance and water depths with observed water level measurements within the sector [4]. Traditional tillage methods, not supported by positioning technologies (such as GPS, for instance), were used to prepare the soil surface prior to sowing each year. At the beginning of the two experimental agricultural seasons (i.e. 2022 and 2023), the microtopography of the soil surface was precisely measured in order to detect potential levelling irregularities. This was done through a photogrammetric survey carried out with a DJI Mavic 2 Pro drone mounting onboard an Hasselblad L1D-20c camera and its 20MPx 1" CMOS sensor. The acquired images were processed with the photogrammetric software Agisoft Metashape (version 1.7.0). The obtained model resulted with accuracies of 1.0 cm and 2.5 cm in the planimetric and altimetric components, respectively, when compared with 4 well distributed Check Points (CPs), previously surveyed with GNSS and not considered in the Bundle Block Adjustment for accuracy estimation purposes. A derived 3.17 cm ground resolution Digital Terrain Model (DTM) was then used as input to the hydrodynamic model.

The performance of the border irrigation intervention was evaluated by combining two performance indices, i.e. efficiency (EI) and adequacy (AI) of the irrigation event. Specifically, we defined as efficient the irrigation event that minimizes deep percolation and surface runoff losses. On the other hand, an irrigation event is adequate if it recharges the water content in the root zone at least to the field capacity. The first index ranges from 0 to 1 and the second from 0 to ∞. Both were calculated in each cell of the 2D mesh used to divide the irrigation sector into basic computational elements for the model. The performance of the irrigation event was derived from the intersection of the two indices calculated on the irrigation sector. Specifically, the percentage of irrigation sector area for which both the efficiency and adequacy indices are greater than 0.8 was calculated. The simulations considered an irrigation flow rate of 330 l/s and an irrigation event duration of 36 min, with a target depth of 150 mm.

Results

The distributed values of the efficiency and adequacy indeces on the irrigation sector in both experimental years are shown in Figure 1. The irrigation event resulted efficient (i.e. EI greater than 0.8) in about 49% of the irrigation sector area in the year 2022 and in about 50% of the area in the year 2023. The irrigation event resulted adequate (i.e. AI greater than 0.8) in about 87% of the sector area in 2022 and in about 98% of the area in 2023. The irrigation event was simultaneously efficient and adequate only in about 34% of the irrigated sector area in 2022 and 14% more in 2023 (i.e., about 48% of the area), although the land preparation operations performed at the beginning of each of the two agricultural seasons resulted in a root mean square deviation between the two DTMs of only 7 cm, as shown by the difference in elevation between the 2023 and 2022 digital terrain models presented in Figure 1.

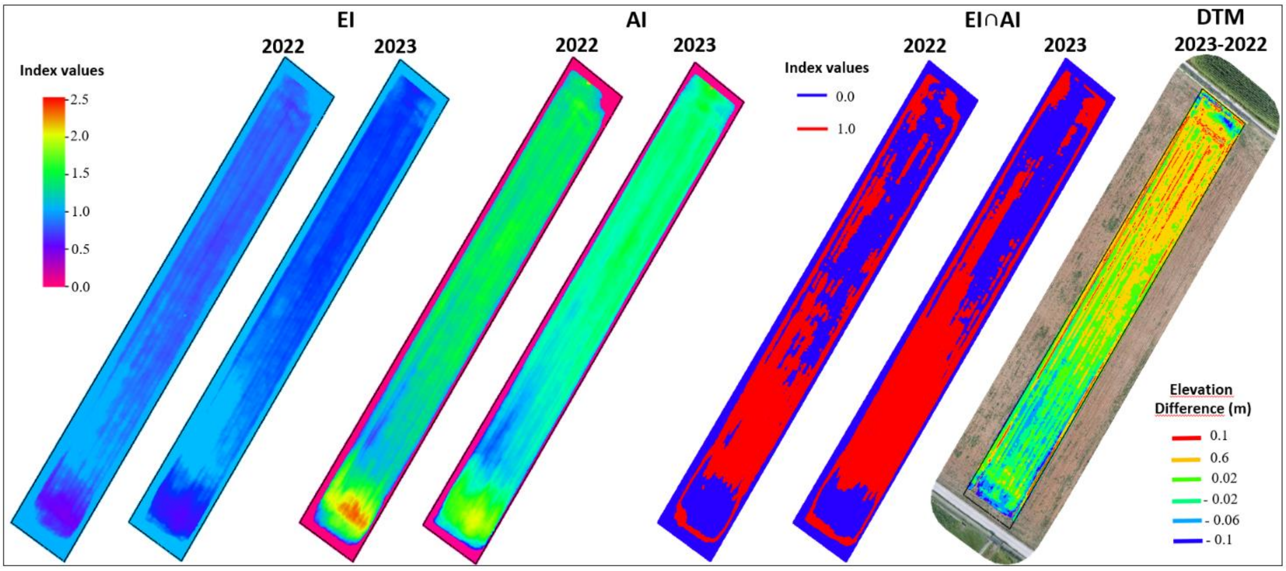

Figure 1. Distributed values of efficiency and adequacy indices, their intersections and differences in digital terrain models.

Discussion and conclusions

In this work, the effect of land preparation on the performance of border irrigation has been studied using high resolution topographic information of the soil surface combined with the application of a hydrodynamic model. The results of the simulations show that the traditional tillage operations could lead to significant differences in the performance of border irrigation between consecutive years if not properly supported by precision land levelling technologies. Despite minimal differences in soil surface elevation between consecutive years, the presence of furrows and ridges generated by the passage of the traditional tillage vehicle can significantly affect the dynamics of waterfront advance jeopardizing the efficiency and the adequacy of watering interventions.

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AgriTech06 - What lessons can be learned from smart farming to set up the agroecology of tomorrow?

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Introduction

Innovation in agriculture is now driven by smart farming (SF), which uses ICT in agriculture. This includes technologies like Internet of Things, Big Data, cloud services, and distributed ledger technologies. Despite optimistic expectations of increased efficiency and productivity, SF has progressed slowly in the past 25 years. [1,2]. The technocentric focus on SF adoption hinders the potential of technological solutions to support small-scale approaches. [3]. This tendency also implies that SF instances remain focused only at field scale: not surprisingly the original definition of precision agriculture is strictly focused at field scale [4], missing a systemic perspective. Unlike previous green revolutions, today agriculture technology providers hold significant bargaining power and offer farmers data-centric technological solutions. The management of agricultural data is a crucial aspect, potentially creating a competitive advantage and wielding power in the sector [5]. The regulatory framework in Europe lacks completeness, particularly in addressing issues related to ownership, use, and management of non-personal data. This leads to mistrust and concerns regarding data management and control, hindering the achievement of true interoperability of data and technologies. The lack of interoperability and widespread data siloing practices create multiple use cases that regulatory frameworks struggle to address and resolve. This forms a vicious circle in agricultural data management, contributing to the slow adoption of digital agriculture in recent decades.

Objectives

Large farms, often monocultural enterprises, have been the primary adopters of SF due to their greater capacity to bear costs and risks. Meanwhile, small farms, which contribute significantly to food production, have been left behind. This raises the question: Does SF still serve as a pathway to more sustainable food systems? In our view, SF should be integrated into a systemic perspective. Some scholars suggest that agroecological solutions may be more effective than digital technologies in agriculture. [3]. The concept of agroecology (AE) changed its meaning over the years. Initially born as a scientific discipline, foreseeing the application of ecological principles to agriculture, AE was then translated into a set of principles and management policies. Last, AE has also incorporated social principles, broadening the scope from farming to value chain management. In attempting to learn from previous experience, the systemic way of thinking offered the agroecological perspective represent a big opportunity to make the agricultural system advancing towards sustainability. Unlike SF, AE is dispensed across the three main dimensions of field (FI), farm (FA) and food system (FS). The objective of this research is to offer an overview of how AE principles can be effectively translated into practice throw conceptual tools.

Materials and methods

In this research the consolidated set of agroecological principles summarized in [6], in turn built upon FAO elements of AE [7], was considered. The successfully adoption of these principles depend on the way they are methodologically translated into practice and shared between FS stakeholders. According to this perspective, the principles have re-grouped at the different scales (FI, FA, and FS) in order to find suitable methodologies able to fit the diverse scopes, objectives, and stakeholders involved. A literature search was performed to highlight the main conceptual findings in order to foster the comprehension and the adoption of AE at the different scale.

Results

Different kinds of empirical evidence are needed to address the subset of principles according to the respective scale (Table 1). The prosed approaches and activities are interative, with continuous improvements to be acknowledged with knowledge progressions at the different scales. In this way, incremental interventions at FI and FA scales can bring about the food system transformations that are needed at FS (see e.g., [8]). Unlike the technocentric approach characterizing SF, this conceptual framework is based on a farmer-centric approach where the farmer is expected to receive the needed attention and to play an active role in the co-creation process on the selection of the best techological, social and governance solutions to be implemented. Through a systemic approach famers may also increase their ability to invest in digital technology, and to use them effectively creating environmental benefits.

Table 1. Methodological framework for agroecological principles at different scales

Principles	Scale	Approach	Activities
Soil health	FI	Technology and practice training	Monitoring soil and plant; biocontrol and site-specific applications (e.g., weed control using a functional approach [9], water resilience [10], cover crops [11])
Biodiversity, synergy, recycling, animal health	FI-FA	Resource audit	Diversifying crops and rotations [12], local resource assessment [13]
Connectivity, input reduction, economic diversification, co-creation of knowledge, social values and diets, fairness, land and natural resource governance, participation	FA-FS	Value chain analysis at regional scale	Participatory methods (farmer-to-farmer exchange and stakeholder involvement [14]) Consumer communication, logistics [15]; Enhancing actors knolowdge [16]

Source: author's elaboration on the set of principles reported in [6]

Discussion and conclusions

The conceptual framework proposed in this work can serve as a support for food system stakeholders to let small-scale farms thrive according to agroecological perspectives. However, some approaches will require a rethinking. For instance, the FS area of investigation appears too broad to produce significative insights within short time scale and at a reasonable cost. For this reason, the analysis should be limited at regional scale, addressing the needs of local communities.

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SIDE EVENT by CREA

CREA RESEARCH ACTIVITIES ON PRECISION AGRICULTURE AND IRRIGATION

CREA01 - SIGRIAN and DANIA to support water related policies for efficient and sustainable irrigation

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Introduction

Irrigation is fundamental for crop productivity and positively affects Gross Saleable Production [1]. So, efficient water management is strategic to ensuring the sustainability and competitiveness of agriculture. In Italy, 63% of water withdrawals for irrigation [2] is distributed in a collective form by reclamation and irrigation consortia and land improvement consortia ("Irrigation boards"), ensuring maintenance of the irrigation network and planning of water distribution in relation to availability and crop needs.

For programming, implementing, and monitoring water-related agricultural and environmental policies at the national level, it is essential to have a common database, shared among the competent institutions, regarding the irrigation context and the investment needs and priorities.

To support this decision-making process, CREA-PB has developed two different national information systems, SIGRIAN and DANIA, on behalf of the Italian Ministry of Agriculture.

Objectives

SIGRIAN and DANIA were developed, at different times, to facilitate integrated management of information on water use in agriculture, to support water-related agricultural and environmental policies, in the context of the Water Framework Directive (WFD) and the Common Agricultural Policy (CAP), for sustainable and efficient use of water in agriculture, mainly referred to collective irrigation.

Materials and methods

SIGRIAN[1], the "National Information System for Water Management in Agriculture" is a WebGIS platform providing an overview of the Italian irrigation system. It collects information on irrigated areas of more than 600 Irrigation boards, regarding: water supply points and the relative amounts of water granted and actually withdrawn; irrigation districts and relative irrigable and irrigated areas, the prevailing on-farm irrigation systems, crops irrigated, and amount of water used; and off-farm distribution networks. As stated in the national law (MASAF Decree 31/07/2015[2]), irrigation boards must transmit information on measured or estimated water volumes for collective irrigation (withdrawals, uses, return flows) to SIGRIAN within set deadlines. This information must be technically validated by the Regions and Autonomous Provinces. DANIA[3], the "National Database of Investments for Irrigation and Environment" has collected data on projects on irrigation networks implemented by irrigation boards, both planned and funded, for irrigation purposes or protection from hydrogeological hazards over the last five years. For each project, technical, financial and environmental parameters are collected, allowing them to be catalogued (and thus selected) and monitored on the basis of objective criteria [3]. DANIA also records the compliance, by each Irrigation board, with the quantification of the irrigation volumes in SIGRIAN.

The two databases are "indirectly" linked thanks to the presence of ID keys. They are available online for the planners of the Italian irrigation sector, such as Ministries, Regions, Irrigation boards and their associations, and the River Basin District Authorities.

Results

In decision making process, SIGRIAN and DANIA data helped national and regional institutions to: define sensitive areas and therefore intervention priorities; plan measures; implement intervention plans; monitor the effectiveness of these actions in terms of expected results.

In defining priorities, SIGRIAN data was used in the socio-economic analyses required by WFD at the River Basin District level [4] and for the definition of CAP context indicators [5]. Within the framework of precision irrigation investment financing through the Rural Development Plans[4] and

[1] https://sigrian.crea.gov.it/

[2] https://www.gazzettaufficiale.it/eli/id/2015/09/14/15A06988/sg

[3] https://dania.crea.gov.it/

[4] Reg. (EU) 2115/2022

the Sectoral Plans[5] of the CAP, SIGRIAN data was used to assess and validate the amount of water used *ex-ante* by a given project for a given crop, in order to estimate the water savings guaranteed by the investment. In fact, several estimation methods can be applied, included the "irrigation advisory services", as suggested even by MASAF guidelines. DANIA helped the Ministry of Agriculture in programming, implementing [6] and monitoring [7] infrastructural intervention Plans for irrigation network efficiency.

The combined use of two databases makes it possible to increase the effectiveness of the use of information allowing to promote the quantification of irrigation volumes (MASAF-MASE Decree n. 0485148 of 30/09/2022[6]), to estimate the impact of policies ex ante and to monitor it ex post, combining context and results indicators.

Discussion and conclusions

The two databases have their own specific application for which they were designed. The combined use of DANIA and SIGRIAN facilitates the management, connection, and optimization of multiple types of information. The advantages offered by the introduction of information systems to support agricultural water management policies are particularly significant in Italy, due to the diversity and number of stakeholders involved.

Moreover, the joint use of these datasets can improve the quality of policy programming and monitoring, in the pursuit of sustainable development. The potential of these tools is strongly linked to their harmonized and centralized management by CREA PB and to their adequate compilation and updating by final users, as the true owners of knowledge.

As we have seen, the two databases have assumed an institutional role over time; recognizing the importance of their adequate compilation and updating, regulatory acts have been issued by policy makers to encourage users to enter and update information correctly and on a regular basis.

Acknowledgements

SIGRIAN and DANIA were developed under the European Agricultural Fund for Rural Development and Italian Development and Cohesion Fund, respectively.

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CREA02 - The Rural Development Policy for precision irrigation

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Introduction

The EU Climate Adaptation Strategy states that ensuring sustainable water use in the agricultural sector requires an approach based on high-tech solutions[1]. This includes precision irrigation (PI), which requires data acquired from monitoring devices and the application of forecasting tools and modern technologies, regarding the type of irrigation (e.g. micro-irrigation) and information management for irrigation intervention planning (e.g. automated irrigation system)[2]. In fact, modern irrigation technologies are easily controlled and automated, and are therefore more suitable for PI [3]. There are several barriers to the adoption of high-efficiency technologies, including low networking[2] and the absence of adequate assistance [4]. Therefore, policy support is needed to encourage the adoption of PI practices and to finance modern irrigation technologies. The Rural Development Policy (RDP) of the Common Agricultural Policy (CAP), funded through the European Agricultural Fund for Rural Development (EAFRD), has over the previous programming periods allowed the Regions to develop strategies for increasing water efficiency in agriculture. The current period 2023-2027 confirms and strengthens funding opportunities for PI and high-efficiency technologies, albeit with a different programming structure based on a single National CAP Strategic Plan (CSP). Currently, the RDP is the main instrument for financing interventions for the management of water resources distinguished by type (investments, agro-environmental practices), scale, and operator (on-farm and off-farm interventions). Given that the RDP provides resources dedicated to multiple objectives, it is necessary to analyse the programming tools and interventions actually financed in order to understand the potential of this policy to promote the adoption of highly efficient technologies, including PI.

Objectives

The aim of this work is to illustrate the contribution of the RDP to PI, including via indirect support through the financing of modern irrigation technologies. In particular, we seek to identify the contribution of the previous and current programming to the interventions under study, including by broadening the currently funded interventions.

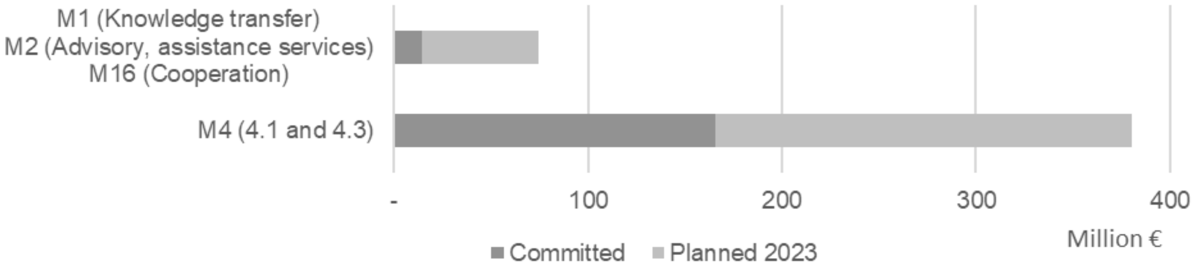
Materials and methods

Data for the 2014-2022 RDP was collected from the National and Regional Rural Development Programmes (RDPs) and the Annual Implementation Report. In order to broaden some currently funded interventions, case studies of the National Rural Network project "Eccellenze Rurali" were identified, among projects regarding innovative and virtuous experiences of water and territory management. The analysis of the 2023-2027 period is based on the CSP approved by the EC at the end of 2022.

Results

For the 2014-2022 period, Regions supported PI mainly through measures contributing to Focus Area 5a “Increase water efficiency in agriculture”, within investment measures (M4) and measures for innovation and knowledge transfer (M1, M2 and M16) (Fig.1). M4, with on-farm (submeasures 4.1.”Investments in agricultural holdings ") and off-farm investments (submeasures 4.3, "Investments in infrastructure related to development, modernisation or adaptation of agriculture and forestry”), also financed telecontrol systems and irrigation advisor systems. In four Regions, M1 and M2 have been activated for the transfer of knowledge about PI; in one case, M16 financed the validation of innovative technologies for PI (Veneto). Even if not directly targeted at Focus Area 5a, Emilia-Romagna financed the adoption of sustainable field irrigation practices, including advisor systems with M10 (agro-environmental measures). In addition to Regional measures, submeasure 4.3 of the National Programme for Rural Development funded the modernization and digitalization of collective irrigation networks, creating favourable conditions for the adoption of efficient irrigation systems and PI techniques at the farm level.

Figure 8 RDP Public expenditure for Precision Irrigation support



Source: Annual Implementation Report (2022)

Among the thirteen proposals submitted for the call "Management of the Water Resource" of the *Eccellenze Rurali* project [5], three are involved in the conversion and modernization of irrigation systems towards micro-irrigation and the automation and control of water distribution[7]. Another project developed a DSS, IRRIFRAME, that provides the farmer with indications on irrigation times and volumes[8]. Irrigation advice systems can help to quantify the water amount used ”ex ante” and ”ex post”, and are thus a useful tool for quantifying the water savings guaranteed by an irrigation investment, as per the RDP preconditions for funding. The CSP of current period continues to offer the same opportunities, but provides more specific interventions for PI: the agri-environment-climate commitments SRA02, "commitments for sustainable water use" (which offers payments for the adoption of irrigation advisor methods), and SRA24, "precision farming practices" (which incentives irrigation on the basis of the principle of soil water balance with special precision equipment). Regions planned an expenditure of about € 56 million for SRA concerning PI. In addition, off-farm irrigation investments (SRD07 and SRD08) may include automation and remote control systems favourable for PI and on-farm irrigation investment (SRD01 and SRD02), and can provide support for irrigation automation, control, and scheduling instrumentation. The budget for these interventions is € 2.5 billion, however it should be noted that they do not concern only irrigation investment s [6].

Discussion and conclusions

The analysis shows that the RDP represents an opportunity to encourage the adoption of PI practices and highly efficient technologies that allow control, programming, and automation of irrigation. In previous programming periods, several of the measures under study were financed and implemented. The current CSP continues to offer funding opportunities through more specific interventions.

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[8] https://www.reterurale.it/flex/cm/pages/ServeBLOB.php/L/IT/IDPagina/23551

CREA03 - Precision farming's Operational Groups

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Introduction

Over the last twenty years, agricultural production processes have changed, and continue to do so, due to the introduction of the 4.0 innovative technologies (satellites, Global Position System, Geographical Information System, dedicated software, etc.) [1]. Similarly, the agro-food supply chains, fundamental for the competitiveness of the Made in Italy brand in general and the region of Basilicata in particular [2] are also undergoing innovative change processes. All these innovations also allow sustainable management of the agricultural landscape.

One of these technologies is Precision Farming (PF), a multidisciplinary and technologically advanced form of agriculture that produces economic and environmental benefits [3]. The economic benefits are due to the reduced quantities of production inputs, labour savings (reduction of working hours and operator stress, as well as the management of large companies with the same workforce), the possibility of operating in any climatic condition, and fuel economy. The environmental benefits are represented by the reduction of negative impacts on air, water, and soil, entailing also significant indirect economic benefits as environmental restoration costs decrease [4].

Precision farming spread in Lucanian agricultural and agri-food farms thanks to the rural development policies, which encourage sustainability and reduced consumption of renewable and non-renewable resources, thus preserving quality while reinforcing the link with the territory.

Some Lucanian agricultural entrepreneurs, interested in experimenting with innovative and sustainable agriculture, have intensified relations with the local scientific world, advisors, training institutions, and small and medium-sized agro-industrial enterprises, establishing Lucanian Bioeconomy Cluster [5, 6]. European Innovation Partnerships (EIPs) then formed within this Cluster. In Basilcata region eleven operational groups have established.

This poster summarizes the main characteristics and goals of the Operational Groups (OGs) that have applied Precision Agriculture as a digital innovation [7, 8, 9].

Objectives

This study was carried out to analyse the partnerships of RDP Basilicata that have transferred and tested the use of Precision Farming in agriculture. The reference measures of Basilicata RDP are: support for the establishment and management of EIP Operational Groups (sub-measure 16.1); and support for pilot projects and the development of new products, practices, processes, and technologies (sub-measure 16.2).

The main objectives were to verify the progress relating to the diffusion of smart technology in the Lucanian agri-food chains and the response of agricultural and agri-food companies.

Materials and methods

The OGs, voluntary aggregations of public and private actors, have a common goal: to increase productivity through already mature innovations that involve a more rational use of production inputs and, consequently, to increase the sustainability of production processes from the technical, economic, and environmental points of view.

The collaborative relationship between public and private actors plays a crucial role in the development of agro-food supply chains and of rural areas and is subject to in-depth, multi-disciplinary scientific analysis [10].

The authors studied the Lucanian OGs to understand their needs and goals. The authors conducted desk analyses and interviews (in person or by telephone) with the scientific managers of the projects and/or the representatives of the main partners responsible for innovation.

Results

Each OG is different in terms of the number and type of partners, but all partnerships include research institutions, extension services, and agricultural, agribusiness, and forestry entrepreneurship. These elements characterize the EIPs.

The desk analysis revealed that the OGs launched an innovative ferment in the primary sector of Basilicata to bridge the gap between those who use new technologies and those who still do not due to technical, economic or social reasons.

Seven OGs (Cerealia, OrtofruttaBasilicata, Olivo & Olio, Vite & Vino, AgrotechBasilicata, Nutribas and AcquaBasilicata) share and disseminate PF by means of different technological innovations that are able to interact, all of which aim to rationalize and optimize the use of productive inputs, renewable and otherwise.

These OGs spread the usefulness of sensors, from the simplest ones for measuring soil water content in order to limit waste and improper irrigation (AcquaBasilicata), to more complex sensors for the control and monitoring of the soil-plant-atmosphere system (OrtofruttaBasilicata and AcquaBasilicata), to digital sensors mounted on tractors (Cerealia, OrtofruttaBasilicata, Olivo & Olio, Vite & Vino, AgrotechBasilicata and AcquaBasilicata), which receive data detected via satellite remote sensing or drone flight.

Unfortunately, the introduction of digital technologies in Lucanian agriculture has not yet given entirely positive results. Some methodologies, such as drone flights for PF, are not always economically advantageous and sustainable for small agricultural farms while they are more effective at the territorial level (Cerealia, Olivo & Olio).

Discussion and conclusions

Analysis of the Lucanian EIPs (the incubators for the digitalization of agri-food 4.0) showed the maximum expression of digitization is Precision Farming. The AgrotechBasilicata OG is the expression of digitized production, through satellites, drones, proximity sensors, and more.

PF, initially welcomed with extreme caution and scepticism, is also spreading to small and medium-sized enterprises while experimental applications of Smart Agriculture have been launched in recent years.

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CREA04 - Analysis and implementation of a predictive model for sustainable water management

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Introduction

The key elements of the EU regulatory framework in water resources management are the Water Framework Directive (Directive 2000/60/EC) and the CAP. The former defines good ecological status on the basis of quantitative aspects related to surface water bodies, i.e. hydro-morphological elements (e.g. flow regime). The goal of the Directive is to achieve good quantitative status of all groundwater bodies by 2015, and at the latest by 2027, where justified exemptions apply. This means that water abstractions should not cause a lowering of groundwater levels such as to lead to a deterioration of groundwater status, thus the failure to achieve the objectives.

Regarding the CAP, among its nine strategic objectives for 2023-2027 is the sustainable management of natural resources (including water). The fifth objective, called Efficient soil management, aims to promote sustainable development through the efficient management of water for irrigation use, as well as water management also at the territorial scale to mitigate soil erosion. All of these aspects have involved the integration of community policies, materializing in the eco-conditionality that relates to compulsory management criteria (Cgo) and the maintenance of land in good agronomic and environmental conditions (Bcaa), and to payments for the provision of environmental public goods and services, financed by agri-environmental measures. At such a time in history, the issue of sustainable water resource management is directly related to the variable of water stress on lands where it is crucial to pay attention to the water withdrawals that have been made.

Objectives

The project idea aims to optimize a Water Stress (SI) monitoring and management model on the Apulian scale through the implementation of a systematic process of data collection (hydrological bulletins from the Apulia Region Civil Protection Service, Acquedotto Pugliese and Consorzi di Bonifica supplies, IRSA/CNR groundwater estimates) to be analysed and processed through LCA-Life Cycle Assessment, WF-Water Footprint and AWARE-Availability WAter REmaining, with the involvement of key public and private stakeholders. Data collection and analysis processes will be managed through a decision support tool (DSS).

Materials and methods

The research project included an initial phase of studying the analysis methodologies being applied. Then, the protocols for data collection and analysis inherent to regional water resource supply and demand in the various civil and productive sectors are defined, as well as the application of LCA and AWARE methodologies for the calculation of WF and water stress (SI). The data collection and application of the LCA and AWARE methodologies, as well as the calculation of WF and SI, will be carried out through the implementation of a DSS computer structure.

Results

The project intends to create a database on Apulian water stress organized by territory and by water use destination (civil, industrial, agricultural, ecosystem), resulting from the processing of data collected and organized in the database on needs and availability. The application of the analysis methodologies for scheduling uses will be entrusted to a specially designed DSS.

Discussion and conclusions

The project enables coordination among actors involved in water resource use. Knowing the main sources of supply and demand in various regional civil and productive sectors, the structural characteristics of these sectors, as well as the type of current water distribution and supply, enables the planning and related implementation of good practices for water use. They can optimize water distribution not only in terms of quantity, by identifying periods, volumes and duration of supply, but also in terms of quality, for example, by assessing the possibility of allocating saline and wastewater.

In this sense, innovative technologies and efficient water scheduling systems capable of supporting even the use of peculiar waters (saline, high in organic carbon, or rich in minerals such as calcium and magnesium) could provide rapid feedback on water quantity and quality. Best practices, distinguished by area and water use and based on the level of adoption, based on an analysis of the evolution at the territorial scale, enable the implementation of sustainable consumption and production patterns. In addition, from the analysis of the current state, a more accurate and targeted planning of future activities can be carried out, aimed at increasing the number and intensity of good practices adopted and achieving sustainable production and consumption patterns in irrigation resource use more quickly.

In quantitative terms, the sustainable water use model should tend toward the adoption of verification tools aimed at monitoring the actual consumption of the resource, as well as certification systems capable of measuring sustainable water use in the framework of complex models capable of considering the entire process, from water withdrawal to final use. For example, quantifying the number of certifications obtained annually (at the company and/or territorial level) or of processes and activities periodically subjected to verification, makes it possible to measure, at the close of each cycle, the level of interest and sensitivity to the issue related to responsible production and consumption.

This information, in the context of annual planning, makes it possible to assess the progress of sustainable models and understand to which sectors, technologies or systems to direct future efforts in order to consolidate achievements.

Considering water quality, the project's evidence could support the inclusion in water resource management of the concept of alternative water resources, which involves the responsible and efficient use of unconventional water, such as rainwater, reclaimed wastewater, water from condensate or desalination, and water from sewage processes. The recovery of these waters would have a twofold effect: optimizing the use of conventional water and enhancing the value of products that may otherwise be wasted with an additional burden on the environment. Thus, the results of the project make it possible to survey the number of facilities dedicated to reuse, as well as to take a view and quantify the level of reuse and valorisation of wastewater.

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CREA05 - Tools for managing and analysing agricultural data for integrated and sustainable production

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Introduction

Precision Agriculture (PA) is becoming increasingly popular at the national and international levels. Many farms are adopting Information and Communication Technologies (ICT) and new tools, such as sensors, drones (Unmanned Aerial Vehicles - UAV), Farm Management Information Systems (FMIS), and satellite images in their production activities. ICT generate huge amounts of data of various nature and types (Big Data) that can be analysed to generate information that can help improve the decision-making processes of farmers and decision makers. Big Data Analytics (BDA) tools are needed to record, organize, and analyse the enormous amount of heterogeneous data that is and will become available through ICT technologies.

Objectives

The project idea consists in the development and implementation of an ICT cloud tool for farmers and decision makers to organize and process data regarding the farms that have voluntarily joined the National Integrated Production Quality System (SQNPI), which verifies adherence to the Integrated Production Regulations (DPI) by region. The project is expected to improve the economic and environmental performance of individual companies, depending on the implementation of the directives provided by the SQNPI, and thus to strengthen the productivity and sustainability of the entire sector.

Materials and methods

1) Establishment of an ICT Platform to collect and store large amounts of information (Big Data) to verify adherence to the DPI by companies in the main regional agri-food chains, which participate voluntarily in the National Integrated Production Quality System (SQNPI)

The Platform will support an integrated system of analysis, monitoring, and planning of business activities through the identification of pedoclimatic, agronomic, and organizational patterns that define qualitative patterns of production. This approach allows a radical change in the business management paradigm, based on the digitalization of operational activities and aimed at encouraging the agro-ecological transition. The Platform will be based on the computational infrastructure of Cloud Computing – a basic computational platform - able to provide computational support to the Platform itself through a series of middleware components, including the following types of platform: IOT, Big Data Analytics, georeferencing, Document Management, BPM and ESB.

2) Definition and implementation of technologies for digitizing "static" and "dynamic" company information, which are integrated with the ICT Platform

"Static" information does not vary during the production cycle in the short-medium term and regards mainly the spatial, pedological, and structural characteristics of a company (land use, labour, and capital). It will be collected from different sources, including the Land Registry, the Company File, and the Campaign Notebook. "Dynamic" information varies during the production cycle in the very short term, and regards mainly climate, management (use of technical means) and plants. Suitable instrumentation (agrometeorological units, tensiometers, IR, thermal detectors, as well as measuring devices for photosynthesis, stomatic conductance, lymph flow rate, and hydraulic conductivity) will be used to gather this type of information.

3) Analysis of Big Data

This will be done through: data cleaning and data organization; execution of data mining methodologies; development of learning algorithms through machine learning; and verification of the economic and environmental sustainability of the patterns identified in relation to DPI adherence. The results obtained will be integrated with methodologies widely used in the fields of economic research (Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA)) and environmental research (Life Cycle Assessment - LCA) for the verification of the economic and environmental sustainability of the identified patterns.

4) Identification of suitable spatial, soil, climatic, management, and plant combinations to ensure adherence to the DPI

5) Testing innovative production certification strategies based on Blockchain technology, so as to define innovative protocols for good practices that can promote adherence to DPI through business management models based on the digitalization of activities and the agroecology transition of crop operations

The protocols will allow the development of guidelines aimed at: providing strategies for forecasting the yield, demand, and supply of agricultural products on local, national, and international markets, so as to improve business and supply chain performance; creating an advisory network for producers on the optimal use of technical means, such as water resources, fertilizers, and pesticides, thus improving food and environmental quality and safety; allowing the use of innovative tools for the monitoring of retail sales, in order to improve the traceability of products along the supply chain, and thus ensure healthier and safer food for the consumer; defining and implementing simulations and scientific models to support public decision-makers in promoting food security and the protection of agroecosystems.

Results

The expected result of the project is the dissemination among regional farms of digital technologies based on ICT tools, thereby fostering ecological transitions to sustainable food systems. The project will identify innovative management models and encourage the modernization of business activities and the supply chain through their digitalization. This will support the green and digital transitions of the regional agricultural sector, rendering it increasingly sustainable and resilient.

The results of the project are in line with the recent strategies of the 2030 Agenda, the European Green Deal (COM (2019) 640 final), the EU's "Farm to Fork" policy (COM (2018) 392 final) and the European Recovery Plan (Council Regulation (EU) 2020/2094). The project output will improve the economic and environmental performance of companies, as well as their social functions in terms of food certification and safety, thereby strengthening the productivity, profitability, and sustainability of the primary sector of Puglia.

Discussion and conclusions

The project promotes the introduction into agriculture of new technologies that help to reduce natural and chemical inputs and modernize irrigation equipment and practices. It promotes productive reconversion towards species or cultivars with reduced water needs, compatible with local economic needs, crop change strategies and farm agricultural systems shared with agricultural organizations. In addition, it promotes capacity building regarding the use of more efficient irrigation technologies through innovation transfer initiatives, water saving training and information dissemination, and spreading criteria for the correct design and management of irrigation systems and the rational planning of irrigation interventions in relation to the water needs of crops and soil characteristics.

The results of the project will promote a paradigm shift in regional business operations, with a qualitative leap in their contribution to the creation and development of productive centres of excellence in the national agri-food sector. This will increase the productive capacity and efficiency of agricultural enterprises, while also improving their environmental and social performance, ensuring continuous employment and the involvement of new high-technical-scientific professionalism. The impact of these actions on productive activities and the whole community could be of great social and economic importance, especially if coordinated at the national level and accompanied by intense promotion and enhancement of agriculture 4.0 at all levels (consumption, communities, and institutions).

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CREA06 - Enhancing the medicinal plant supply chain using smart agriculture: a Lucanian experience

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Introduction

Over the past decade, consumer lifestyles have shifted towards the consumption of healthy and environmentally sustainable products, and this has led to the rediscovery of knowledge, traditions and ancient flavours like Medicinal Plants (MP). In Italy, medicinal plants include between 20,000 [1] and 100,000 [2] botanical species [3]. Growing attention to MPs has also been observed in Basilicata, a region that boasts over 400 species of indigenous medicinal herbs, both cultivated and wild, which characterize many landscapes, represent good opportunities for production, and are an essential element of local gastronomic traditions, linked to the history and culture of specific places [4]. The cultivation of MPs in Basilicata has been evolving to respond to various types of demand (protection of biodiversity, nutrition, sustainability, multi-functionality, pharmaceutical, etc.) and produces plants for fresh consumption, spices, essences for the preparation of liqueurs, and essential oils for cosmetics. Today, a technological revolution is taking place in the Italian agri-food and forestry sectors that is closely linked to the use of digital applications and artificial intelligence. Agriculture 4.0, also known as Smart Agriculture [5] includes Precision Farming can improve the yield and sustainability of the crops as well as overall production quality, potentially even in the most disadvantaged rural areas. Italian agriculture is still indisputably traditional, and Agriculture 4.0 systems are only used to manage 4.11% of the total cultivated area [6]. In Basilicata, the production sectors have not reached the same degree of efficiency, as indicated by the analysis carried out through the regional FADN (Farm Accountancy Data Network) sample in the period 2011-2016 [7]. While the primary sector is undergoing a profound revolution, in which new technologies are changing the way they "do agriculture", the agricultural sector in Basilicata, and the medicinal subsector in particular, still seem far from being able to fully exploit the power of digitizing various production stages. Digital agriculture solutions have mainly captured the attention of large agricultural entrepreneurs, including those of medicinal plants, producer associations and large-scale retailers.

Offering these solutions to smaller farms will help to bridge the information and production capacity gap, to resolve local production (medicinal plants) and economic problems, encouraging them to adopt sustainable practices within specific and complex farming systems [8,9].

Objectives

This research presents the results of technological needs in Lucanian medicinal agriculture at each phase of production through the supply chain. The machinery and tools used in medicinal plants sector are often the result of the adaptation of technologies used in other sectors – such as horticulture – by farms, whose individual needs vary by crop. For the MPs crop in the open field, as in all other agricultural production, technological development must keep pace with the needs of producers, providing machines and equipment suitable for their purposes, and with the specific structural and functional features necessary for the various stages of their production cycle [10]. Among the various equipment, a relevant place is held by precision irrigation which allows to obtain higher crops with less water.

Materials and methods

A questionnaire was distributed to farms regarding the technological innovations needed to produce their MP, structured for online self-completion via a link. To enable quick completion, the questionnaire included thirty-four closed questions, mostly multiple-choice. An intense outreach phase preceded the survey: all farms were contacted by phone and many were also offered a telephone or on-farm interview. The questionnaire was completed by fifty Lucanian medicinal farms included in the database created by CREA to trace the regional MP supply chain. The questionnaires were collected via an Internet platform (Microsoft FORMS), with the responses recorded and processed automatically.

Results

Seventy-seven percent of respondents said they needed more investment in technology, especially in the open field production stages. In detail, 52% ranked this of the “highest importance” and 29 % of "medium importance."

For 63% of the respondents, the natural drying phase requires innovation: considered “very important” by 41% and “quite important” by 35%.

For 59% of the surveyed companies, it is necessary to invest in new technologies for the irrigation and collection phase: 46% ranked this as “very important” while 25% ranked it as “quite important”.

The activities for which technological investment is considered “less important” are marketing (56%), and product washing (60%).

The Lucanian MPs sector is characterised by a prevalence of micro-farms. Of the sample, nearly half of these were managed by women. The predominant level of qualification is a secondary school diploma, followed by a degree in agricultural sciences.

Discussion and conclusions

The survey confirmed a strong demand for new technologies, to be used primarily in the cultivation (including irrigation) phase and secondarily in the harvesting and drying phase. Introducing innovation in MP cultivation is strategic to the development sector.

There is a need in this sector for the introduction of process innovations, the replacement of dated agricultural machinery that is often adapted to the different stages in the cultivation and processing of medicinal plants. The introduction of new technologies would thus be aimed at improving crop management, from planting to irrigation to harvesting.

Agricultural activities must be innovated while also preserving and enhancing local biodiversity through the use of sustainable practices (organic or integrated farming) with low environmental impact. Innovative production tools are also needed, such as circular management models oriented towards the recovery and reuse of processing waste, by-products, or waste.

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CREA07 - Increasing agricultural sustainability by combining remote sensing and agro-ecological techniques

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Introduction

Sustainable soil management is essential for achieving key European agricultural policies including the Green Deal, the Farm to Fork strategy, and the Climate Adaptation strategy [1]. Soil erosion, compaction, organic matter loss, and biodiversity loss are significant threats to soil health in Europe. Climate change effects such as rising temperatures, rising greenhouse gasses, and changes in precipitation patterns contribute to climatic variability. Sustainability is central to the European Green Deal, and precision farming (PF) is tagged as a sustainable practice in the agricultural context, alongside agroecology, agroforestry, and organic farming. Integrating PF to agroecological practices can prevent nutrient loss, improve pesticide management, decrease fuel use, reduce emissions, ensure efficient land use and mitigate risks and losses due to extreme flood events that are increasingly affecting all European countries. Precision farming can improve agricultural processes, optimize natural resource management, and reduce chemical factors. Agroecological practices provide resilient farming systems by increasing biodiversity, choosing suitable crops and varieties, improving soil characteristics and water use efficiency, and rationalizing fertilizer use. Remote sensing, along with smart sensors, allows for comprehensive assessments of crop growth and health, aiding in monitoring and identifying factors that may impair yield. Additionally, the use of remote sensing data enables monitoring and mapping changes in crop phenology while optimizing planting and harvesting schedules.

Objectives

An exploratory investigation was applied to infer a fundamentally general relationship among explanatory (soil mineral status) and response variables from remote sensing in a typical Mediterranean field. The aim of this study was to test the hypothesis that an integrated PF and agroecological practices approach could increase the sustainability of agricultural production specifically in case of intense and unforecastable climatic events. Further objectives included testing the accessibility of precision techniques with machinery commonly found on farms with a low level of digitisation ("smartish farming") and the creation of an information platform managed by means of a user-friendly device. Several data layers including (i) photosynthetic activity from remote sensing, (ii) spatial variability of physico-chemical characteristics of soil and (iii) regional guidelines for integrated agronomic production were integrated to provide spatially-explicit fertilization plans.

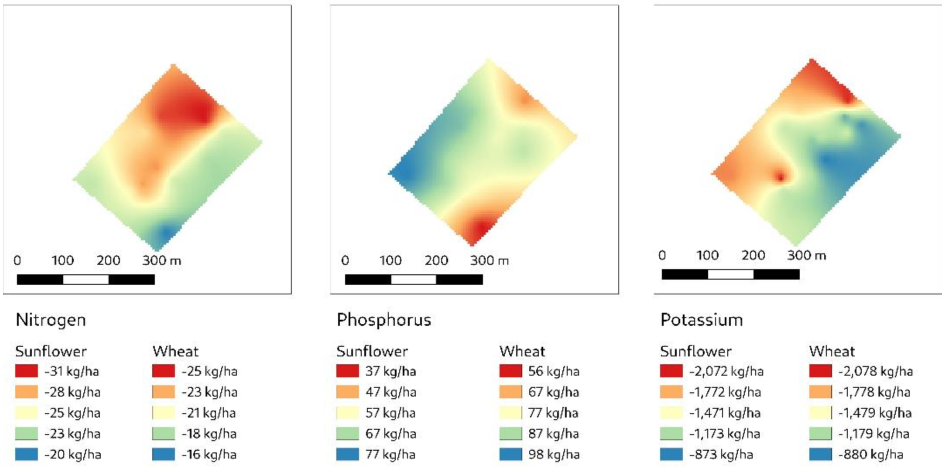
Materials and methods

A 5.0 ha experimental field crop, spatially located in the northeastern outskirts of Rome, central Italy was set up in 2018, where a two-year rotation of wheat and sunflower crops was implemented [2]. Its soil tends to retain great amounts of water particularly after heavy rainfall, resulting in water stagnation lasting for several weeks. The detailed soil characterization comprehending physical and chemical properties was carried out on 20 randomly selected points, according to the Italian official method of analysis by a UNI CEI EN ISO/IEC 17025:2005-certified laboratory. The experimental field was split into 6 plots according to two factors: vulnerability to flooding (low, mild, extreme) and practice (PF + agroecology practice, traditional practice). The flooding vulnerability classes were defined according to key soil composition parameters. An ordination analysis (Principal Component Analysis) showed that silt, active limestone and sand content clearly differentiated the sampling points into 3 classes which matched with elevation gradient. The coupled PF and agroecology practice included intercropping, green manure cover crops and variable-rate fertilization according to NDVI characterization of the previous year wheat productivity. Traditional practice underwent conventional farming methods, no cover crops and calendar-based fixed-rate fertilization. A linear mixed model was set up to investigate the effect of chemical and physical properties of the soil and soil/vegetation moisture on the Normalized Difference Vegetation Index (NDVI). NDVI was calculated from Sentinel 2 imagery, of the wheat crop growing during winter and spring of 2019, on the same 20 sampling points identified for soil analysis.

Results

Vulnerability of soils to extreme events significantly impacts productivity sustainability. The results highlighted the need to consider soil chemical and physical characteristics in fertilization plans to avoid incorrect supply of one or more macronutrients, particularly nitrogen. The spatialized fertilization plans and the relative doses, calculated in accordance with the regional guidelines, showed a different pattern of within-field variability for N, P, and K. The maps confirmed that N and K concentrations were above the demand for both sunflower and wheat. Based on the scheme indicated in the regional guidelines, two R packages and a web app were developed for the calculation of the concentration of fertilizers provided to soil and their spatialization (Figure 1) [3,4].

Figure 1. Spatialized fertilization plans for the three main macronutrients for sunflower and wheat crops.



A flooding event between December 2020 and January 2021, with 342 mm of rainfall distributed in two weeks, occurring before and during the stem elongation phase, determined the death of submerged wheat plants and a subsequent lag in the NDVI [5]. The mildly and extremely vulnerable plots were the most affected, although the difference was significant only in extremely vulnerable compared to non-vulnerable plots. The NDVI lag on vulnerable plots was reflected in the grain yield which showed a severe reduction (on average 1.5 t ha-1 less than not-vulnerable, and 1.1 t ha-1 less than mildly-vulnerable).

Discussion and conclusions

An agro-ecological approach combined with remote sensing can provide useful insights for a more sustainable and targeted fertilization. Fertilization plans that overlook soil chemical and physical features may wrongly lead to an over-fertilization of one or more macronutrients. Integrating satellite data with knowledge of spatial soil variability facilitates variable rate fertilization approaches, even using equipment commonly found on the farm. On lands vulnerable to flooding, stable production can only be guaranteed when precision farming and agro-ecological practices are combined with water management techniques. The maintenance of the farm's hydraulic network and field convexity required by some cross-compliance standards can reduce the impact that extreme meteorological events will have in the future on soil integrity and yield stability.

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CREA08 - Precision Irrigation based on data processing from informative sources

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Introduction

Agriculture is one of the most demanding production sectors in terms of water needs, using about 70% of the total annual freshwater withdrawal [1] (OECD, 2017). In extensive agriculture, water is often distributed through abundance-based irrigation methods. In the current context of reduced global water availability, these systems can be considered inefficient. For example, in sprinkler irrigation the percentage of water loss can be as high as 45% due to evaporation and other factors, while in trickle irrigation even higher losses are found [2,3] (Uddin, 2012, Afrin, 2010). For this reason, it is increasingly advisable to study systems to program irrigation cycles based on information from different sources and to avoid water losses.

Some technological advances have been made in this direction; for example, precision irrigation is an attractive approach that allows the application of water in small but optimal doses, both in the right place and at the right time. Many of the precision irrigation systems rely on humidity sensors; these sensors are geo-located and monitor the water content of the soil at different depths, providing remote information and notifying or directly commanding the start of irrigation only where and when it is required [4,5,6,7]. Proximal information can contribute to irrigation management with the support of satellite information [8].

Objectives

The aim of the research was to verify the applicability of prescription maps into a traditional irrigation context, organized with conventional irrigation technologies, i.e., not based on variable rate systems. The maps were created using both proximal and remote sensing, obtained respectively from soil sensors and satellite information systems (Sentinel 2).

Materials and methods

The experimental tests were conducted in a corn field of the CREA Research Institute, in Lombardy; the area is included into a territory suited for the cultivation of corn, but recent climatic alterations are determining in the last years a decrease in water availability. The soil moisture values, and the environmental parameters were acquired and transmitted in real time by a network of nodes using LoRa (Long Range) technology on a cloud platform for high-frequency monitoring of soil variability. Furthermore, during the irrigation period (June-September) the distribution maps of the reflection bands of the twin Sentinel-2 satellites were acquired. The integration methodology between proximal and remote sensing utilized for the preparation of prescription maps has been described in a previous study [8]. The maps obtained were adapted to the traditional distribution by sliding, dividing the land into sectors through the preparation of embankments every 16 rows of corn. Therefore, three irrigation distribution methods were studied: the first in which all available hours for irrigation were divided equally by the 16 sectors; the second in which the irrigation time of each sector was calculated according to the prescription map obtained only with satellite information; the third in which the prescription maps were obtained by integrating proximal and satellite information. In all methods the water was drawn from ditches into the prepared areas by a pump with a 300 mm delivery pipe, connected to a 65 kW tractor, with a flow rate of 1080 $m^3 h^{-1}$. For the study, 3 soil moisture conditions (dry, medium, humid) were taken into consideration before the irrigation event.

Results

The liter values, shown in Table 1, for corn irrigation showed statistically significant differences both between the average values recorded in the single sectors and between the overall sums in the season. In particular, the uniform distribution method showed a higher seasonal sum value than the two variable distribution methods. The overall means were also statistically significant. The analysis of variance (ANOVA) showed a statistically significant effect on the liters distributed by the mode (p-value <0.001) and the soil moisture condition (p-value <0.05).

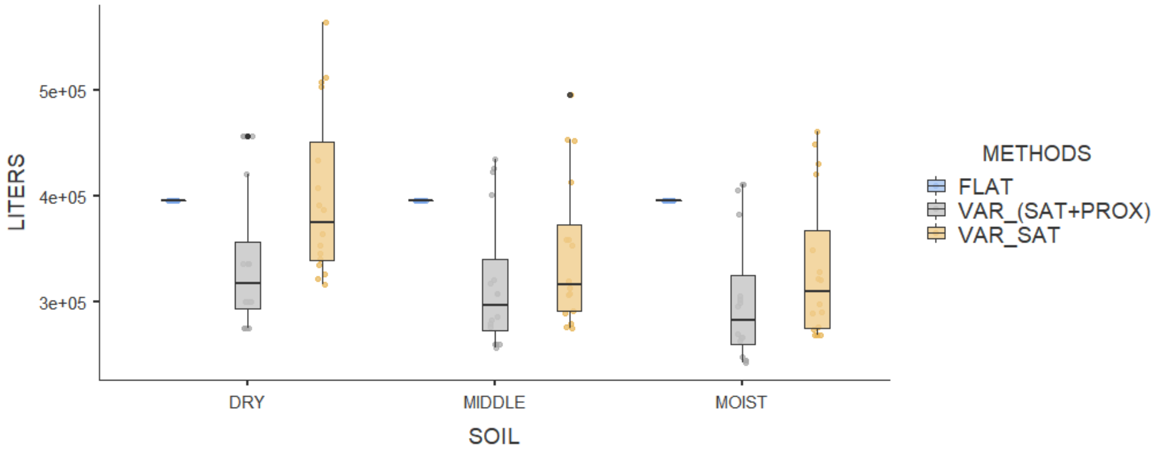
Table 1. Comparison values between irrigation distribution methods.

Condition	Sum	Mean*	St. dev.	Minimum	Maximum
FLAT	1.90 10^7	396,000 a	-	396,000	396,000
VAR (SAT)	1.73 10^7	359,922 ab	77,478	268,977	563,124
VAR (SAT+PROX)	1.54 10^7	320,902 b	65,351	242,880	456,000

*Different letters indicate significant differences according to Tukey's test (P<0.05).

According to initial soil moisture condition (dry, middle, moist) a significant influence has been identified on liters distributed according to the prescription map used (satellite vs. satellite + proximal). The results shown in Figure 1 demonstrate how in dry soil conditions the prescription map sent a quantity of water much higher than the average in the same sectors.

Figure 1. Variability of water quantities in the three methods and in the three moisture conditions.



Discussion and conclusions

The study presented and carried out to verify the effect of precision irrigation, with an adaptation to conventional techniques has shown significant and encouraging results in terms of water savings, which resulted as high as 20% in the entire irrigation season. The method that allowed greater optimization of the water resource was the variable one based on satellite information, with the integration of ground sensors; however, even the method based on satellite information alone has contributed to water savings of almost 10%. The latter method showed lower performance in very dry soil conditions, probably caused, in this circumstance, also by the reduction of the soil variability reading.

Acknowledgements

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CREA09 - Low-cost sensors for greenhouse environment monitoring

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Introduction

Greenhouse vegetable and flower productions occur in different environments and latitudes, requiring remote and proximal sensing for timeliness and straightforward monitoring of crop features (e.g., plant growth and development, nutritional status, biotic and abiotic stresses, yield and quality) [1–4]. The precise management of crops relies: on the one hand, on the monitoring of the canopy biomass, which implies a deep knowledge of production factors also resulting from leaf reflectance measurements [5,6]; on the other, on the monitoring of internal greenhouse environment using different sensor configurations, hardware architectures, and control techniques [7,8].

Objectives

The presented study deals with setting up a simple, low-cost, *Arduino*-based system to monitor the environmental parameters in a small-scale greenhouse to evaluate the feasibility of the low-cost sensors for continuous greenhouse environment monitoring.

Materials and methods

A greenhouse (12 m long, 2.5 m wide and 2 m high), made of a metal structure and with a plastic covering, was set up at the CREA-IT facility of Treviglio (45°31'17.18 N; 09°33'50.82 E). It was subdivided into three longitudinal sectors (S1 and S3– lateral; S2 – central). Table 1 reports which low-cost sensors, freely available on the market, were used to monitor the greenhouse micro-environment.

Table 1. Details of the low-cost sensors

Sensor label	Sensor type
DS18B20	Digital thermometer providing 9-bit to 12-bit Celsius temperature measurements. It communicates over a 1-Wire bus requiring only one data line (and ground) for communication with a central microprocessor [9].
CJMCU-SHT10	Humidity and temperature sensor powered with the voltage of 3.3 V. Temperature measurement range is from -40 °C to + 123,8 °C, for the humidity is from 0 to 100 % R.H. [10].
TEMT6000	Incident light sensor based on a phototransistor that produces a voltage output between 0V and +5V that is directly proportional to the incident light [11]

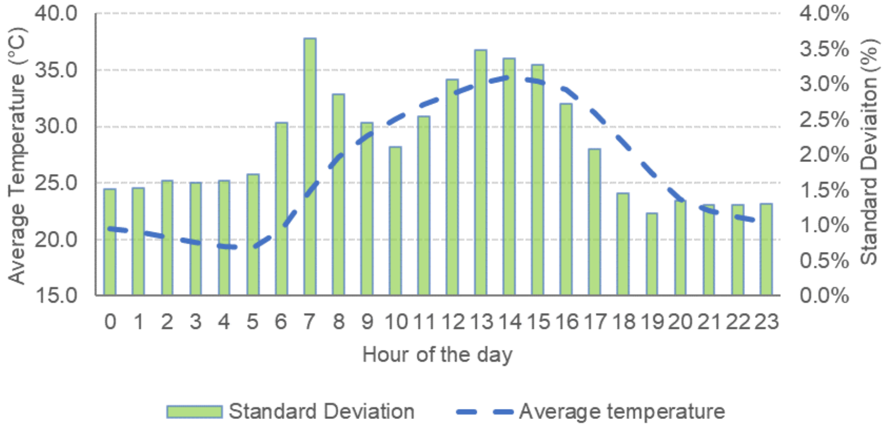
The low-cost sensors used to monitor the greenhouse micro-environment were all based on the Arduino board [12] and made it possible to measure air and soil moisture content and the amount of incident light.

Data processing foresaw preliminary processing with M.S. Excel spreadsheet and statistical processing using R software [13], Minitab 17® [14] and Surfer® software [15] to produce interpolated graphs through the kriging algorithm [16].

Results

Substrate temperature acquisitions ranged between 16.6 °C and 36.6 °C: the pot positioning inside the greenhouse significantly affected the maximum average temperatures achieved in each greenhouse sector. The air temperature inside the tunnel greenhouse also varied throughout the days (Figure 1). The Standard deviation of the measurements pointed out the existence of high (from 6.00 AM to 5.00 PM) and low standard deviation hours (from 6.00 PM to 5.00 AM), which imply a dynamic environment inside the greenhouse. Plotting the isocurves of the average t° throughout greenhouse width and height made it possible to evaluate air temperature dynamics longitudinally and transversely to the greenhouse volume.

Figure 1. Hourly average air temperatures and the related percentage standard deviations



Discussion and conclusions

The recorded variabilities occurred when the solar radiation began to heat the greenhouse cover (between 6.00 and 7.00 AM) and a few hours after the maximum peak of solar radiation (843.4 ± 133.3 W m^{-2}). The analysis of the variance carried out on the response values of the temperature and the recorded humidity showed statistical significance for the effect of the position of the sensors both longitudinally and transversally. Based on the results, the system could detect the conditions inside the greenhouse daily and catch the dynamics of air and substrate temperature.

Acknowledgements

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CREA10 - Automatic feeding systems for Ruminants: the farmers' point of view

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Introduction

Automatic feeding systems (AFS) for total mixed ration administration to animals ease the workload of dairy farmers, save time, and increase workload flexibility. As a matter of fact, the workload resulting from dairy farming requires attention because of the low scores on quality assessments related to the physical work environment [1] and the repetitive, physically very strenuous tasks required [2,3].

Objectives

Knowing the impression of farmers on automation systems for rationing and managing bovine ration is essential since they are the final recipients of such technologies. Within the framework of the AUTOFEED project [4] dairy and beef farmers owning or willing to buy an AFS underwent a fact-finding survey to highlight the reasons driving the purchase and the potential advantages deriving from their use in the farm.

Materials and methods

Using the Microsoft Forms® platform, a cognitive questionnaire was created, written both in Italian and in English, consisting of three sections:

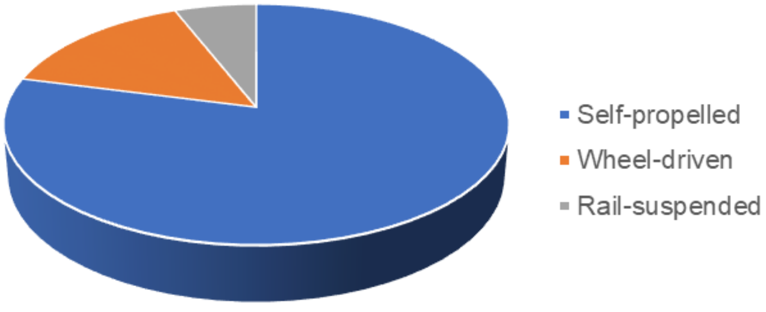
1. an introductory part focusing on the characteristics of the farm (type of production and the adopted level of automation);
2. a section aimed at farmers already owning an AFS system (focusing on the technology, the costs, the reasons behind their investment in automation, and the comparison with the previous rationing mode in terms of energy and labour saving);
3. a section aimed at farmers without an AFS system (focusing on their interest in purchasing the technology and the expense they are willing to pay).

The questionnaire was administered to the farmers in person, during guided visits carried out to a sample of production plants viewed, through direct telephone interviews, or even by compilating it online directly on the project's Autofeed website or on the Facebook® and LinkedIn® channels. Data processing foresaw preliminary processing with M.S. Excel spreadsheet and statistical processing using R software [5], Minitab 17® [6].

Results

The farmers who participated in the survey were mainly rearing cattle (herds with less than 500 heads) followed by meat and mixed-type farmers. The most spread adopted technology among farmers foresees that automatization covers the initial filling operation. The loading of TMR ingredients may occur either in a stationary mixer, which provides for TMR mixing and shredding, or directly in a self-moving mixing/chopping TMR delivery wagon. However, other kinds of wagons were also chosen (Figure 1). Smaller farms with fewer heads chose more straightforward solutions (here, the automation excludes the filling of the mixer and refers only to the chopping-mixing and distribution of TMR ingredients).

Figure 1. Representation of the design of TMR delivering wagons resulting in Italian animal farms



On the other hand, 32 % of interviewed farmers currently do not own feeding robotic technology: 75% of it is willing to purchase it with an average indicative expenditure between 500.00 and 1500.00 € per head (such investment intention increases as a function of their current milk production). Improving feeding accuracy and animal welfare are the reasons behind the willingness to buy an AFS, with the reduction of labour and the improvement of the flexibility of working hours. The correlations between purchase intention and perceived benefits are all greater than 0.80 with $p < 0.001$ a statistical significance.

Discussion and conclusions

The AFSs represent the last frontier of robotization of TMR rationing. Together with milking and manure management, feed automation represents a radical innovation that results in profound changes in cattle management. The interviewed farmers pointed out that transitioning to mechanized feeding leads to direct benefits, with a significant increase in the amount of ration ingested by the animals, on average equal to +2.50 kg/day, and subsequent increases in milk production (+2.94 kg/day). Such an improvement in production performance results from the increased daily frequency of administration of the ration (from an average of 2 to 10 daily distributions) and the increases in TMR ingestion resulting from the forage pushing activity (from an average of 5 to 13 daily passages). A more systematic distribution method, such as that ensured by feeding robots, also improves the well-being of the raised cattle, following the reduced competition among the animals for feed: the manger always contains fresh available feed. Such a situation decreases the feed waste and positively affects the cows' health (e.g. animals spend less time waiting to access the ration, increase the frequency of visits to the milking area and the resting activity). Fostering automation and robotization in animal farming goes far beyond the technical aspects. For the new generations of farmers (more prone towards digital technologies), AFS may represent an excellent opportunity to continue farming even in challenging territorial contexts. Totally or partially automated feeding systems are a valid option for farmers as long as there is integration into equally modern and advanced farm management.

Acknowledgements

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