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Foreword

Prof. Bruno Tisseyre, Conference Chair

May 25, Montpellier SupAgro, Montpellier, France

Dear Reader,

In 2001, the city of Montpellier hosted the 3rd European Conference on Precision Agriculture (ECPA). Now, 18 years later, we are very pleased to welcome the Precision Agriculture scientific community back to Montpellier for 12ECPA.

We sincerely hope this 12th European Conference on Precision Agriculture will result in a profitable meeting for everyone and will provide some solutions to the challenges that modern agriculture is facing.

We are grateful to Montpellier SupAgro, Irstea and the International Society of Precision Agriculture (ISPA) for supporting us in the organisation of this event. We are grateful to all the members of the Poster Scientific Committee for their invaluable contribution in assuring the scientific quality of the Posters presented at this conference.

We appreciate the financial contribution of all the sponsors of 12ECPA, which includes private companies as well as public institutions and consortia. We would also like to express our gratitude to all the authors and attendees. The conference is nothing without your support and engagement. We will have more than 120 oral communications (compiled in a Conference Proceedings) and nearly 100 posters that the extended abstracts are presented in this book. This is a strong indication of the trust placed in this conference as a source of knowledge related to Precision Agriculture.

Finally, as the Chair, I am indebted to the support and hard work of the conference Organising Committee over the past 2 years in bidding for and delivering this conference. It is simply not possible to do this without a fantastic team behind the scenes. The Organising Committee is composed of academics and engineers from a joint team of Montpellier SupAgro (Institute for Higher Education in Agriculture) and Irstea (National Research Institute of Science and Technology for the Environment and Agriculture); The UMR ITAP team. We are all both honoured and delighted to have worked for you and to have helped advance methods and techniques in Precision Agriculture.

Bon congrès à tous !

Bruno

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Scientific Committee (posters)
The mission of the Scientific Committee has been to guarantee the academic quality of the posters and their extended abstracts of the 12th European Conference on Precision Agriculture by reviewing and assessing each of the proposal received (more than 150 abstracts were received). The committee was chaired by Dr. J. A. Taylor, in his capacity as the editor of the 12th ECPA book of poster abstracts edited in this electronic book. The Scientific Committee was made up of renowned researchers involved in the organising committee. Abstracts of posters have followed a review process in order to guarantee the academic quality of 12th ECPA.
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PREDICTIONS OF CU, ZN AND CD IN SWEDISH AGRICULTURAL SOIL FROM PORTABLE X-RAY FLUORESCENCE (PXRF) DATA: POTENTIAL FOUNDATION FOR ELEMENTAL MAPS FOR USE IN PRECISION AGRICULTURE?

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In Sweden, there are currently no public field scale maps of trace elements of importance for crop production (e.g. copper (Cu), zinc (Zn) and cadmium (Cd)) available at a scale useful for guiding variable management practices within fields. At present, in order to create such maps, soil has to be sampled and analysed. Conventional digestion laboratory analysis for elemental concentration quantification of soil are expensive, time consuming and reliant on chemicals such as digestion acids. Portable X-ray fluorescence (PXRF) technology has been proven to be a faster and cheaper, regardless of *in-situ* or *ex-situ* use, alternative to conventional lab analysis (Lemiére, 2018). PXRF measurements should be very suitable for spatial modelling of trace elements, as this allows for a high sampling density (Weindorf et al, 2012; Lemiére, 2018). The aim of the present study was to create national prediction models of concentrations of the micronutrients Cu and Zn, but also of the toxic heavy metal Cd from PXRF measurements in Swedish agricultural soils and to evaluate prediction accuracy when deployed within agricultural fields. In Sweden, there is often a deficiency of Cu in sandy soils, whereas the availability of Zn is less commonly regarded as a problem. Very high Cd concentrations is a problem typically related to the soil parent material, and the variation within fields can be substantial (Söderström & Eriksson, 2013).

A total of 994 samples representing Swedish agricultural soil was used for model calibration. The models were cross-validated using the leave-one-out method. A dataset consisting of 179 samples from nine farms (≈ 20 per farm; the farm dataset) was used for independent model validation. Hence, the models were validated on a national scale, using cross-validation, and on a field scale. All samples were air dried, sieved (2 mm) and homogenized before the PXRF measurements. Both datasets were analysed with ICP-AES/MS for Cu, Zn and Cd concentrations, after digestion with 7M HNO_3. In order to construct widely useful models, an element had to be above the limits of detection (LoD) in more than 90% of the measurements of the national dataset to be included in the predictor set. The predictor variables were zirconium (Zr), strontium (Sr), barium (Ba), rubidium (Rb), lead (Pb), Zn, iron (Fe), manganese (Mn), vanadium (V), titanium (Ti), calcium (Ca), potassium (K), caesium (Cs) measured with the PXRF device. These were then subject to a univariate feature selection process in order to only include the most important elements for each model. Finally, one multiple linear regression (MLR) model were calibrated for each response variable (Cu, Zn and Cd).

The results from the farm validation of the Cu, Zn and Cd models are shown in Figure 1. The coefficients of determination (R^2) were 0.73, 0.96 and 0.50 for Cu, Zn and Cd respectively. The cross-validation of the models exhibited similar R^2 values at 0.72, 0.92 and 0.51 for Cu, Zn and Cd respectively. The Cu model made it possible to predict Cu concentrations below the LoD for Cu itself of the PXRF device (≈ 20 mg kg^{-1}), but was unable to in detail predict higher concentrations (Figure 1a). The Zn model predicted well across the whole range of concentrations (Figure 1b). Furthermore, using Zn as measured directly by the PXRF resulted in a lower R^2 of 0.81 for the farm dataset (not shown) compared to Zn predictions by MLR. This means that the modelled Zn was more accurate than only using the PXRF measured Zn. The Cd model was unable to predict the high concentrations (Figure 1c).

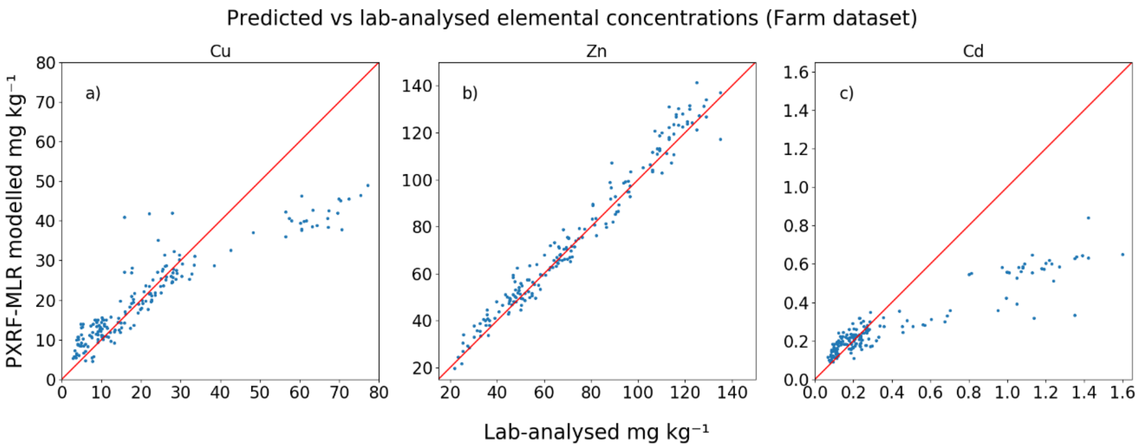

Figure 1: Elemental concentrations predicted from PXRF measurements from the national models compared to 7M HNO_3 digestion and inductively coupled plasma (ICP) analysis of a) Cu, b) Zn and c) Cd at the farm level.

The results for Cu show that it could be possible to do field scale maps for exploratory screening if a soil might be Cu deficient or not (above or below the threshold of 7 mg/kg^{-1} used in Sweden; Börling et al, 2017), even though the predictions were less accurate at higher concentrations. PXRF-based predictions of soil Cd concentrations could be useful for identifying parts of fields or farms where the Cd concentrations in the soil is likely to be low, e.g. for decisions on where to spread sewage sludge. The poor prediction accuracy of Cu and Cd at high concentrations may be due to the fact that there were no concentrations above 50 and 0.8 mg/kg for Cu and Cd respectively in the calibration data. Hence, the models had to extrapolate beyond those concentrations resulting in the underestimations seen in the farm validation. The results indicate that the nationally calibrated Zn model of PXRF measurements would be accurate enough for field scale predictions. Furthermore, the results indicate that using MLR on PXRF data can help predicting values below the LoD for the respective elements and improve prediction accuracy. However, depending on the purpose, these results show that the MLR-models might not be good for predicting Cu and Cd. Future research shall be focused on using a larger, more comprehensive, national dataset for model calibration and non-linear models to improve prediction accuracies of Cu and Cd across the ranges of concentrations.

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AUTOMATIC CONTROL OF THE GROWTH OF PLANTS USING ARTIFICIAL INTELLIGENCE AND INTERNET TECHNOLOGY

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One of the main challenges in agriculture is to fulfil the food demands of a constantly growing population while protecting the economical, ecological, and social resources. To tackle this challenge, an appealing alternative is indoor farming, such as vertical farming or greenhouses, where crops are produced in reduced areas using automatic or semi-automatic processes under controlled conditions. This permits using less agrochemicals, a more precise management of water, as well as an implementation in very close proximity to the final consumers (Shamshiri et al., 2018). However, in spite of the promising results obtained so far, there is still a lot of room for improvement. Most of the current approaches for automatic crop production apply the same treatments for the entire crop, independently of the individual needs of each plant. This prevents exploiting the full potential of each plant, missing valuable opportunities to maximize production and to minimize the environmental impact by precisely adjusting the treatments (e.g. water and nutrient doses) according to each plant's needs. On the other hand, for an efficient management and supervision of the automatic crop production, it is important that these systems are provided with suitable interfaces to efficiently assess, in real time, the evolution of the entire crop to optimize, for example, harvesting strategies or to quickly react to unexpected contingencies.

We present an Internet platform that combines advanced artificial intelligence (AI) techniques of machine learning and decision-making with Internet and database management technology for the remote monitoring and automatic control of the growth of plants in large horticultural crops. The AI techniques are used to automatically decide the best treatment for each plant according to the plant's individual needs rather than establishing general protocols for nutrient, water, and light/shading common to all the plants, as done traditionally. This permits reducing the resources needed for an optimal crop yield, making a more sustainable management of water and nutrients while reducing costs. The AI mechanisms are based on a novel machine learning approach that is able to automatically learn the correlations between gradual and small changes observed on plants with past events taking place on the plants (e.g. the gradual and delayed growth of leaves produced by past supplies of water and nutrient) (Agostini et al., 2014). These gradual and delayed correlations are encoded into predictive models compatible with AI task planning approaches (Ghallab, 2004), which permit evaluating the results of applying different treatments to a plant so as to select the most optimal ones. These predictive models are automatically learned from observations of (real and simulated) plants' evolution under different treatments. During the learning process, the planning approach might not able to select the next treatment for a plant due to (still) missing predictive models. In that case, the system requests the user to instruct the treatment.

We have implemented an intuitive graphical web interface that allows supervising the entire crop in real time and from any place with Internet access. Fig. 1 shows a snapshot of the web interface for an example application of a crop consisting of 40 simulated plants[1]. Each plant is represented with a circle whose diameter is proportional to the plant size and whose colour ranges from yellow to green, depending on the proportion of yellow and green leaves of the plant. This schematic representation provides an intuitive idea of the plant state. However, the

[1] We use simulated plants for the example application to generate data in a short time. However, the platform is also suitable to handle real crops.

actual state of the plant, used by the planning approach to make decisions, is characterized by a set of parameters, such as the size and colour of leaves, height of the plant, and growth rate, obtained from sensing mechanisms. The web interface also shows a graphical representation of the ongoing treatment for each plant. In case a treatment instruction is needed, the available treatments are deployed and the user is requested to select one of them by clicking on its image or by typing its name. Fig. 1 shows the treatments defined for the example application (bottom-left panel), such as the treatment "strong nutrient" that administers relatively high doses of nutrients to the plant. Each treatment consists of hourly doses of water, nutrient, and light applied to a plant in a 24 hours basis. For each plant, the planning approach selects, every 24 hours, the best treatment based on the plant's history (past states and treatments). The plant history, as well as the future treatments to be applied on the plant, resulting from the planning process, are deployed in the timeline panel (top-left). In case of instruction request, only the history of the plant is shown, which is used by the user to decide the next treatment. After the treatment selection, the system automatically supplies the corresponding hourly doses to each plant in sequence, plant by plant, according to the ongoing treatments. The currently visited plant is indicated by marking in red the corresponding labels.

Figure 1: Snapshot of the graphical web interface of the Internet platform for automatic crop production.

The presented Internet platform can be customized for any desired number and type of plants. It can also be easily combined with different sensing and acting mechanisms, for plant state characterization and treatment execution, respectively, thanks to a MySQL database interface that permits an efficient (and remote) management of information between the sensing and acting mechanisms and the AI techniques for planning and learning.

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EMPLOYING FALSE COLOR INFRARED CAMERAS FOR BIOMASS ESTIMATION ON NATURAL GRASSLAND.

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Introduction

Natural grasslands occupy up to 40.5% of Earth's terrestrial surface (Monson, 2014) and provide important ecosystem services as well as supporting livestock production systems. Broadly, grazing-management is a fine equilibrium between three parameters: stocking rates, biomass and grazing-period. From these, biomass estimation is the most critical parameter to measure, thus, manage, given that its estimation is part of a complex and dynamic system, made even more difficult by the large spatial heterogeneity, seasonal and inter-annual variability of forage resources.
Remote sensing techniques have long been proposed as a solution to such topic (Tucker, 1979). However, it has not become a widely utilized tool given the absence of an accurate, timely and cost-effective methods available for end-users, mostly due to inadequate spatial and temporal resolutions of available data. To bridge such gap, remotely piloted aircraft systems (RPAS) have been the subject of intense research in the recent past. In fact, within the past five years, several purposely built RPAS multispectral sensors became commercially available and a large extent of image-processing (mosaicking and radiometric calibration) can now be executed on the cloud (i.e. remotely.) Prior to such developments, however, modified digital cameras (off-the shelf) were commonly employed as false colour-infrared broadband sensors.
This study examines the use of a RPAS and modified digital cameras as a tool for instantaneous measurement of forage biomass (dry matter per hectare) utilizing digital number (DN) as a proxy for reflectance values. The ability of automating a mostly manual task (biomass estimation) using a simple method could be worthwhile to end-users.

Materials and Methods

The imagery and data collection took place on July 31st, 2014 at the Rannells Ranch (Kansas State University Experimental Station), located on the Flint Hills (Kansas – USA). The study area is part of a native tallgrass prairie: a community of several different grass species, which dominated the trial area.
To achieve a wide sampling range (i.e. biomass gradient), the trial area encompassed both a recently grazed and a non-grazed paddock. On each of the paddocks, two transversal transects were drawn and nine quadrants were distributed in an equidistant fashion along each of the four transects (whole trial n = 36). Quadrant's dimensions are 0.5x05m or 0.25m^2. Each of the sample-points was clipped to ground level, dried at 64ºC for 72 hours. Samples' dry matter (DM) was weighed (+- 0.2 grams accuracy).
The aerial platform was a fixed-wing built in-house to carry a modified Canon S-100. Broadly, the modification was the removal of the near-infrared (NIR) filter and posterior substitution for a longpass-filter which allowed the red-channel to capture the near infrared (NIR) range of the spectrum. Thus, the camera was mostly acquiring the blue, green and NIR regions of the spectrum. From these bands, a Green Normalized Difference Index (NDVI) and a Blue NDVI are generated from the average pixel response within quadrant. The camera was not spectrally nor radiometrically characterized and no invariant target was utilized as a calibration reference. Mosaicking and orthorectification was carried out on Agisoft

PhotoScan. The following regression models are fitted against the dataset: ordinary linear model (LM), multi-adaptative regression spline (MARS), random forest (RF) and support vector machine (with polynomial kernel - SVM) having both GNDVI and BNDVI as inputs. Model performance is assessed against the repeated cross-validation results (4 folds, 50 repeats).

Results

DM values range from 352 to 5950 kg.DM.ha^{-1}. From the algorithms tested, SVM was the best performing with an average r-squared value 0.60 and root-mean-square error (RMSE) of 1169.6 kg. Ranges displayed on Figure 1 are generated from the 200 results from the cross-validation procedure.

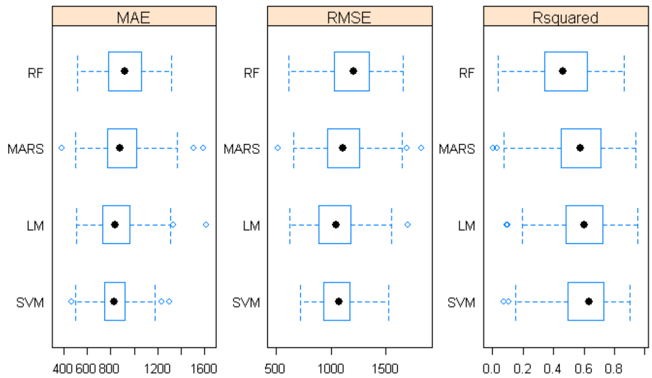

Figure 1 :Performance of regression models .

Conclusion

The results from the modified camera (broadband, non-radiometrically corrected) displayed a wide variability within the performance assessments (RMSE, MAE and r-squared). As seen in Fig.1, results are far from stable for any algorithm. Thus, from this analysis it cannot be stated that the method is consistently accurate. Also, due to the nature of the dataset, results may not be transferable to any other date or location.

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ESTIMATING SPATIAL VARIABILITY OF CROP YIELDS USING SATELLITE VEGETATION INDICES

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INTRODUCTION

The application of remote sensing for estimating the crop yield is generally dependent on the relationship between final yield and the quantity and quality of the electromagnetic radiation reflected or emitted by the vegetation (Ferencz et al, 2004). A reliable yield prediction early in the growing season could be a useful tool for strategic planning. This research reports on the integration of satellite vegetation indices (VIs) derived from Landsat 5, 7 and 8 imagery at various crop stages and yield monitoring data, to estimate the final yield.

METHODS

Five years georeferenced grain harvest data were filtered (Sudduth & Drummond, 2007) to obtain the final grain yield (GY). An average 6170 GY data points per year were archived in a 11.07 ha experimental field located in a flat area in Northern Italy (44.5° N, 12.1° E). Multispectral images were downloaded from the USGS Earth Explorer data hub with the satellite medium resolution (30 m pixel size), and geometric, radiometric, atmospheric and cloud corrections were applied to a total of 150 images covering the following time frames: 1st February - 30th June for Durum (2010) and Bread Wheat (2012 and 2014), 1st May - 31th August for Sunflower (2011) and 1st May - 15th July for Coriander (2013). Then, various VIs were computed: simple ratio (SR), normalized difference vegetation index (NDVI), soil adjusted vegetation index (SAVI), enhanced vegetation index (EVI), green normalized difference vegetation index (GNDVI), and green chlorophyll index (GCI). Final GY (t/ha) and selected VIs were analysed using geostatistics (ArcGIS version 10.3) by computing the empirical semivariograms and interpolated with the spherical model.

Prediction accuracy of the model used was assessed in terms of coefficient of determination (R^2) and root mean square error (RMSE). Output GY raster data (30 m cell size) were used for Pearson's correlation with the same spatial resolution as satellite imagery (126 data points). Dates showing highest correlations between VIs and GY were recognized as the best times/crop stages for final GY prediction. Then, we applied geostatistics to the best VIs in critical crop growing period (Woodcock, 1988), to assess the correspondence with GY at same pixel level (Stępień et al, 2016). Based on the three correspondence levels, final agreement was calculated with the formula:

$$F_a = \frac{(P_g \cdot 1.0) + (P_m \cdot 0.5) + (P_l \cdot 0)}{P_t \cdot 100}$$

Where: F_a=final agreement (%); P_g=number of pixels with good agreement; P_m=number of pixels with medium agreement; P_l=number of pixels with low agreement; P_t=total pixel number

RESULTS

Simple ratio and NDVI were the two VIs most frequently chosen (six and four times, respectively) during critical growing period, this latter ranging from vegetative (BBCH ~30's) to reproductive stage (BBCH ~70's) (Table 1). At the opposite end, SAVI never exhibited correlations high enough in these stages, to be included. Pixel level study demonstrated a final agreement between VIs and GY in the range 64-86%. Final agreement was adversely related to its CV, meaning that more consistent correspondence levels were conductive to higher overall agreement, and vice versa. Good prediction accuracy of the spherical model was proved by R^2 values close to 1, and modest RMSE values with respect to GY averages (these latter, 4.23, 1.44, 4.23, 1.82 and 5.89 t/ha in the five respective years). The two estimators validated the good fit of the spherical model (Bhunia et al, 2018).

Table 1 : Correlation and final agreement between VIs and GY

Crop and year	**VI**	**R^2 with GY**	**PP (BBCH)**	**Fa %**	**CV %**	**Prediction accuracy (R^2)**		**Pred. accuracy (RMSE)**	
						GY	**VI**	**GY**	**VI**
Durum Wheat 2010	NDVI	0.88	36-43	73	41.9	0.98	0.99	0.33	0.009
	NDVI	0.88		72	43.6		0.99		0.01
Sunflower 2011	GNDVI	0.75	51-67	65	50.6	0.71	0.99	0.14	0.005
	SR	0.73		64	56.4		0.98		0.07
Bread Wheat 2012	EVI	0.70	33-36	65	49.9	0.98	0.99	0.33	0.007
	EVI	0.85		70	47.1		0.99		0.019
	SR	0.80		67	47.3		0.99		0.02
	SR	0.86		70	46.2		1		0.06
Coriander 2013	EVI	0.92	63-81	75	38.6	0.99	0.99	0.15	0.007
	NDVI	0.90		76	39.6		0.98		0.01
	SR	0.93		84	31.9		0.99		0.06
Bread Wheat 2014	SR	0.94	37-77	85	27.1	0.99	0.99	0.42	0.14
	NDVI	0.93		78	36.0		0.95		0.005
	GCI	0.93		83	31.9		0.99		0.05
	SR	0.93		86	27.5		0.99		0.06

PP, prediction period (BBCH stage); Fa, final agreement. All R^2 values are significant at $P \leq 0.01$.

CONCLUSION

Landsat satellite imagery with its spatial, spectral and temporal resolution proved a good potential for estimating final GY over different crops in a rotation, at a relatively small field scale (11.07 ha). This sets the premise for a wider use of satellite data in yield predictions, beside their role in supporting site specific management decisions.

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WEEDING BY YNCREA: MIXING EXPERTISES TO CREATE SYNERGY FOR THE DEVELOPMENT OF A ROBOT DEDICATED TO WEEDING OPERATIONS

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Introduction and scope of the project

Precision agriculture, a management practice based on the use of data collected on fields using information technologies, aims at supporting farmers' decisions and at monitoring amount of agricultural inputs in the right place at the right time (Finch et al., 2014). It is not anymore a new domain in agriculture with many decision support tools widely disseminated to farmers during the last two decades. In the robotics domain, especially, agriculture is gaining some benefits using this technology by reducing farmers workload mainly for repetitive tasks such as land preparation, irrigation, spraying, mapping or harvesting (Vasconez et al., 2019).

In the pedagogical domain, precision agriculture courses have integrated the direction of student training as engineers in Agronomy with developments of agronomic technologies and decision support tools. For ISA (Lille, France), an institution training future engineers in Agriculture in the North of France, the topic of precision agriculture is taught in order to inform students about decision support tools and their components, from data acquisition and data analysis to provision to farmers, and to communicate with the different stakeholders participating in the development of these tools (researchers, computer scientists, data processing specialists, contractors) but also with the farmers who are the main concerned stakeholder to receive them. Since 2013, ISA Lille has been joined by two neighboring schools, named HEI and ISEN Lille, specialized respectively in the training of generalist and electronic and numeric specialists engineers. The association of the three schools is nowadays well known as Yncréa Hauts-de-France, which aims at training students, developing research in different domains as well as working with companies. With the scope of this grouping, transdisciplinary projects occur each year with groups of students coming from different schools, and thus with different expertise and fields of study, in order to respond to different problems, mainly coming from companies proposals.

This year, a group of students had the target to build a weeding robot, in order to answer to a competition named "Rob'Olympiades" (Arvalis, Les Culturales 2019, Poitiers, France), but also to demonstrate the ability of such teamwork to provide a valuable solution domain by combining different expertise in agriculture, in mechanics, in electronic, in programming and in robotics in general. In addition, this event fits completely with the actual trends of agriculture as it aims at enhancing innovations to support farmers in technical and environmental aspects.

Beyond this contest, the robot will participate in all Yncréa Hauts-de-France activities related to precision agriculture, such as teaching or research activities.

Robot specifications and construction

For the competition, the robot has been included in the "complete conception" challenge where the goal was to have a robot where all components were totally built by the participants. The abilities of the robot, called Weed'Ync (Weeding by Yncréa), are a) to detect maize rows with 75 cm of inter-row, b) to detect mustard plants (weeds) within this inter-row region, c) to spray a liquid product in the region where these weeds are detected, by

indicating each spray with a sound. It was not possible to use any corrected GNSS location system, such as RTK, and to use Wifi connection.
The mechanical concept of the robot is presented in the Figure 1. The detection of the maize rows is performed using a Lidar fixed on the front of the robot. The detection of weeds uses a classic RGB camera, and a machine-learning method as image analysis. The spraying is done with a ramp composed of rail and a nozzle able to move along the inter-row region. All components weresourced from public commercial companies, and the mounting was built within the fabrication laboratory of ISEN Lille.

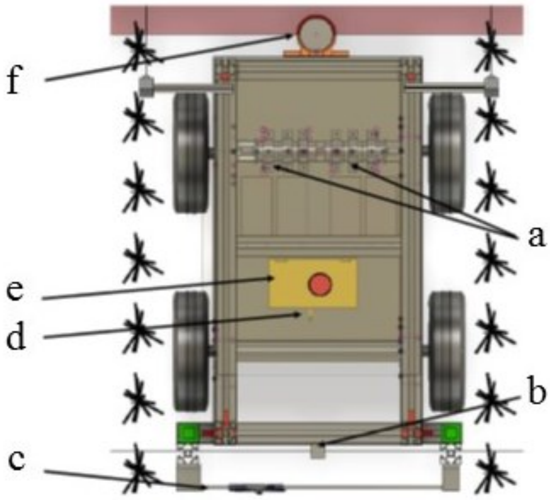

Figure 1: top view of the schematic conception of Weed'Ync including, a) the wheels motors, b) the RGB camera for weed detection, c) the spraying ramp, d) the weeding liquid pool, e) liquid pump connected to the ramp and f) the Lidar for the rows detection

The different abilities of the robot function by using a couple of processors: a Raspberry Pi (Raspberry Pi Foundation, UK registered charity 1129409) and a 128-core Jetson Nano (Nvidia, Santa Clara, CA, USA). The programming scripts are written in Python and run under Melodic Morenia Robot Operating System (ROS, Open Source Robotics Foundation). The systems making the robot operational are all open source, allowing flexibility within the construction of the robot, and to imagine future modifications through other projects.

Performances of the robot and perspectives

After preliminary tests, the robot is operational in terms of movement between the rows, of mustard weed detection and of dedicated spraying. In a near future, our aim is to detect more weed species using probably another type of camera. In addition, by changing the mechanical base, it would be interesting to build another prototype to fit with intra-row weeding process.
In conclusion, this project is demonstrating the complementarity between agronomic and electronic, mechanics and programming competences. Yncréa is a good example of such complementarity in both pedagogical and scientific research aspects.

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MONITORING WHEAT CROP N STATUS UNDER HUMID MEDITERRANEAN CONDITIONS BASED ON CHANGES IN NDVI

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Introduction

Nitrogen (N) is an essential nutrient for crop growth and productivity, being the most critical growth restricting nutrient in cereal cropping systems. Rapid increases in cereal yields became possible with the introduction of N fertilizers which are often applied in excessive quantities causing N losses and environmental damage. Precision management is a promising strategy to match N supply with N demand taking into account the space and time. Remote sensing measurements are usually taken in a mid-moment of the wheat growing period for adjusting N fertilizer rate (Aranguren et al, 2018). Although NDVI at stem elongation (GS30, Zadoks et al, 1974) is a criterion for stablishing the required N fertilization practices, the time elapsed between GS30 until harvest is long and many factors can affect the N uptake by the crop (Ravier et al, 2017). Therefore, it is necessary to follow crop N status throughout vegetative growing season. The aim of this study is to start developing threshold NDVI values during wheat growing season that did not lead to a decrease in yield.

Materials and Methods

Three field trials were established in Arkaute (Araba, Basque Country, Spain) at NEIKER-Tecnalia facilities in three consecutive wheat growing seasons 2014–2015, 2015–2016 and 2016-2017 (defined as 2015, 2016 and 2017) in different fields under rainfed conditions. The climate of the area was humid-Mediterranean according to the temperature regimen of "Papadakis" classification. Wheat (*Triticum aestivum* var. Cezanne) was sown. Three kinds of initial fertilization were applied: dairy slurry (40 $t.ha^{-1}$), sheep farmyard manure (40 $t.ha^{-1}$) and conventional (no organic fertilizer basal dressing and 40 kg N ha^{-1} at tillering (GS21). These three types of fertilization were combined with five N rates (calcium-ammonium-nitrate, NAC 27 %; 0, 40, 80, 120 and 160 kg N ha^{-1}) at top dressing applied at GS30. The experiment was a factorial randomized complete block design with four replicates. Yields were harvested at crop maturity using a plot harvester (1.5 m x 8 m). For comparisons among fields, yields were converted to 12 % dry matter basis.

RapidScan CS-45 (Holland Scientific, Lincoln, USA) is a portable handheld entirely self-contained ground-based active canopy sensor that measures crop reflectance at 670, 730 and 780 nm and provides the NDVI. The measurements with RapidScan CS-45 were taken as the sensor was passed over the crop surface at approximately 1 m at constant walking speed. Measurements were taken at GS30, second node (GS32), leaf flag emergence (GS37) and mid-flowering (GS65). Two rows per elemental plot were scanned and NDVI values were averaged to generate a value for that plot.

Results and Discussion

Grain yield was significantly influenced by the amount of mineral N fertilizer at GS30 in the three growing seasons. Overall, wheat grain yield varied between 4300 – 8700 $kg.ha^{-1}$ in 2015, 5900 – 10.700 $kg.ha^{-1}$ in 2016 and 3800 - 7000 $kg.ha^{-1}$ in 2017. The maximum wheat yield was achieved with 80 $kgN.ha^{-1}$ at GS30 in all cases except for sheep manure in 2016 and 2017 (Table 1).

NDVI values at the treatments that achieved the highest yields are shown in Table 1. NDVI values showed that when crop N status is higher than 0.65 at GS30 and higher than 0.70 from GS32 to GS65, yields are high (2016). However, when crop N status remains low throughout the growing cycle (values lower than 0.60 from GS30 to GS37 yields are negatively affected even if and values increase to 0.65 at GS65 (2017). The lower the crop N status value (< 0.45 in organic treatments from GS30 to GS37) the higher is the impact on yield. Only in 2017 the organics applied as initial fertilizers produced less than the conventional treatments for each N rate applied at GS30. In cases where there is a low crop N status at GS30 (0.55 in conventional and 0.40 in organic treatments) but it is recovered by GS32 (values around 0.77 – 0.80), yields can be partially regained. Those results showed a great potential of the active canopy sensor RapidScan CS-45 to follow wheat N status during the crop growth, as Lu et al. (2017) showed for rice. Given that remote sensing measurements are not laborious, crop N status should be periodically monitored. The research with ground-based remote sensing tools could help in the implementation of satellite remote sensing.

Table 1: Optimum N rates at GS30 for achieving the maximum yields for each initial fertilization treatment and their corresponding NDVI values at GS30, GS32, GS37 and GS65 wheat growing stages (Zadoks et al., 1974) in 2015, 2016 and 2017.

Growing season	Treatment	N rate at GS30 for maximum yield (kg N ha^{-1})	Yield (kg ha^{-1})	NDVI values			
				GS30	GS32	GS37	GS65
2015	Conventional	80	8,215	0.54	0.80	0.76	0.69
	Dairy Slurry	80	7,762	0.40	0.77	0.78	0.73
	Sheep manure	80	7,966	0.40	0.77	0.75	0.67
2016	Conventional	80	9,682	0.67	0.72	0.73	0.75
	Dairy Slurry	80	10,136	0.65	0.68	0.71	0.72
	Sheep manure	120	10,446	0.65	0.73	0.75	0.76
2017	Conventional	80	6,492	0.59	0.51	0.53	0.62
	Dairy Slurry	80	5,965	0.44	0.41	0.44	0.63
	Sheep manure	120	5,537	0.43	0.36	0.39	0.65

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A TOOL FOR COLLECTIVE MANAGEMENT OF CROP GROWTH WARNINGS BASED ON SENTINEL-2 VEGETATION INDICES

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Within the framework of the INTERREG-POCTEFA programme, the PyrenEOS project has developed a Decision Support Tool (DST) for monitoring warnings related to the vegetative development of crops at plot scale. This monitoring service is based on time series of vegetation indices (VI) derived from Sentinel-2 images.

The DST offers users without previous expertise or knowledge about remote sensing, a classification tool that allows analyzing and categorizing crop growth variability between fields or within-plot variability for a particular date, based on earth observation data. The results obtained with this classification tool can be easily and visually interpreted by the user.
There are four reference models to classify the plots:
• By frequency series, with a distribution by quartiles in four classes
• By selecting a reference agricultural plot
• Using the average value of the most favorable quartile in the frequency distribution
• Using a value of VI selected by the user

The classification tool allows farmers to easily handle collective management information, for instance, by using as reference over-fertilized plots in order to adjust Nitrogen fertilization for any particular field in a region or collective management area, such as an irrigation district or a cooperative.

Users can consult the classification according to three vegetation indexes: normalized difference vegetation index (NDVI), soil adjusted vegetation index (SAVI), and merris terrestrial chlorophyll index (MTCI) and the response of reflectance in the short-wavelength infrared (SWIR).

In addition, this service allows the user to analyze the intra-field variability, by zoning into 4 classes, that can be used to conduct soil or plant samplings, or to evaluate different crop responses to nutrients or soil characteristics (*Figure 1)*. This tool provides the option of exporting maps in shapefile, which can be integrated in variable rate machinery.
The DST has been integrated into the AGROasesor platform, which is being developed within the LIFE program. Its main goal is to create an on-line platform that will support collective management of crop information, based on a complete set of information at field scale from AGROasesor platform.

It has been possible to integrate the interoperability of WMS and WCS services between the PyrenEOS and AGROasesor platforms, to provide alerts to farmers and advisors, with coverage in 5 regions of Spain.

The relevance of the classification tool as part of the DST for providing information on crop development, has been demonstrated by a pilot program involving farmers and cooperatives.

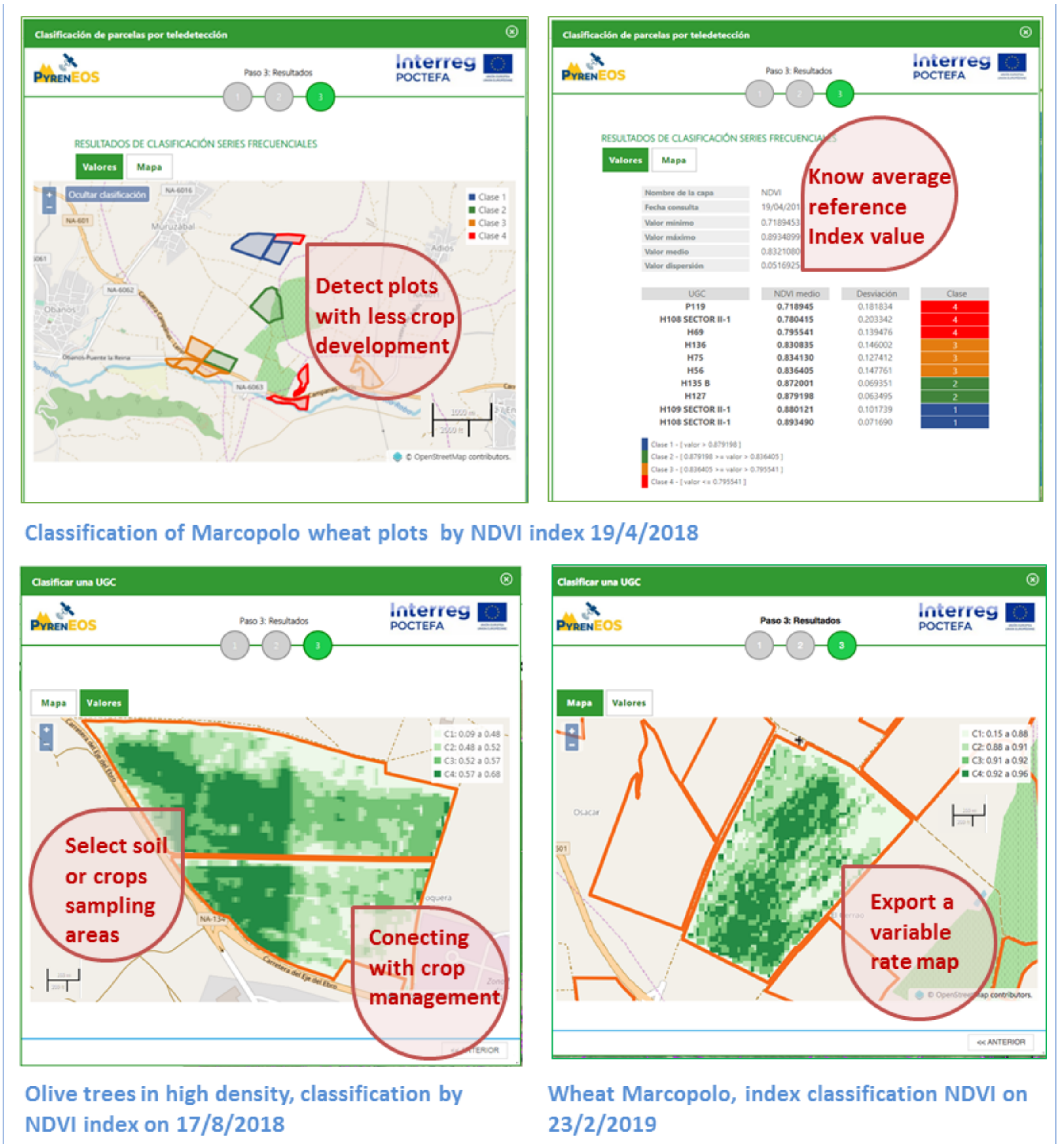

Figure 1. Visualization examples of DST classification in AGROasesor platform

JUJUBE FRUIT TREE YIELD PREDICTION AT FIELD SCALE ASSIMILATING LAI FROM TM8 DATA INTO WOFOST MODEL

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Introduction

Jujube tree (*Zizyphus jujuba Miller*) is an important economic tree species. Its fruit not only has important nutritional value but also significant medical value. The field-scale jujube growth and yield estimates before harvest allow farmers to improve yield management decision-making, such as irrigation, fertilization, pruning and density selection. Cropping systems modelling based on mathematical descriptions expresses and quantifies the crop development process influenced by climate, soil and management conditions, which has been considered as a mature method for yield prediction. The uncertainties of input parameters for crop model may affect the accuracy of crop growth simulation and yield assessment. Assimilation methods are often used to integrate remote sensing data into crop growth models to reduce the uncertainty, mainly including calibration methods, forcing methods and updating methods (Jin et al., 2018). However, few studies are focused on yield estimation of perennial fruit tree crops by integrating remotely sensed information into crop models. This study presented an attempt to assimilate a single leaf area index (LAI) near to max vegetative development stages derived from Landsat TM8 into a calibrated WOFOST model to predict yields for jujube fruit tree at field scale.

Methods

In order to calibrate the WOFOST model for our research use, field experiments were conducted in two jujube orchards during the three growing seasons located in the district of Alaer in Xinjiang, China. 181 yield samples accounted for 18,823 pixels in TM8 satellite imagery. 55 sample spots in 2016 and 2017 were designated for LAI measurements during the main fruit-filling period when the TM8 satellite covered the study area. The parameters for WOFOST model were calibrated based on collecting data from field detailed experiments (Bai et al. 2019). The fitted equation between NDVIs and LAIs was established and validated, thereby estimating LAI values for 181 samples. LAI derived from TM8 data at a near peak vegetative stages (July 24, 2016 and July 27, 2017) was forced into the calibrated WOFOST model to re-correct the TDWI value of each sample using the Shuffled Complex Evolution (SCE) optimization algorithm (Ma et al. 2013). The corrected value of the state variable (LAI) determined the growth rate of the state variables at next time step. Therefore, it was assumed that the final simulated yield approximated the actual yield (Tripathy et al., 2013).

Results

The positive results achieved by assimilation method were confirmed by the indices of agreement and error between simulated and observed yields (Fig 1(a) and Fig 1(b)). The assimilation method showed the highest performance, with a R^2 of 0.62 and RMSE of 0.74 (10.9%) t ha^{-1} and R^2 of 0.59 and RMSE of 0.87 (11.1 %) t ha^{-1} for 2016 and 2017, respectively, followed by remotely sensed NDVI regression method, and finally without assimilation. Best MAE values were also achieved by assimilation method, showing a improvement of 31 % and 28 % versus the remote sensing regression method, 38 % and 47 % versus the simulation without assimilation in 2016 and 2017, respectively. The assimilation method resulted in relative bias errors that were distributed more centrally around zero compared with other two methods (Fig 1(c) and Fig 1(d)). The absolute RBE for yield simulation was lower than 15 % in 80 % and 72 % of the samples, lower than 20 % in 92 % and 90 % for 2016 and 2017, respectively.

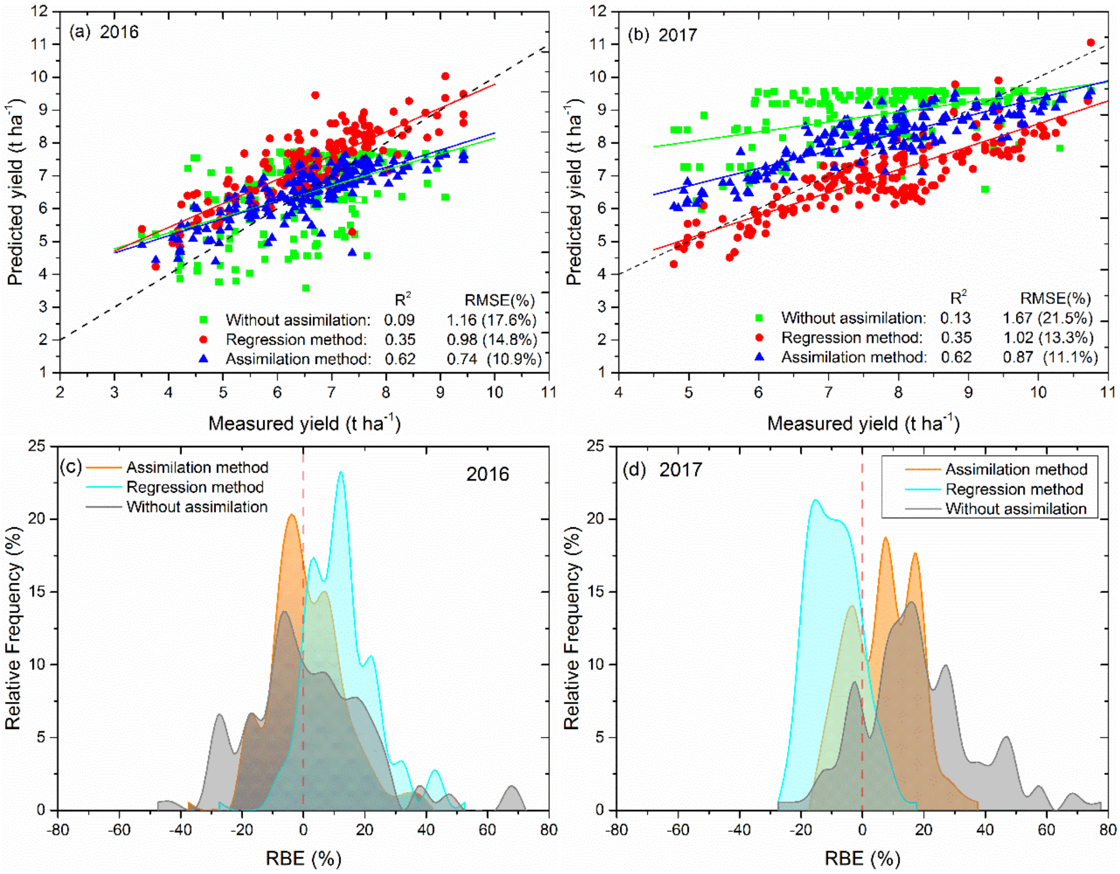

Figure 2: (a) and (b) - Predicted versus measured yields based on three methods for 2016 and 2017. (c) and (d) - Frequency distributions of relative bias error (RBE; %) resulting from the comparison between observed and simulated yields for 2016 and 2017. RBE % = 0 % (red line) represents the perfect prediction. Bin size w = 5.

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AN APPROACH FOR BUILDING A DIGITAL MODEL OF VINE CANOPIES BY USING A MULTICHANNEL LIDAR

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Characteristic properties of the plants should be taken into consideration when applying plant protection agents if optimal dosage level is to be achieved. To do so an autonomous system has to be build. This sistem adjusts the flow rate of plant protection agents according to the characteristics of the vine canopy. Such system should follow a build in model, described in this work. This system was first established by analysing the readings describing the plant in question and comparing them with actual vine canopy properties, on its leaf area. The problem with the usually applied sensors, such as ultrasonic or single channel LIDAR sensors, with which we want to measure the canopy properties, are that they can not see what is behind occluded areas. This is the reason why we have investigated an approach for building a model of the surrounding territory using a multichannel LIDAR sensor (Velodyne VLP-16).
For the reconstruction of the vine plant canopy we separately measured leaf surfaces of the first and second canopy using a multichannel LIDAR, which was installed on the farm robot, as depicted by Figure 1.

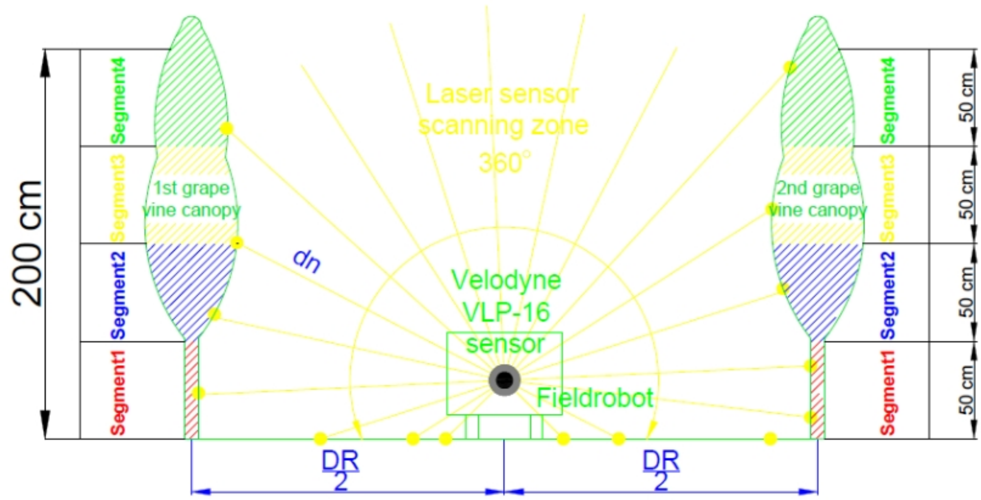

Figure 1. Measuring leaf surface of the vine plant canopy with the multichannel LIDAR.

Digital vine plant canopy reconstruction was demonstrated in the three-dimensional virtual space, using ROS and Matlab R2015a software in which a graphical representation was created. With the digital reconstruction of the vine plant canopy the analysis of the natural characteristics of the canopy was performed. This had made possible to make a connection between the number of points in cloud points of the four individual segments of the first and the second canopy and the actual leaf surface. The highest value of the correlation coefficient was 0.9633 for the ratio between the number of points on leaf surfaces to the actual leaf surface, which was measured using the Optomax system.
Without a doubt, the presented optical measurement system provided a precise and detailed information about the structure of the vine plant canopy. Our next step of this research is to put the system on tractor and include artificial intelligence that will be used to control the doses based on the individual properties of each vine plant.

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COMPARING UAV-BASED HYPERSPECTRAL DATA OF CORN WITH PROXIMAL SENSOR DATA

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Introduction

This presentation talks about the relationship between unmanned aerial vehicle (UAV)-based remote sensing data and ground-based sensor data for corn. A UAV equipped with a hyperspectral sensor was flown over the corn plot. The hyperspectral data was used in the determination of different vegetation indices. Proximal sensors include handheld spectro-radiometer, water potential meter and chlorophyll meter. Correlations between the vegetation indices, chlorophyll content, and water potential are shown and discussed.

Materials and Methods

An experimental corn plot was designed. The plot had total of three replicate rows, with a 3 m gap between them. It was a strip-plot design with four nitrogen treatments forming main plots and five irrigation treatments forming subplots. The subplots were drip irrigated at 0% 25%, 50%, 75%, and 100% irrigation level as estimated by evapotranspiration calculations. Similarly, the nitrogen treatment was slow release nitrogen at 0%, 25%, 50%, and 100% of the nitrogen recommended for corn growth. The soil moisture and nitrogen levels were determined prior to beginning the study.
The UAV used for this study was a Matrice 600 multicopter from DJI. It has an unladen weight of 9.6 kg and can carry a payload of up to 6 kg. It is 167 cm long and 0.76 cm high, and was flown at a speed of 1 to 5 m/sec for data collection. The UAV is equipped with a Nano Hyperspec sensor from Headwall. It captures data in 400-1000 nm spectral range, and has 640 spatial bands, 270 spectral bands and frame rate of 300 Hz. The proximal sensors used were a spectro-radiometer, chlorophyll content meter and water potential meter. The spectro-radiometer is also a hyperspectral sensor, and can provide spectral data in 325-1070 nm spectral range. The chlorophyll meter measures chlorophyll content, and can provide information on leaf nitrogen content. The water potential meter measures the water potential by determining the relative humidity of the air above a sample in a closed chamber.
The airborne and proximal sensor data were collected almost every week. The airborne data were collected at close to noon time. Proximal sensor data were collected either before or after the airborne data were collected. The hyperspectral data from the UAV was processed using Headwall's Hyperspec III and AgView software.

Results and Discussion

The hyperspectral data were used in the determination of normalized differential vegetation index (NDVI), water band index (WBI) and other vegetation indices (Bhandari et al, 2018). NDVI is a ratio of (ρ_{NIR}-ρ_{RED})/ (ρ_{NIR}+ρ_{RED}), where ρ_{NIR} and ρ_{RED} are reflectances in the NIR and red spectrums. NDVI was compared with chlorophyll meter data. Studies have shown that NDVI is a good indicator of leaf chlorophyll concentration and nitrogen contents (Ercoli et al, 1993). A Pearson correlation coefficient (ρ) of 0.53, significant at probability level (p) of 0.0023, was obtained. WBI is a ratio of the reflectance at 970 nm to that at 900 nm. It was compared with leaf water potential. The higher the water content in the vegetation canopies, the stronger the absorption at 970 nm relative to the absorption at 900 nm. Figure 1 shows the relationship between WBI obtained using the UAV data and water potential with a correlation coefficient of 0.63. This result is better than previously reported for corn (Jones et al, 2004).

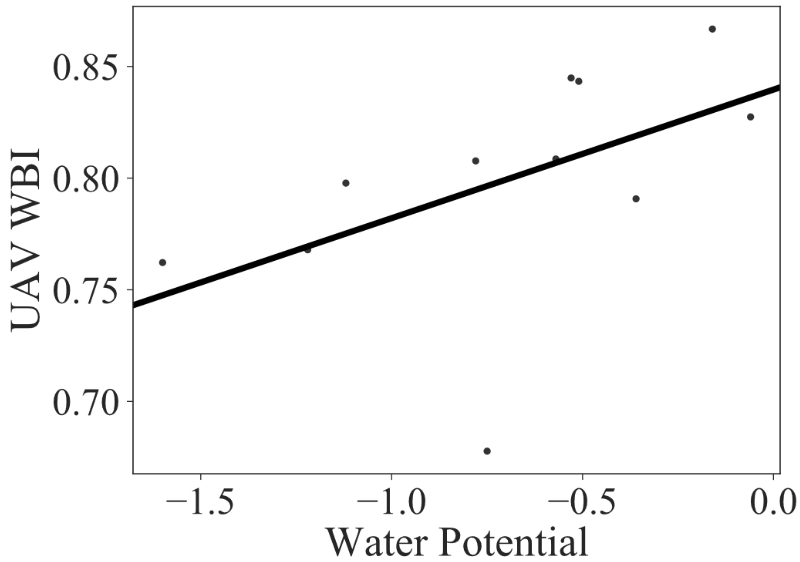

Figure 1. Relationship between UAV WBI and water potential ($\rho = 0.63$, $p = 0.016$).

Conclusions and future work

With the data collected so far, the WBI calculated using the hyperspectral data and water potential had the highest correlation, followed by the correlations between the NDVI and chlorophyll meter data. Though better correlations were obtained than reported in the previous studies for corn, more work is required to improve the correlations and to increase confidence in the remote sensing techniques so that UAV-based remote sensing data can be readily used for precision agriculture. Future work will involve collecting more airborne and proximal sensor data. The data collection methods will be revisited and improved.

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VARIABLE-RATE APPLICATION OF NITROGEN FOR EVERYONE IN DENMARK

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The use of GPS in precision farming has developed over the last 25 years. For at least 20 of the 25 years, technical problems have challenged the use in practice, and, to some extent, technical problems are still a challenge. For example, lack of technical standards made cooperation between tractor terminal and spreader difficult, and loss of GPS signal happened frequently. For a long period of time, the price of VRA equipment for spreading fertiliser was also prohibited for large scale use.

However, today most technical problems have been solved, standards are more common, and the price of equipment is cheaper. Today, equipment prepared for VRA is common in practice, and many newer tractors are equipped with RTK GPS for auto steering. Additionally, most fertilizer spreaders are prepared for VRA as a standard. Free access to satellite images of biomass for the whole country (and the rest of Europe) is available throughout the year.

A large proportion of Danish farmers already have equipment for VRA today, including access for free biomass data. However, few farmers have actually used the equipment for VRA of fertilizer for their crops. To prevent a lack of application maps in becoming the barrier for making VRA mainstream, SEGES has decided to create basic application maps for about 90 percent of all fields with winter wheat and winter oilseed rape in Denmark, along with giving free access to the maps for everyone. From 2018, farmers have been able to download free maps in the web-based programs CropSat.dk and CropManager.dk.

SEGES has decided to boost variable rate application of nitrogen in Denmark. Fertiliser planning and the applications for single payment of about 90 percent of all fields in Denmark are made in the SEGESowned computer program, MarkOnline. Data is stored in a SEGES database, called Dansk Markdatabase. Data is used to create VRA maps for each field (of winter wheat and oilseed rape thus far), and farmers can easily find, see, download and use the maps. The first generation of the VRA algorithm is solely based on biomass measured from satellite. So far, we have developed algorithms for:

- First application of nitrogen in winter wheat and oilseed rape in spring - based on biomass in November
- Last application of nitrogen in winter wheat in May - based on biomass in May.

The principles in the algorithms are the same. Nitrogen application is decreased in areas with high biomass and increased in areas with low biomass. An example of the model’s use for the last application to winter wheat is show in figure 1.

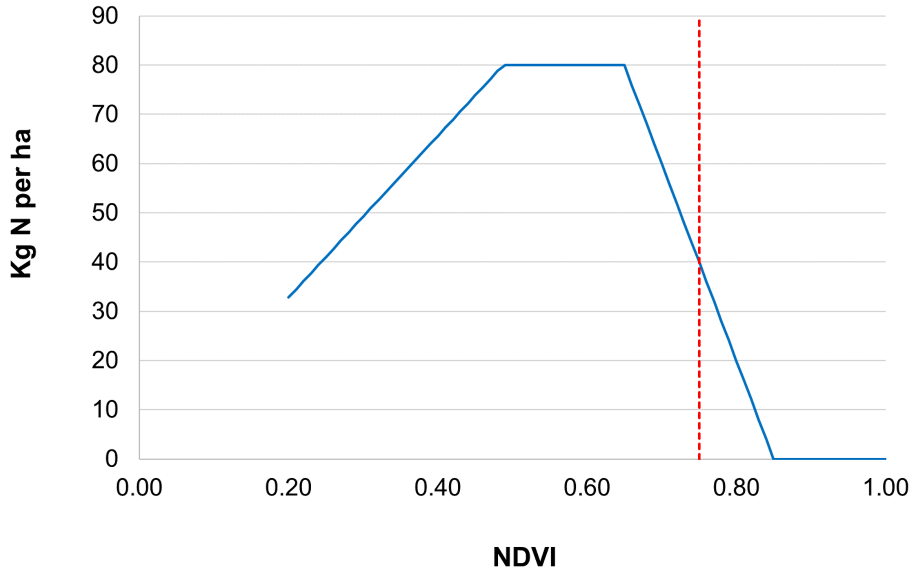

Figure 1: Example of nitrogen application in a field of winter wheat with an average NDVI of 0.75 in the beginning of May. If the variation in the field is low, only a little part of the scale is used (fx 40 +/- 10 kg N), but if the variation is high the whole range of the scale is used (40 +/- 40 kg N).

This principle is chosen because data from Danish and other Northern European trials have shown that the response of nitrogen is highest in areas with low biomass. However, in areas with extremely low biomass, nitrogen application is also reduced or even cut off, due to a generally low nitrogen response in these areas These areas include water logged areas, areas with structural damage, headlands etc. The algorithm is using variable rate application on the amount of nitrogen, the farmer decides.

Before downloading the application maps, the farmer can make manual adjustments of the model-suggested application rates, if he sees areas where the model is making obvious errors. Thus far, the model is not estimating the absolute nitrogen demand in the field. If the farmer decides to apply 40 kg nitrogen per hectare on average, the algorithms variate the nitrogen and make sure the average application is still 40 kg.

For SEGES the ‘easy-to-use’ approach is important. We want to make VRA available for everyone, and we are convinced that using even a simple algorithm is better than a flat rate application. Lack of algorithms must not be a barrier of VRA. In the years to come, we plan to include more information in the algorithms, such as soil type, topography, yield maps etc, and we want to include estimates of the absolute nitrogen rate. We are also focused on stimulating the farmers to use the VRA maps in practice.

DEVELOPMENT OF A DYNAMIC NITROGEN FERTILIZER MANAGEMENT METHOD TO OPTIMIZE THE AGRI-ENVIRONMENTAL PERFORMANCE OF THE SOIL-PLANT SYSTEM FOR WINTER WHEAT

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On earth, nitrogen (N) is one of the most abundant components, however nitrogen deficiency is a limiting factor for crop production whereas an excess leads to nitrogen pollution. To minimize N losses and maximizing grain yield and grain protein content, a balance approach is used to manage fertilization (COMIFER, 2013). Even if this method is based on scientific knowledge, in practice it remains difficult to apply. Indeed, it seems to be difficult to estimate actual nitrogen crop requirement, this approach is based on many estimates particularly on the target yield which can be poorly defined for farmers (Ravier et al., 2017). Besides the use of the balance-sheet method, Decision Support Tools (DST) are developed to adapt N fertilizer rates at the crops' status during the crops' growth. However, the use of this method and DST does not lead to a minimization of N losses for several years and weather conditions are not taken into account (Ravier et al., 2017). Considering these issues, fertilizer management needs to be rethought by considering temporal and spatial variability of crop requirement. Fertilization method based on monitoring of crop N status during crops' growth allows for a better adaptation of annual context and reduce the risk of nitrate pollution from agriculture (Goffart et al., 2013).

To provide a dynamic monitoring of the nitrogen crop status, predicting the Nitrogen Nutrition Index (NNI) is a good indicator. It is the ratio of measured N concentration and the critical N concentration for a defined biomass. Thereby it's a good mean to determine the N required by a crop (Chen et al., 2013). Monitoring NNI by remote sensing is a rapid, non-destructive and an accurate method to manage fertilization (Niu et al., 2019). An Unmanned Aerial Vehicle (UAV, ADT drones, Soissons, France) equipped with a six lens multispectral camera (Mapir, San Diego, CA, USA) is used to monitor crop N nutrition. In a first step, among seventeen wavelengths (405 nm to 945 nm), we have to find the best wavelengths or wavelengths combinations to monitor the winter wheat crop nitrogen status. In order to find how to monitor N crop status by remote sensing, we also measure the N content on the winter wheat field chemically (Kjeldahl method) and with a Dualex probe (Force A, Orsay, France). Dualex is able to measure flavonol and chlorophyll content to determine the nitrogen balance index (NBI).

In order to have a correlation between the actual N measured and N estimated by remote sensing, wheat crop experiments showing various patterns of NNI dynamics are monitored. Three N fertilization experiment fields are studied to have a fertilization's gradient: 0U to N fertilizer rates calculated with balance-sheet method + 80U (Table 1). Measurement are taken at Zadoks' stages: Z30, Z32, Z39, Z60.

Once the NNI monitoring protocol defined, our aim is to propose a new dynamic fertilization method based on remote sensing NNI's monitoring for winter wheat. During crops' growth, in favorable weather conditions crop N status will be measured by remote sensing. Then, NNI is compared with threshold NNI path (Ravier, 2017) to determine when to apply fertilizer. Crops are able to tolerate N deficiencies during some growth phase (Ravier, 2017). STICS model (INRA, France) will be used afterwards to define decisions rules. Dynamic monitoring have several advantages: (i) this method does not need target yield and soil N analysis, (ii) N applications are made in optimal conditions and a better timing to match crop N demand, (iii) the use of an UAV equipped with a multispectral camera eases to consider crops spatial variability. From such method, efficiency of N inputs as well as the reduction of N-based pollution are aimed to be increased.

Table 1 : Site location and fertilizers' rates

	Location (GPS latitude – longitude coordinates)	Fertilization strategies× Repetition	Fertilisation's gradient
Houvin-Houvigneul (62, France)	50.308324 , 2.385824	16×4	0U – 290U
Gouy sous Bellonne (62, France)	50.312658 , 3.043879	13×5	0U - x+80U with and without PK
Gembloux (Belgium)	50.553665 , 4.745088	5×4	0U - 315U

The aim of this presentation is to expose our methodology and present first obtained results.

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ESTIMATION OF EAR DENSITY IN WINTER WHEAT CROP BY STEREOSCOPIC IMAGING FOR CROP YIELD PREDICTION

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Ear density is a valuable component for yield estimates in cereal crops. In the context of high-throughput crop phenotyping, various computer vision-based methods have been proposed to objectify ear counting in the field, relying on either 2D or 3D measurements. Although some of the existing processes can already perform better than humans, there is still room for improvement (Fernandez-Gallego *et al.*, 2018). This research explores the added value of a third dimension through stereoscopic RGB-D images for the estimation of the ear density on winter wheat (*Triticum aestivum L.*) compared to 2D images (Cointault *et al.*, 2008). The image dataset was acquired during a field fertilization trial on winter wheat (2018, Gembloux, Belgium) in order to capture images of contrasted ear densities. Images were acquired by a custom stereovision device composed of two industrial-grade RGB cameras rigged in a known geometry providing a nadir view of the crop canopy. Image processing is based on a segmentation process using the combination of colour and depth information. Topological skeletonisation and morphological operations are implemented to address organ overlapping and identify each ear as an individual object. Furthermore, the canopy height measurement enables the automated estimation of ear density by computing the effective area in each frame. Results focus on comparing performance of ear counting processes when depth information is added to the processing pipeline. Average accuracy is higher than 90%. However, some samples show a high relative error rate resulting in a mean-normalized RMSE of about 10%. Possible causes and solutions for high-error samples are identified and linked to fertilization modalities used in the trial. The use of a stereovision system is discussed for estimating ear density in cereal crop. In such an approach, the depth measurement significantly increases the estimation accuracy. In addition, such a 3D vision system appears to have the potential to monitor growth dynamics of dense crops. The sensitivity of the method to environmental conditions should be assessed in order to validate the acquisition procedure for various natural conditions.

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PRECISION ULTRASONIC SONAR FOR PASTURE BIOMASS

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Modern farming is an intensive business in which optimisation of resources through observation-based farm management software is an important component of 'precision agriculture'. For management of grazing animals such as dairy cows, the quantity of economic interest is the biomass, or the mass of 'dry matter' (DM) per unit area of ground, which is the mass of pasture per unit area when the pasture has been cut and dried. It is this dry matter which contains the food value for the livestock. Current methods for estimating biomass include: cutting, drying, and weighing; measuring the compressibility of pasture using a 'rising plate meter' (RP); measuring the height of pasture using a 'CDax' pasturemeter (C-Dax Ltd, Palmerston North, NZ) or ultrasonic sensor; and using multi-spectral satellite image data. Cutting, although an absolute measure, destroys the pasture. Underlying the use of pasture height as a measure of biomass DM is the assumption that the bulk density of the pasture is constant for a range of farm pasture conditions. In practice, it has been found that this was not true and the correlation between DM and height was not strong (King et al., 2010; Moeckel et al. 2017).

The use of an ultrasonic sensor mounted on a farm bike and remotely sensing pasture properties is attractive because of potential low cost, low power, compactness, and the ability to both sense the depth of the pasture as well as pasture density information within the pasture layer. It is necessary to design for appropriate lateral and along-axis (vertical) spatial resolution. An 80 mm diameter spiral array of sensors is used to give a narrow ultrasonic beam having a half-power footprint diameter of 150 mm at the ground 1 m below the array (Patent 740348, 2018). Vertical resolution of 11 mm is achieved by using a linear FM chirp signal and matched filter. Profiles through the pasture were obtained at 100 s^{-1}. Figure 1 shows one profile, where the range to the ground is estimated via three methods, with a distance resolution of a few mm.

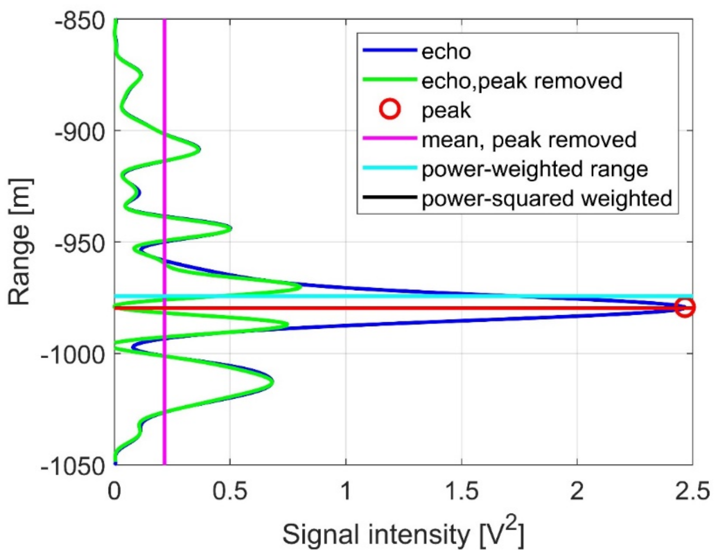

Figure 3: A single ultrasonic profile through pasture.

Echoes were obtained from blades of grass in the pasture canopy and from the ground. However, because of the strongly reflecting ground surface, secondary reflections also occur (reflection from ground then pasture, or from pasture then ground), giving echo signals at a range greater than the direct range to the ground. This means that care must be exercised that the correct distance to the ground is estimated. Such multiple reflections were also encountered in satellite synthetic aperture radar estimation of vegetation properties (Chen et al., 2018).

Laboratory calibration with disks of diameter 6 mm to 60 mm show excellent agreement with an ultrasonic scattering model developed for this instrument. While this allows for absolute reflectivity to be estimated, the scattering process involves pasture swards of varying orientation, and multiple swards in the scattering volume at times. This means that careful field calibrations are required. Analyses were performed on 78 pasture quadrats of size 1500 x 500 mm from a range of sites and seasons. Correlations between direct measurement of biomass (through cutting, drying, and weighing) and a number of estimators of biomass showed statistically significant improvement in DM estimation using an all-ultrasound estimator which combines pasture depth with ultrasonic reflectivity. The coefficient of determination, R^2, between direct biomass measurement and predictor variables was 0.2 for pasture height methods, such as CDax pasturemeter, 0.5 for the RP, and 0.6 for the all-ultrasound method.

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THE ASSOCIATION OF SOIL TYPES AND RAPE BIOMASS FOR NITROGEN VARIABLE RATE APPLICATION

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Since 2013, *Défisol* operates as Research and Development branch of *be Api*. Our company provides a wide variety of services on crops mapping for nitrogen fertilization. Our expertise offers a holistic approach of the field crop and integrates wide range of biotic and abiotic parameters (e.g. climatic factors, crop species, pests...). We mix cutting-edge technologies of remote sensing and teledetection with local soil variables to produce maps at large spatial scales. These maps are widely used as management tools for farmers and agricultural companies.

This study has a dual objective:

1. To evaluate the necessity of to sample the biomass every time we collect spectronomics data
2. Evaluate the need to use a soil map for more accurate nitrogen recommendation

To do so, in the last two years we surveyed a 30 ha field in North-Western France (Normandy, Eure) with drones and satellite imagery (NDVI, i.e. Normalized Difference Vegetation Index). This land covers a wide diversity of soil textures. The NDVI maps were compared with local biomass samples, allowing us to generate a biomass variability map. In order to optimize the recommendation, we designed a modulation of yield objectives depending on soil properties.

Our results clearly show that the calibration of satellite imagery with local biomass sample give the best predictions and more accurate maps of nitrogen uptake. We demonstrated that without the calibration with field measured at each satellite survey, the local discrepancy of the crop Nitrogen uptake could be in the same field both:

- underestimated by up to 54% at the parcel scale, i.e. an over-estimation of 35 unity of Nitrogen per hectare.
- overestimated by 16% at the parcel scale, this difference could reach 45 unity of Nitrogen per hectare.

Regarding the consideration of the soil nature in the land we compare two cases:

- (i) The non calibrated biomass map with a homogeneous soil type on the entire land (a yield objective of 40 hundredweights per hectare)
- (ii) The calibrated biomass map with all three types of soil in the land (a yield objective of 36,40 and 44 hundredweights per hectare).
-

The discrepancies of nitrogen recommendations between the two are shown in the following map.

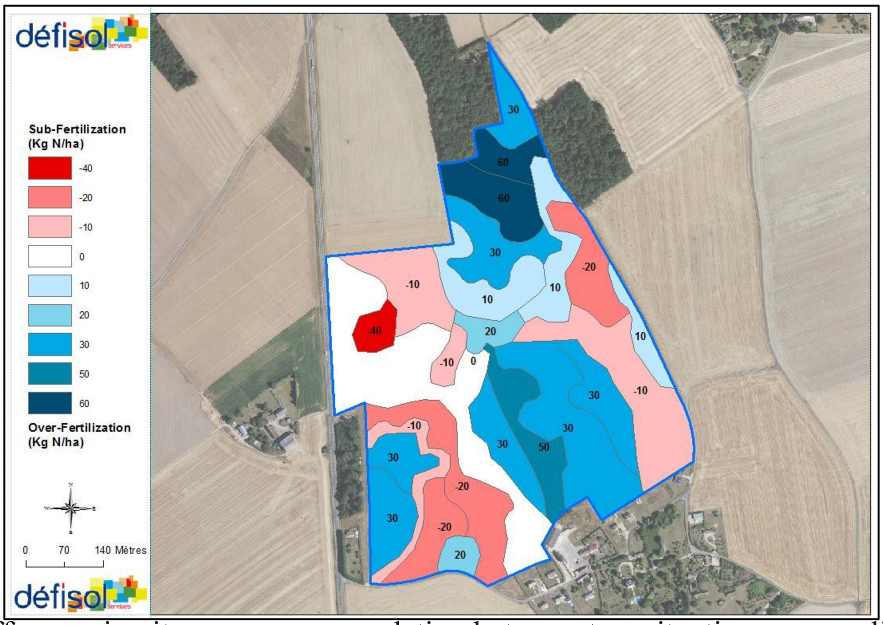

Figure 1: Difference in nitrogen recommendation between two situations: non-calibrated biomass
/ calibrated biomass with consideration of soil types

The results are the following:

- On 32% of the land, the first case induces an over fertilization of 20 to 60 unity of Nitrogen per hectare. In this case there is a significant risk of nitrogen washout in the environment
- On 15% of the land, the case (i) leads to a under fertilization of 20 to 40 unity of Nitrogen per hectare. This could lead to a lower yield in this area
- Finally the total recommended fertilizer usage is quite close (185 unity of Nitrogen per hectare (i) to 182 unity of Nitrogen per hectare (ii)) but the distribution is different

Intra-parcellar cartography of soils and satellite imagery are a real opportunity for soil heterogeneity characterization and the optimization of nitrogen fertilizer usage. These informations will have to be calibrated with measurements and physical observations (weighing biomass or soil profiles), and at the end, validated by the end users : the farmers. These methods must be validated and deployed at a larger scale to face environmental and economical issues of the farmers.

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USING PROXIMAL IMAGERY TO IMPROVE CARBON AND NITROGEN BALANCES APPROACHES OF A WINTER WHEAT CROP UNDER VARIOUS NITROGEN FERTILIZATION STRATEGIES

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In order to estimate the carbon sink or source power of ecosystems, their carbon balance is established (Gourlez de la Motte, 2019). For crops, these balances assess the entering and leaving carbon fluxes through three main components: (1) gaseous exchange measurements (photosynthesis, autotrophic and heterotrophic respiration), (2) biomass carbon accumulation by weighing and analysis or inferred through other parameters (such as height or reflectance indices), and (3) carbon soil content by successive samplings and leaching estimations through modelling (e.g. Hydrus or EPIC) (Izaurralde et al., 2006; Reichstein et al., 2007; Doltra & Muñoz, 2010; Chapin et al., 2012). The same balances can be performed for nitrogen, though uncertainties remain concerning N_2O flux measurements and the quantification of N based inputs (Lognoul et al., 2017; Bodson et al., 2017).

Nowadays, computer vision is increasingly employed in precision agriculture to investigate crop phenotypes (Araus & Cairns, 2014). Imaging spectroscopy (e.g. multispectral and hyperspectral) is identified as a mature and reliable technique for plant phenotyping, while stereovision provides complementary 3D architectural information (Thenkabail et al., 2012; Li et al., 2014). The analysis of the raw data collected provides information on a wide range of plant traits, such as estimates of nutrient (e.g. N, C, P, S, K) and water content, photosynthetic capacity, or biomass (Pimstein et al., 2011; Thenkabail et al., 2012; Mahajan et al., 2014). The information gained from those imaging methods only concerns the above-ground parts of the vegetation.

In this context, this study will aim at investigating the carbon and nitrogen balances of above-grounds parts of winter wheat (*Triticum aestivum* L.) in fields located in the Hesbaye area (Gembloux, Belgium), under contrasted nitrogen fertilization strategies, by combining two non-destructive approaches. Stereoscopic and multispectral imagery at a proximal distance will be combined with gas measurements to improve the carbon and nitrogen balances of crop. These estimations will be compared with destructive sampling and nutrient content analysis. Carbon and nitrogen soil content and leaching estimations will not be included in the balances, which will centre on the above-ground parts of the crops.

The designed method along with the accuracy of the expected results are discussed.

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PREDICTION OF ORGANIC MATTER AND CLAY CONTENTS USING DIFFUSE REFLECTANCE SPECTROSCOPY VIA PARTIAL LEAST SQUARES REGRESSION ANALYSIS AND RANDOM FOREST

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INTRODUCTION

Results of the use of precision agriculture techniques are still poorly understood in mixed production systems, such as integrated crop-livestock systems, as well as the knowledge of the spatial and temporal variability of the attributes that interfere in the production in these systems.

The characterization of the spatial and temporal variability of soil attributes is fundamental for understanding the impact of integrated systems on soil fertility, especially for application of precision agriculture techniques, such as variable rate fertilization. However, cost of soil analysis in a large number of samples may make this characterization unfeasible. On the other hand, diffuse reflectance spectroscopy (DRS) is a low-cost and non-destructive rapid prediction tool that can be applied for the simultaneous characterization of different soil attributes, and may contribute for the feasibility of characterization of soil attributes.

In general, the characterization of soil attributes using DRS is made by developing chemometric models based on Partial Least Squares Regression (PLSR). However, in the recent years, advances computational techniques, such as machine learning algorithms (MLA), have provided new techniques for data modeling. In this sense, this study aimed to model and predict clay and organic matter contents using DRS via PLSR analysis and Random Forest (RF) regression algorithm.

MATERIAL AND METHODS

The study area is located in Caiuá municipality (West region of São Paulo State, Brazil), and currently cultivated with pasture. The soils present in the area are originated from sandstones from the Bauru Group. Soil samples were collected from 276 sample points in the 0 to 20 layer and 159 sample points in the 20 to 40 cm layer (total of 435 samples) over an area of 200 hectares. The granulometric and organic matter analyzes were performed in the soil samples. Reflectance values were recorded in visible-near infrared (VIS-NIR) range at a spectral resolution of 1 nm using the FieldSpec 4 spectroradiometer (Analytical Spectral Devices, Boulder, CO, USA). Spectralon® (PTFE) powder was used as white standard. Reflectance values were converted into absorbance measurements using the following equation: [log10 (1/Reflectance)]. In addition, the mean centering was applied as a pretreatment method of the spectra. Partial least squares regression analysis and Random Forest were performed to relate spectra and soil attributes. We used at least 400 decision trees in each RF implementation following preliminary tests of model performance. The number of spectra variables randomly sampled at each split was equal 30 and 24, respectively, in the prediction of OM and clay contents. Coefficient of determination (R^2), root mean square error (RMSE), and residual prediction deviation (RPD) were calculated to evaluate the accuracy of the models. The classification proposed by Chang et al. (2001) was considered for RPD values, in which RPD > 2 indicates good, 1.4 < RPD > 2 indicates reliable, and RPD < 1.4 indicates not very reliable predictions.

RESULTS AND DISCUSSIONS

The clay and organic matter contents ranged from 22 to 241 g kg^{-1} and from 5 to 22 g kg^{-1}, respectively. Table 1 shows the cross-validation results of the prediction models for soil attributes obtained by PLSR and RF. Soil attributes prediction models were satisfactorily calibrated using PLSR (residual prediction deviation – RPD > 1.4, R^2 > 0.6). On the other hand, the RF models did not performed well for predicting soil attributes in the study area, showing the lowest value of R^2 (0.38) and the highest value RMSE (2.33 g kg^{-1} or 20.5 %) in the prediction of organic matter content. For clay content prediction, the RF model performance was slightly superior, albeit still lower than the results obtained by PLSR. We also calculate the values of RPD for the RF results, which according with the classification proposed by Chang et al. (2001), the prediction of clay and organic matter contents using RF may be considered unsatisfactory.

Our results demonstrate that DRS has potential to be used for predicting clay and organic matter contents of soil using the PLSR method, and then enabling the characterization of spatial and temporal variability of these soil attributes. In our study, we emphasized the potential of the RF algorithm to predict soil attributes in integrated crop-livestock systems. Although the literature have demonstrated that RF has outperformed other classical methods (e.g. Santana et al. (2018)), RF did not bring any real improvements to the soil attribute predictions in our study. However, these results can be used as an insight-stimulating case study for further investigations.

Table 1. Summary of results obtained from the PLSR and Random Forest of the soil studied attributes.

Attribute	VIS-NIR			
	Cross-validation (PLSR)			
	F[a]	R^2	RMSE	RPD
Clay	9	0.61	26.50 (28.6%)	1.6
Organic matter	13	0.71	1.56 (13.7%)	1.9
	Cross-validation (RF)			
Clay	-	0.50	30.06 (32.5%)	1.4
Organic matter	-	0.38	2.33 (20.2%)	1.3

[a]Number of PLSR factors used in the model; R^2 = coefficient of determination; RMSE = root mean square error; RPD = residual prediction deviation.

CONCLUSIONS

VIS-NIR spectra provides potentially valuable information for spatial-temporal mapping of soil attributes in integrated crop-livestock systems. The best modeling approach for prediction of clay and organic matter in the study area was the PLSR analysis. Considering the cost of improving accuracy of soil attributes estimates by soil lab analysis, it seems sensible to invest in further studies that focus on new strategies of data modeling for spatial and temporal soil monitoring, such as new machine learning algorithms.

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ADOPTION OF VARIABLE RATE IRRIGATION IN NORTH-EAST ITALY

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Introduction

Water supplies are becoming a concern for some European countries (European Union, 2009) and approximately 70% of water worldwide is used for agriculture (OECD, 2012). Studies have suggested that Precision Agriculture might improve water management (Cassman et al., 2002; Oenema & Pietrzak, 2002), and more precisely Variable Rate Irrigation (VRI) to enhance water-use efficiency (Hedley & Yule, 2009) and yields (King et al., 2006). However, in Italy, only 200 farms use VRI, mostly for the production of herbaceous crops (Ministero delle Politiche Agricole Alimentari e Forestali, 2016).
This study hypothesizes that the decision to adopt VRI is not solely based on the net benefits but is also affected by perceptions and intentions regarding the technological and social context. Hence, the main objective of the current study was to shed light on factors affecting adoption of VRI in Italy by considering the case of fruit and winegrape producers and applying the Technology Acceptance Model (TAM) as a theoretical framework/model.
TAM aims to understand and explain factors that influence the user in the decision-making process when adopting information technology systems. TAM uses causal relationships between 1) external variables 2) perceived usefulness 3) perceived ease of use 4) behavioural intent and 5) actual use. The external variables directly affect perceived usefulness and ease of use, and indirectly influence behavioural intentions and actual system use.

Materials and Methods

The structured questionnaire applied to this study was designed based on the TAM3 model (Venkatesh & Bala, 2008), literature review, and results from a previous qualitative study. The questionnaire, after a pre-test, was structured in 4 parts: (1) intention to adopt precision agriculture technology (PA) and technology usage; (2) opinions toward innovative technology; (3) socio-demographic information of the respondent and (4) characteristics of the firm. In the attitude section, respondents were asked to give their opinion about statements related to VRI according to a 7-point Likert-like scale, ranging from 1 (Totally disagree) to 7 (Totally agree). Prior to part 1, respondents were informed about PA and prior to the opinion section they were informed about VRI. Data were collected with fruit producers or winegrowers who have never adopted VRI technology; operating in the North-East of Italy (Emilia-Romagna, Veneto, Friuli and Trentino-Adige regions). These regions are important areas of fruit and wine-grape production. A convenience and a snowball sampling was used.
A paper-based producer survey was administered at the “FuturPera” Agricultural fair from 16-18 November 2017 in Ferrara, Italy, and an online survey (www.qualtrics.com) between November 2017 - February 2018.
Descriptive statistical analysis was used to describe producers’ socio-demographics and farm characteristics. Data regarding technology adoption was elaborated using the Partial-Least Square Structural Equation Model (PLS-SEM) aimed at understanding how each factor can influence the decision to adopt VRI. Data analysis for PLS-SEM was performed by using the statistical software SmarPLS2 (Ringle et al, 2005).

Findings

Most respondents were male (89%) as expected when targeting farmers in Italy. The average age was 43 and experience working in agriculture was 21 years. Most respondents graduated

from high school (45%) and 38% had a university degree. This might be because the survey was conducted during the fair and used the online platform, therefore, many participants had a higher-level education than the average farmer. The average total farm area was 30 hectares. Nevertheless, farm size was quite diversified: from 1 hectare to 200 hectares.
Thirty-four percent of respondents said that they have already adopted at least one precision agriculture technology. The most adopted PA technologies were sensors monitoring humidity and temperature (64%), automatic section control (30%) and GPS guidance (26%).
Results on the TAM3 confirmed the following hypotheses:

- Perceived usefulness has a positive effect on the behavioral Intention to adopt VRI
- Perceptions of external control have a positive effect on the perceived ease of VRI use
- Perceived enjoyment has a positive effect on the perceived ease of VRI use
- Objective usability has a negative effect on the perceived ease of use VRI use
- The subjective norm has a positive effect on the behavioral intention to adopt VRI
- The subjective norm positively affects which image to adopt VRI
- Results demonstrate a positive effect on the perceived usefulness of adopting VRI

To summarize, results suggested that norm and usefulness are the most important issues for farmers when adopting new technology. They might consider adopting technology if persons whom they consider important think they should adopt it or if they see its usefulness through concrete results. These results are in line with other studies which have measured intentions to adopt PA. Alavion et al. (2016) found that subjective norms are relevant predictors for intentions to adopt PA technologies especially for public professionals.

In conclusion, we propose that in order to promote the adoption of VRI, authorities should demonstrate the usefulness of the technology in a very concrete way, e.g., by giving examples of farmers who successfully adopt it and have fruitful results. In addition, they should provide appropriate policies as well as financial and technical support to encourage producers to adopt the technology.

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VARIABLE RATE NITROGEN IN DURUM WHEAT ACCORDING TO SPATIAL AND TEMPORAL VARIABILITY

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The monitoring of soil apparent electrical conductivity (EC_a) (proximal sensing) and the acquisition of multispectral images (remote sensing) could allow the identification of homogeneous zones within the fields with the aim at obtaining prescription maps as well as optimizing N inputs management (Castrignanò et al., 2009; Casa et al., 2011). In particular, N management represents a challenge in Mediterranean systems where agroecosystems depend mainly on winter cereals (i.e. durum wheat, soft wheat, barley).

A field experiment was carried out in Mosciano Sant'Angelo (N42.706950°; E13.891421°) during 2017/2018. Durum wheat (*Triticum durum* Desf. cv. Aureo) was sown on December 2017 at a density of 450 seeds m^{-2}. Four N treatments, replicated twice, were applied: (i) three standard N applications at 250 kg ha^{-1} (N_250), 150 Kg ha^{-1} (the conventional rate applied by farmers; Conv) and 0 Kg ha^{-1} (N_0) and (ii) one variable rate N distribution (VRA). To perform VRA, the EC_a was measured prior to sowing with a CMD sensor Mini Explorer (Gfinstruments, Czech Republic), connected to Trimble GNSS. In addition, at stem elongation, multispectral images from Sentinel 2 platform were acquired and at stem elongation and booting phases, plant samplings (six sub-samples of 1 m^2 for each treatment) were performed in order to determine the biomass (dry weight, DW) and N content (Kjeldahl method) and to estimate the crop N-uptake (kg N ha^{-1}). N was applied as Urea in two appplications (stem elongation and booting); crop management also included a uniform N application at tillering stages (50 Kg N ha^{-1} as Ammonium Sulphate). VRA was performed with X25 (Topcon, Japan) connected to AXIS fertilizer spreader machine (Kuhn, Italy).

At harvest, six sub-samples of 1 m^2 of whole plants were randomly collected from each treatment in order to determine yield and grain protein content (GPC). The EC_a map clearly showed two homogeneous zones of low and high soil fertility levels (Figure 1).

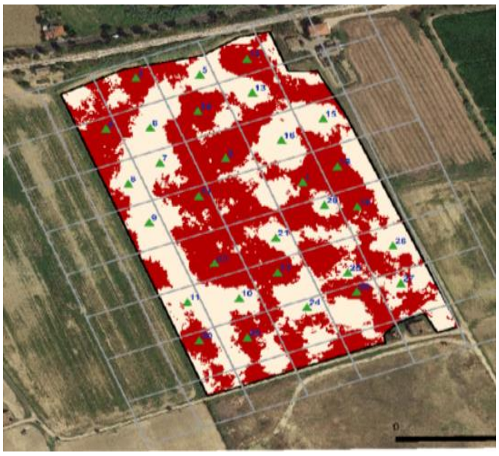

Figure 1: EC_a map; white zones: $EC_a <= 0$ – lower fertility; red zones: $EC_a > 0$ – higher fertility. Each grid bordered by grey lines represents a surface of 50x50 m.

Starting from Sentinel 2 data, maps of Normalized Difference Vegetation Index (NDVI) were obtained (Figure 2a). The NDVI map and N-uptake data were used to process the prescription maps for the two VRA treatments (Figure 2b and 2c).

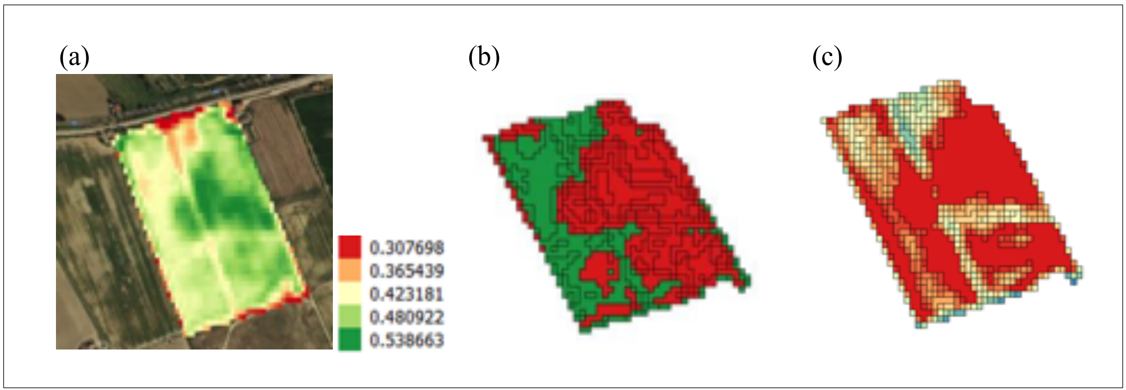

Figure 2: (a) NDVI map from Sentinel 2 data. (b) Prescription map for the first VRA application (stem elongation): red, 30 kg N ha^{-1}; green, 40 kg N ha^{-1}. (c) prescription map for the second VRA application (booting phase): red, 0-15 kg N ha^{-1}; orange, 16-65 kg N ha^{-1}; yellow, 66-96 kg N ha^{-1}; green, 97-135 kg N ha^{-1}; blue, 136-165 Kg N ha^{-1}.

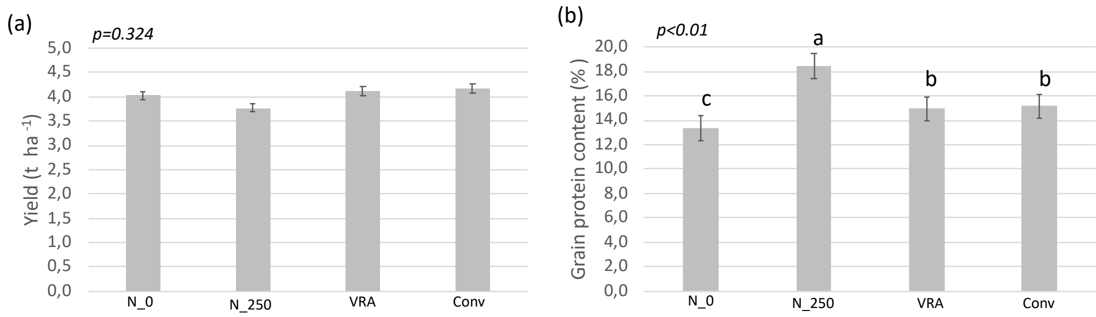

Figure 3: (a) Yield (t ha^{-1}) as recorded for durum wheat under different N management regimes. (b) grain protein content (%) of durum wheat under different N management regimes. Different letters significantly differ (Fisher's LSD test, $P<0.05$).

No significant differences in terms of yield ($p=0.324$) were recorded among N fertilization treatments, despite the highest values being observed for Conv and VRA (4.2 and 4.1 t ha^{-1}, respectively; Figure 3a). Although the highest GPC was achieved with the N_250 treatment, those observed under VRA treatment (14.9%) fall within the quality ranges recognized by contract farming (at least 14.5%).
In conclusion, VRA allowed to guarantee high durum wheat yield performances (comparable to those obtained under the other N fertilization regimes - Conv in particular) characterized by an appreciable protein content (high technological quality) as well as a significant N saving (-33% of N applied with respect to Conv treatment) with positive impacts on environment (leaching, air and groundwater pollution) and management costs.

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VINEYARD MODELLING FOR PRECISION AGRICULTURE: COMPLEXITY REDUCTION OF VINES DENSE 3D-POINT CLOUDS FROM UAVS REMOTELY SENSED IMAGERY

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Introduction

In Precision Agriculture, autonomous robots and machines are empowering farmers to increase crops yield quality and quantity, by acquiring extensive data on crops status and to perform effective, timely and cost-effective managements (Wolfert et al., 2017; Zaman et al. 2019). Autonomous robots for site-specific operations and crop monitoring require enhanced path planning for the proper interaction with crops in complex scenarios (Grimstad & From, 2017; Henten et al., 2013). This can be robustly performed by integrating the standard two-dimensional (2D) georeferenced maps of a field with the information provided by updated three-dimensional (3D) models of the crop. Presently, very dense 3D point clouds are provided by terrestrial laser scanner (TLS) as well as from imagery acquired by unmanned aerial vehicle (UAV), processed using structure from motion (SFM) approach (Comba et al., 2018).

However, due to huge amount of detailed information stored in these datasets, they are usually contained in large size files and they are not suitable for communication in real time processing by onboard control systems. Therefore, the rapid growth of acquisition systems of high-quality big data demand new and improved methodologies and analytical methods to transform them into easy to process, meaningful and simplified information (Wolfert et al., 2017).

Materials and Methods

In this work, an innovative algorithm to process and reduce the complexity of very dense 3D point clouds of vineyards is presented. The objective is to obtain georeferenced low-complexity 3D model for the real-time-path planning and navigation of autonomous vehicles and machines. The algorithm output is a simplified triangulated 3D mesh surfaces for vineyard representation, consisting on a limited number of instances. In addition, the developed algorithm can automatically classify the portion of model representing vine rows and inter-row spacing.

The effectiveness of the proposed approach was evaluated on a set of 10 portions of vine rows models, of around 8 meter length each, composed of a very large number of points. A sample of a detailed triangulated mesh model of a vine row portion, composed of more than 37,000 vertices, generated from a dense point cloud dataset, is represented in figure 1.a. The coherence of the low complexity mesh model with respect to the original detailed one was evaluated according to three different indexes as: (1) *good-modelling* (overlapping volumes between original dense mesh and low complexity mesh), (2) *under-modelling* (volume not covered by low complexity mesh model), (3) *over-modelling* (over estimated volume compared to original dense mesh).

Results

The modelled vineyard dataset results to be more than 400 times lighter compared to the original point clouds dataset, meanwhile assuring minimal loss of information. In Figure 1b, the low complexity triangulated mesh model, composed by less than 1,000 vertices is obtained by processing dense mesh model of Figure 1a. A linear programming approach has been adopted to determine the optimal values of the developed algorithm parameters, which minimize the error function computed as combination of three defined model quality indexes. The algorithm parameters were extensively tested to always achieve a *good-modelling* index greater than 90%, assuring a proper representation of the real vine row layout.

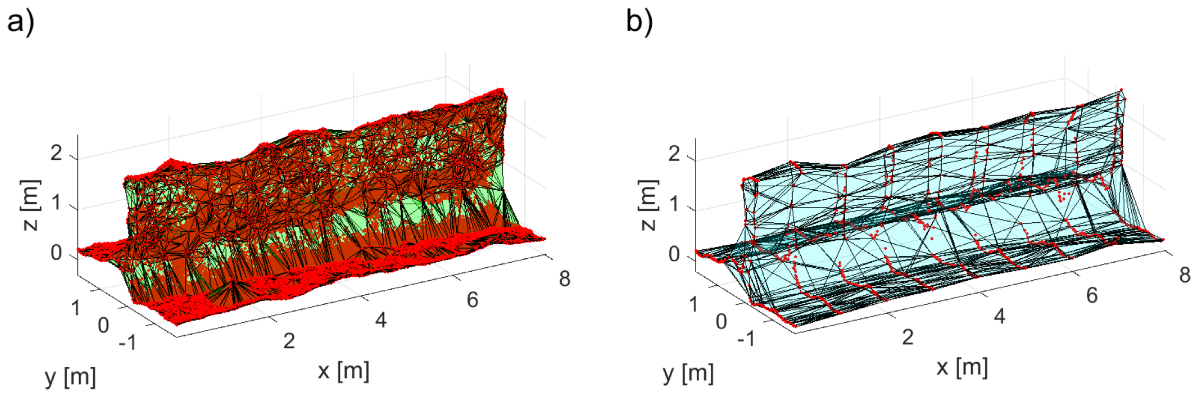

Figure 1: (a) Original dense 3D triangulated mesh of a vine row portion and (b) low-complexity model resulting from its processing.

Conclusions

The obtained low-complexity 3D model with georeferenced information, which is highly detailed while having a very small file size, is compatible with real time path planning of infield robot's navigation. The developed algorithm has been properly calibrated to process complex dense models such as hilly fields and it is not hindered by non rectilinear vine rows. The resulting low complexity model confirms the effectiveness of the proposed method and its fitness for automatic control solutions in precision agriculture applications.

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SPATIALLY RESTRICTED PARTIAL LEAST SQUARE REGRESSION TO EXPLAIN WITHIN FIELD GRAIN YIELD VARIABILITY

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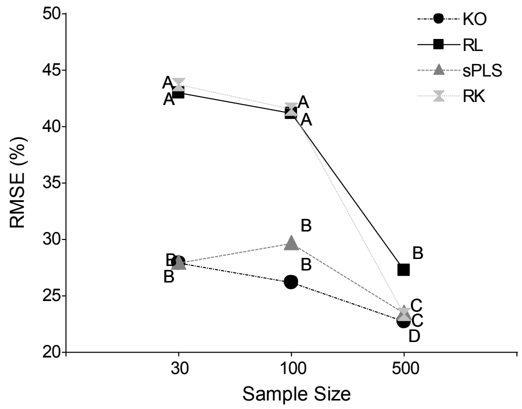
The new information technologies that allow us to capture different types of data associated with spatial localization have been promoted in the last decades. Grain yield and several site variables are intensively measured within a crop field. Therefore, the challenging is to use all available data to better understand the agronomical process underlying within field yield variability. Because of the site variables are usually correlated between them (multicollinearity) and present spatially auto-correlated, the regression models to evaluate de relative contribution of each site variable should account for both types of correlations. Here we propose an extended version of partial least square regression (PLS) (Abdi, 2010) as designed algorithms to treat the multicollinearity and spatial autocorrelation. The algorithm combines PLS and ordinary kriging (OK) and is named as spatial PLS (sPLS). Initially, a PLS regression technique of yield using predictive ancillary variables was carried out in order to model the trend component. In the second step, OK is applied to the residuals of PLS and a spatial prediction of the residuals was created. The final prediction was an additive combination of both models.

A total of 100 grain yield maps of corn crops from Argentinean Pampas were processed with sPLS algorithm using the topographic variables as site covariates. Predictors were computed from a 30-m digital elevation model (DEM). For each yield within the field, 15 topographic indexes were extracted from the DEM (Analytical Hill Shading, Aspect, Closed Depressions, Convergence Index, Drainage Basins, Fill Sinks, LS-Factor, Plan Curvature, Profile Curvature, Sky View Factor, Slope, Terrain Ruggedness Index, Total Catchment Area, Valley Depth and Vertical Distance to Channel Network). The statistical performance of sPLS was compared regarding predictive ability with multiple linear regression model (LR) and regression kriging (RK) (Hengl et al., 2007) that, as sPLS, combines a regression of the response variable (yield) on auxiliary variables (topographic indexes) with kriging of the regression residuals. A 10-fold cross validation was used to estimate prediction errors for each model. The root of the mean square prediction error was expressed as percentage of the mean yield (RMSE). To simulate different scenarios in which explanatory variables are measured within the field, the models were fitted in each field using samples of size 30, 100, and 500 data points. The samples from each yield map were obtained using a conditioned Latin hypercube algorithm including in the process the 15 topographic variables and yield. To compare sPLS with RK and other classical approaches, a Linear Mixed Model (LMM) (West et al., 2015) was fitted on the prediction errors including fixed effects of method, sample size and their interactions, as well as a random effect of yield map. Mean comparison was done using a Fisher LSD method for a significant level of 0.05.

All the methods that incorporated the spatial information in the analysis showed a better performance (lower RMSE) than RL (Figure 1, left). For low sample sizes (30 and 100) sPLS performed better than RK. There were no significant differences between sPLS and OK for the three sample sizes which would indicate that prediction from topographic indices was similar to the one obtained using yield information. However, for the purpose of explaining yield variability, using sPLS was possible to quantify the impact of each topographic attribute on corn yield (Figure 1, right). The Fill Sinks, Valley Depth, Vertical Distance to Channel Network and Closed Depressions had an average relative importance across all the maps, higher than 15%. The results showed that sPLS is a useful tool to explain within field yield variability and can be used with other site variables that can be evaluated with low sample sizes.



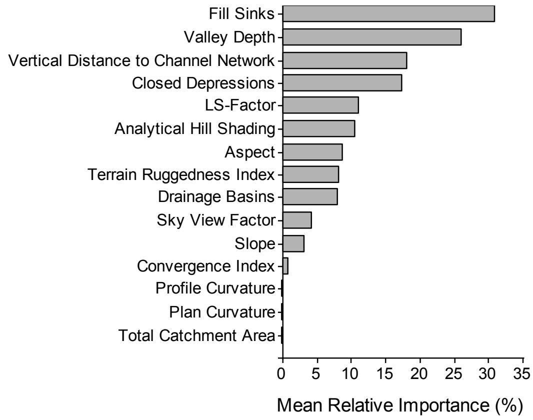


Figure 1: Average Root mean square prediction error (RMSE, %) of four models (left): ordinary kriging (OK), RL (multiple linear regression), spatial partial least square regression (sPLS) and regression kriging (RK). Mean Relative variable importance obtained from sPLS (right).

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FIELD ROBOT REMOTELY-OPERATED TO INSPECT OLIVE TREES AFFECTED BY *XYLELLA FASTIDIOSA* BY PROXIMAL SENSING

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Keywords: Robotics, in-field mounted sensors, computer vision, multispectral imaging, LiDAR, asymptomatic and early detection

The use of remote sensing to map the distribution of plant diseases and detecting infections in early stages has evolved considerably over the last decades. An intelligent and remote robotic solution XF-ROVIM (Rey et al., 2019) has been developed in order to detect early infection of *Xylella fastidiosa* in olive fields using proximal sensing, as part of the diagnostic and surveillance programmes within the XF-ACTORS project (EU H2020 GA Nº 727987). This work shows the development of the robotic platform. The robot can operate remotely driven for six hours and it is provided with a DSLR (Digital Single Lens Reflex) camera, a DSLR camera modified to capture BNDVI (Blue Normalized Difference Vegetation Index) images and a multispectral camera capable of acquiring eight wavelengths in the region from 550 to 850 nm. Also, a 2D LiDAR (Light Detection and Ranging) scanner was mounted to obtain three-dimensional structural features of the trees. An encoder coupled to the motor axis allowed synchronised the advance of the robot to the triggering of the cameras. A lifting platform allowed to rise the cameras up to 2 m to improve the capture of images of the highest trees. Additionally, a GPS (Global Positioning System) and an IMU (inertial measurement unit) served to geolocate all the gathered information and correct the data captured by the LiDAR.
The robotic system developed has been tested in the area of Lecce (Italy) in an orchard of olive trees infected by *X. Fastidiosa*. The surveys were done o test the robustness of the system, including the electronics, the accuracy of the geolocation, the accurate collecting of data, the organisation of the data, the handling of the robot, the duration of the batteries, or the utility of the data collected to detect trees infected by *Xf*. During the surveys, , the robot moved at a speed of 1 m/s capturing around 35000 images (one every metre) with all cameras and collected 3D points using a LiDAR at a frequency of 25 Hz (LiDAR, GPS and IMU were configured to operate in free range and making the synchronisation by time stamp and a resolution of 1 ms). The surveys were carried out under different weather conditions and the robot advanced in each row first collecting data from the trees of one side, and later from the trees on the other side of the same row in its way back, collecting data of the entire tree.
The images acquired using the multispectral cameras have been analysed to calculate the BNDVI and NDVI indices attending to equations in Calderón et al. (2013). Before, during and after the inspection, images of a standardised colour checker (ColorChecker SG Chart, X-Rite Inc, USA) and a white reference target (Spectralon 99%, Labsphere, Inc, NH, USA) were acquired for the correction of the images.

The collected LiDAR coordinates were converted to the WGS 84 / UTM (Universal Transverse Mercator) coordinates system in the 34T zone, being later corrected using the Euler angles (pitch, yaw and roll) provided by the IMU. The previously selected UTM centroids of each tree and a threshold of distance were used to select the points belonging to each tree. In order to calculate the tree leaf indices, each tree 3D structure was divided into a three-dimensional voxel grid of 10 x 10 x 10 cm resolution. The voxels were set to on/off whether or not they contained a point (presence or absence of leaves). Finally, the LAI (Leaf Area Index) was calculated as the sum of the different projected LAD (Leaf Area Density) at the different heights of the tree, being these heights taken every 10 cm (horizontal slices), where the LAD is the effective area density obtained from the ratio of 'on' voxels in the slide divided by the total area of the external contour extracted for that slice (Hosoi & Omasa, 2016). All the software developed to analyse the images and process the LiDAR information has been developed in MATLAB (9.3 R2017b, The MathWorks Inc., USA).

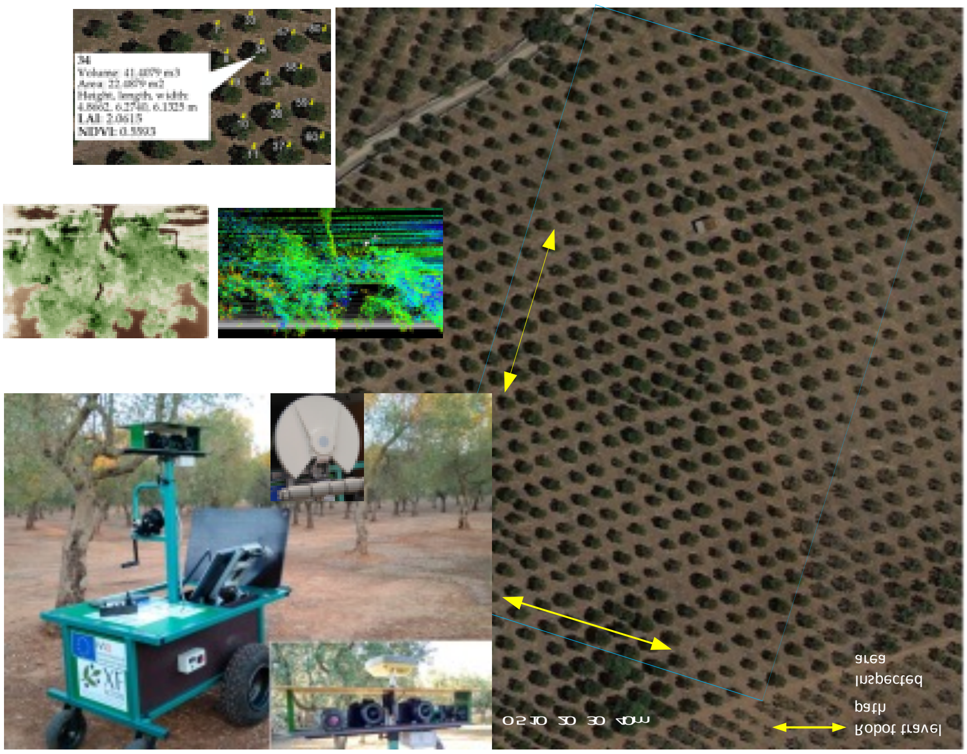

Figure 1. Process of the field inspection. Firstly, Xf-Rovim collects information using cameras and sensors; Then, the images are analysed and the 3D tree structure is created from corrected scanned Lidar points; finally, key indices and features regarding to tree structure are calculated.

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WEED DIGITAL MULTISPECTRAL RESPONSES TO GLYPHOSATE

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The degree of injury caused by pesticides is called phytotoxicity, which can be measured through responses such as mortality, biomass of affected leaves and by means of visual scales such as the proposed by the European Weed Research Council (EWRC, 1964), with which scores of necrosis and chlorosis on leaves and other tissues of plants are attributed. These scales are widely used in scientific works, but the scores are quite subjective, depending on the assessor's knowledge of phytotoxicity, active ingredient and species (Ali et al., 2013; Huang et al., 2015), making it hard to accurately evaluate injury in experiments and making the site-specific management impracticable in major crops. The knowledge of the herbicide response pattern of weeds allows one to stablish a rationale control plan, changing as minimal as possible the agroecosystem, premise of integrated management. Thus, the objective of this work was to examine the optical/spectral responses of glyphosate phytotoxicity in weed species of economic importance in the Brazilian Cerrado (savana) through multispectral digital images and to build prediction models.
Two weed species with different levels of susceptibility to glyphosate, *Eleusine indica* (L.) Pers. and *Brachiaria decumbens* L., were cultivated in pots and subjected to crescent doses: 0%, 25%, 50%, 75%, 100%, 200%, 300%, 400% of the prescribed dose (1,440 g a.i. ha^{-1}) for *E. indica* and 0%, 15%, 25%, 50%, 75%, 100% for *B. decumbens*, in order to simulate a wide gradient of phytotoxicity. Visual scores were given by three trained evaluators at 7, 14 and 21 days after application. Digital images of the pots were taken with the Mapir® Survey 3 digital multispectral camera using the following bands of the electromagnetic spectrum: Green (560 nm), Red (660 nm) and Near Infrared (850 nm), with 12 megapixels resolution and spatial resolution of 0.8 cm/pixel. Images were also captured with the RGB camera of the iPhone 6, with 8 megapixels resolution. Images were taken keeping a standard height of 0.9 m from the ground.
RGB images were converted to the HSV (Hue-Saturation-Value) color space. Afterwards, images were segmented to separate plant from soil through Otsu's method (Otsu, 1979) based on hue histogram. Then, the median of hue for plant pixels and vegetation indices (VIs) such as the normalized difference vegetation index (NDVI), the soil adjusted vegetation index (SAVI), the ratio vegetation index (RVI), the difference vegetation index (DVI), the green normalized difference vegetation index (GNDVI) and the green ratio vegetation index (GRVI) were used as explanatory variables for phytotoxicity in regression models. All images were processed with the package EBImage (Pau et al., 2010) of software R (www.R-project.org/). Dose-response curves were fitted for each species. A log-logistic model (Ali et al., 2013) was used to describe the response of phytotoxicity as function of glyphosate percentage. The goodness-of-fit of models was evaluated by calculating R^2 and the percent absolute mean error.
Differences were observed in terms of effective dose (ED50), which is due to the time needed for the herbicide to cause physiological damages. At 21 days after application (DAA), the ED50 for *E. indica* is estimated to be 6.75% of prescribed dose and for *B. decumbens*, 14.84%. The visual phytotoxicity obtained using the prescribed dose was above 95% for both species. Thresholds for hue ranging from 28 to 45 were capable of discriminating soil reasonably well. Similar values were found by Ali et al. (2013) for hue of non-green parts from 36 to 64 and from 64 to 169 for plant pixels. Figure 1 shows the kernel densities for hue values of plant pixels, the average for each dose. It is observed that non-affected plants of *E. indica* appear greener than non-affected plants of *B. decumbens*, as the first species presents

many pixels with hue around 90 and the second around 80. The sensitivity of *E. indica* is easily observed through the distribution of hue for low doses, starting at 25%, as it is not near the green region (~70-150), even seven days after application. The same occurs with *B. decumbens* at 21 DAA only. This strong decrease suggests an exponential behaviour of hue according to glyphosate injury. Plants receiving increasing doses of glyphosate presented decreasing values of hue. Frequency peaks are observed at hue values around 60 and 70, which are meaningful considering the visual symptoms, more evident at 21 DAA.

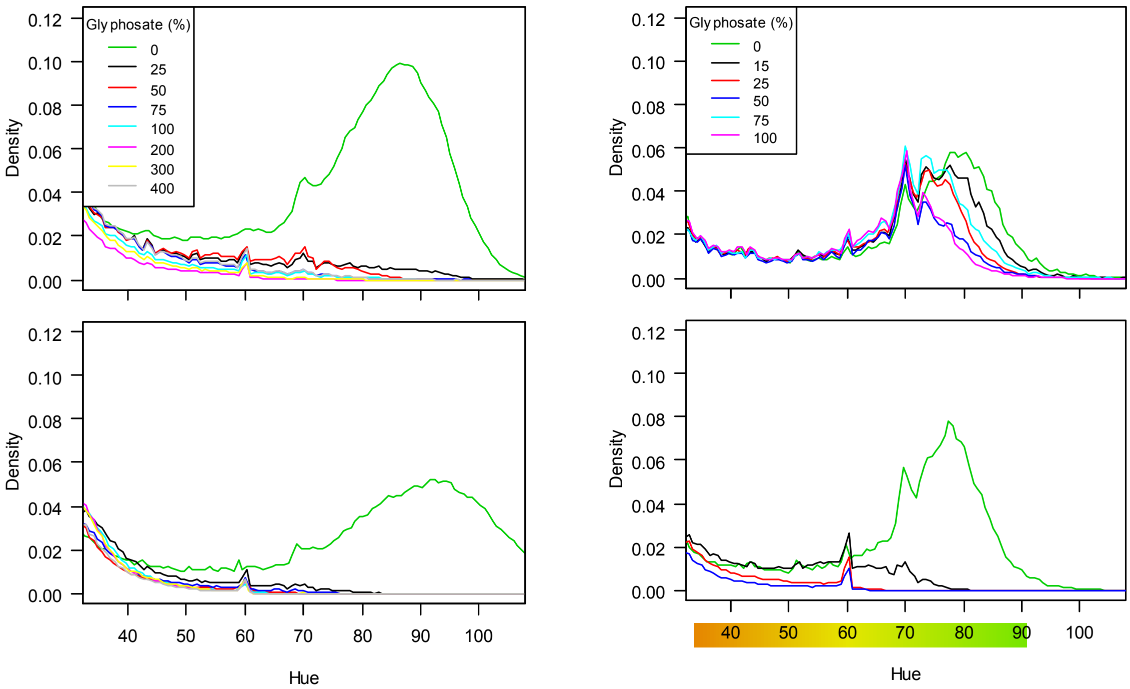

Figure 1: Kernel density of hue values for plant pixels of *E. indica* (left) and *B. decumbens* (right) at 7 (top) and 21 (bottom) days after application of glyphosate (1,440 g a.i. ha^{-1}).

No spectral band alone or vegetation index based on RGN images was capable of segmenting plant and soil accurately. Thus, models based on features of those images could not be fitted.

Using RGB images, both species presented exponential spectral responses of phytotoxicity to glyphosate. The median of hue for plant pixels presented the strongest relationships with phytotoxicity. The injury pattern was modelled by a power equation - a function of median of hue for plant pixels - with prediction errors below 15%.

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AN ECONOMIC-THEORY-BASED APPROACH TO MANAGEMENT ZONE DELINEATION

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In both the academic and popular literatures on precision agriculture technology, a management zone is generally defined as an area in a field within which the optimal input application strategy is spatially uniform. These zones need not be continuous. Despite major advances in and strong adoption of variable-rate (VR) technology which enables the VR management of these zones, the delineation of management zones has remained largely unchanged since the early literature in the 90's. The characteristics commonly chosen to delineate management zones, both in the literature and in commercial practice, are yield and variables associated with yield, such as soil electro-conductivity and soil tests. These variables were selected because previous literature assumed an input should be applied more intensively on higher yielding parts of a field as there is a yield limiting factor missing in the low yielding areas. The Law of the Minimum says that maximum yield is related to the most limiting growing factor; thus, additional units of any other input will not increase yield. However, it can be shown that yield potential does not determine optimal input application. Additionally, the Law of the Minimum allows for nitrogen to be the limiting factor, which would indicate more nitrogen should be applied to the less fertile areas of the field rather than the more fertile areas.

Microeconomic theory makes clear that optimal input application strategies do not necessarily depend on yield levels themselves; rather, they depend on the responses of yields to inputs. The response of yield to many different factors, including managed inputs and soil and field characteristics (e.g., electroconductivity and slope) is known as a yield response function, and the marginal product of nitrogen is the derivative of this function with respect to nitrogen. Solving the profit-maximization problem, the optimal nitrogen rate for a plot is given by a function of the variables in the marginal product of nitrogen. The optimal nitrogen equation demonstrates that using "yield zones" to determine "management zones" is likely to be a suboptimal strategy. A management zone should be an area of the field with the same marginal product function with respect to the input being managed.

There are several limitations and gaps in the existing literature. First the past literature generally manages a defined number of zones or clusters rather than managing each field unit or subplot separately. But if a manageable field unit can be defined according to the size of the machinery and experimental data is available, profits are likely to increase to with VR subplots management rather than VR cluster management. Another limitation of the past literature is the lack of zone prescriptions and economic analysis; many of the work establishes management zones without determining the input rates for each zone or evaluating the profitability of the rates compared to the optimal uniform input rate for a field. Rather, these studies tend to measure the validity of management zones based on the variation of the characteristic within and across zones. This research proposes a microeconomic-theory-based approach to establishing VR treatments.

Two management zones are compared: traditional yield zones created using a fixed number of zones and treatment zones based on the yield response function estimated with the trial data. The yield response function is estimated using a spatial error model to account for the spatial correlation present in field data. Additionally, the value of a soil test is estimated by comparing optimal treatments from two yield functions, one with soil test data and one without. Results indicate cation exchange capacity (CEC) is the soil nutrient affecting the response to nitrogen, and the presence of organic matter increases the response of yield to CEC. The yield function without soil data does not have nitrogen interacting with any field characteristics, so the profit maximizing nitrogen rate is uniform. Four management strategies are determined from the yield functions: variable rate management that chooses plot rate to maximize the profits for the plot, uniform rate management that choose the field rate that maximizes the sum of profits for the field, cluster rate management that chooses the cluster rate that maximizes the sum of the profits for each cluster, and the status quo rate of the farmer.

The profits from the strategies indicate this field does not have enough variability to make variable-rate application of nitrogen profitable over a uniform rate. The lack of variation does not allow this paper to compare the two management zone approaches, but increasing the variability of CEC results in a substantial difference in profits between the variable and uniform rate management. One interpretation of this result is that increasing the variation in soil types across a field gives higher profits from variable-rate application. Intuitively, this is also related to the value of soil tests; the value of a soil test increases as the variation in soil properties increases. This research contributes to the literature because variation and variable rate profits have been explored in the past using overall quality indexes rather than a specific soil nutrient. The results motivate more research on the soil properties influencing variable rate management of nitrogen and seed as well as the levels of variability that lead to significant profits.

VARIABLE-RATE IN REAL-TIME NITROGEN APPLICATION INCREASES ENERGY USE EFFICIENCY IN ARABLE AGRICULTURE

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On-farm energy efficiency is becoming increasingly important in the context of rising energy costs and concern over greenhouse gas emissions. Energy inputs represent a major inputs cost especially for the Greek agricultural industry which is highly mechanized and heavily reliant on fossil fuels. Precision agriculture is an emerging technology that is conceptualized by a system approach towards a low-input, high-efficiency, and sustainable production system. In this context, variable-rate application of in-season nitrogen (N) fertilizers is expected to reduce the net energy usage of agricultural systems as nitrogen is among the most energy intensive factors in the agricultural sector. In this study, an energy input-output balance is compared between two different N fertilization strategies for cotton, wheat and corn cultivations in the Thessaly plain, central Greece: 1. conventional N management (uniform N applications) and 2. an “Opt-N-Air” prototype variable-rate application (VRA) system developed in the HORIZON2020 “FATIMA” project. The VRA system, as described by Stamatiadis et al. (2018), consists of active crop canopy sensors that provide canopy NDVI or NDRE information to a data logger that processes the geospatial data under real-time conditions to convey a 1-Hz N rate signal to a spreader capable to deliver variable rates. The VRA system supplies in-season granular nitrogen fertilizer on-the-go by addressing in-field variation in soil nitrogen availability and crop response. The results of the study refer to six full-scale field experiments (wheat: 2016-2017, cotton: 2015-2016-2017, corn: 2017) with treatments laid out in a randomized complete block design. The calculation of energy sequestered in the crop was based on the farmers’ work schedule, time needed for each operation, the number of workers and the machinery and inputs used (seeds, fertilizers, insecticides and pesticides). Energy output was estimated by crop yields. The VRA system increased energy use efficiency (energy output/energy input) in average by 8.1, 23.4 and 21.7% in wheat, cotton and corn, respectively. The VRA system delivered significantly lower rates of in-season N fertilizer improving the N-use efficiency and thus reducing the total energy inputs in most fields (Fig. 1).

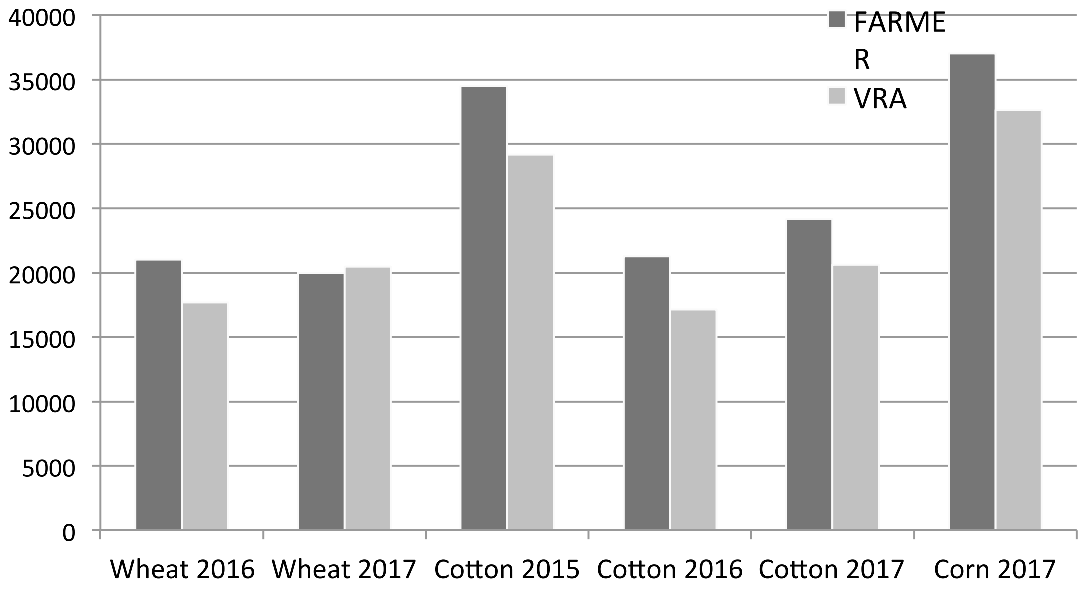

Figure 1. Total energy input (MJ ha^{-1}) in each experimental field under the conventional and VRA in-season nitrogen fertilization

The percentage of total energy embodied into N fertilizers to the total energy input was reduced by an average of 12.9, 25.2 and 18.9% in wheat, cotton and corn cultivations, respectively. These results indicate that VRA system of in-season N fertilization constitutes a promising technology for the reduction of the dependency of non-renewable energy sources in arable agriculture. Due to large energy requirements for mineral N production, the improved N-use efficiency of VRA resulted by spatially adjusting nutrient supply to the actual crop nutrient requirements and is a crucial step to attaining high energy use efficiency with economic and environmental benefits.

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ESTIMATION OF POTATO TUBER YIELD USING DUALEM -II SENSOR IN ATLANTIC CANADA: SITE-SPECIFIC MANAGEMENT STRATEGY

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Increasing agricultural productivity, reducing yield gap to obtain maximum yield and stability is of particular importance to the sustainability of the agricultural industry (Canadian International Development Agency, 2008; Lotter et al., 2003). New Brunswick (NB) and Prince Edward Island (PEI) are contributing 13.6 % and 24.5% of Canadian potato production annually. Given the importance of potatoes to the economy of Atlantic Canada - and Canada as a whole - early tuber yield forecasting is necessary to provide producers with timely information for rapid decision making to optimize management practices. Accurate tuber yield predictions can optimize the gap between actual and potential potato tuber yield. Soil properties, land and crop characteristics are variable spatially and temporally in agriculture fields, causing fluctuation in tuber yield within fields. This situation emphasizes the need to use non-destructive tools, such as electromagnetic induction (EMI) to assess the variations in tuber yield to facilitate effective decision making.
This study tested the potential of using DualEM-II sensor to estimate and map potato tuber yield variations in Atlantic Canadian potato fields to develop management zones for site-specific nutrient management. Four potato fields were selected in PEI and NB. A grid pattern of sampling was established at each site to collect horizontal coplanar (HCP) and perpendicular coplanar (PRP) data using the DualEM-II sensor. Geo-referenced tuber yield data were collected from each sampling location within the four fields. Regression analysis was performed to develop calibrations necessary for predicting potato yield from DualEM-II sensor data. The prediction accuracy was assessed through root mean square error (RMSE), and standard error (SE). Detailed maps were developed in ArcGIS 10.5 software to assess the tuber yield prediction accuracy within selected fields.

Results of descriptive statistics showed that yield was moderately variable with coefficient of variation ranging from 18.9 to 27.5% across the sites. The tuber yield was significantly correlated to ground conductivity data within the fields. Significant correlation was found between HCP and potato yield, with coefficient of correlation values ranging from 0.69 to 0.80 across the study sites. The HCP explained more than 55% of variability in yield with R^2 ranging from 0.57 to 0.66 using cubic models. Cross validation revealed that the predicted yield was non-significantly different from the actual values, and the RMSE was between 12.2 and 17.9%. Maps of actual and predicted crop yield showed similar trends of variation within the selected fields, supporting the correlation and regression analyses results.

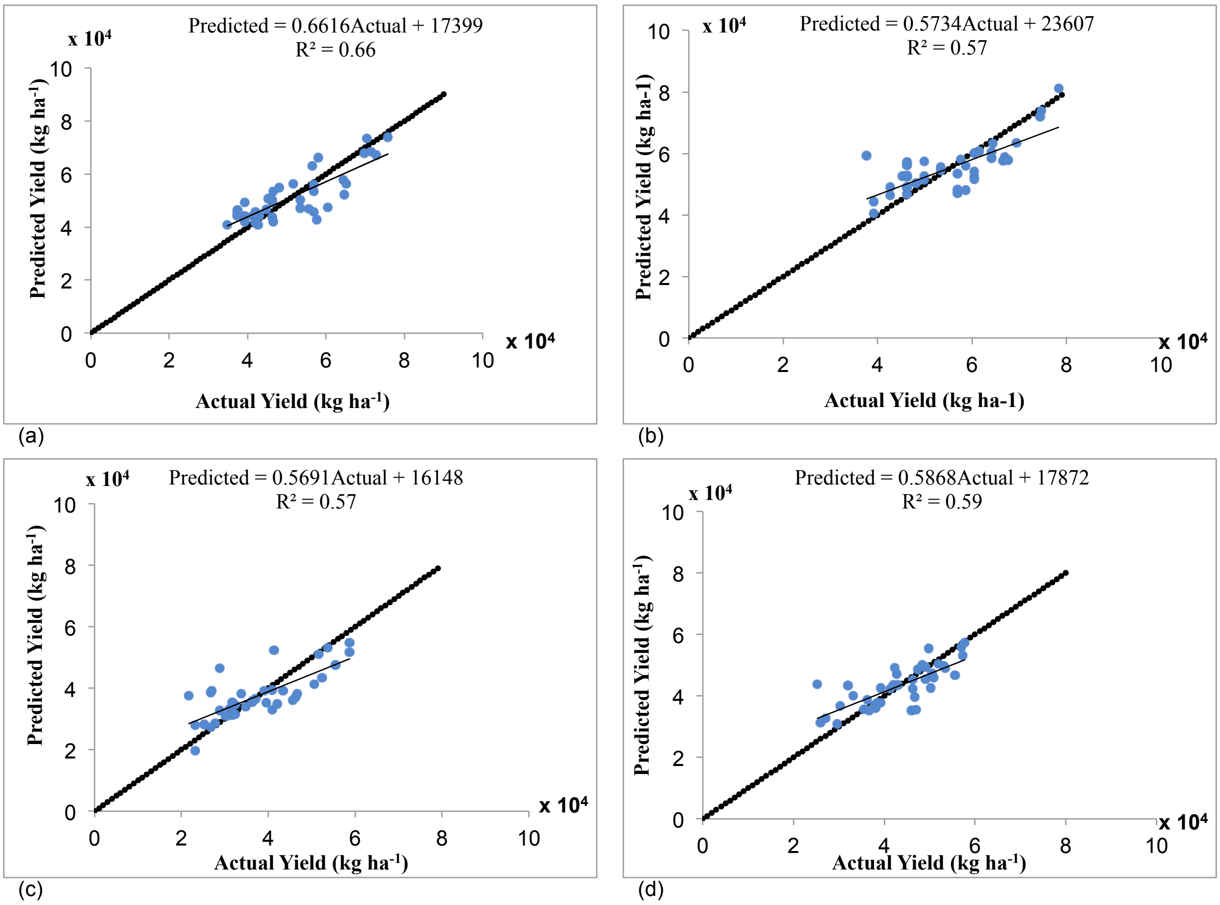

Figure 1. Observed vs. predicted potato yield estimates based on the cubic model of a) Field 1, b) Field 2, c) Field 3, and d) Field 4.

Findings from these investigations revealed that EMI technique can non-destructively estimate potato tuber yield in Atlantic Canada. Prediction of potato tuber yield can help to develop site-specific precision agricultural practices to improve potato yield and quality, and to prevent environmental risks. The mapped information can be used in soil sampling design, provide an initial level of understanding for making site-specific management recommendations to improve tuber yield and quality, and to achieve sustainable production of potatoes in Canada. Furthermore, the EMI based maps can be used to meter fertilizer and pesticide inputs for effective and cost efficient crop production.

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ISOBUS SIMULATOR FOR SMALL-/MEDIUM-SCALE FARMERS AND MANUFACTURERS

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Introduction

Among large-scale farmers and agricultural machinery manufacturers, ISOBUS is a universally accepted standard for controlling implements since it simplifies the implementation of precision farming on farms and agricultural machines. However, for small and medium-scale companies, being a farmer or an agricultural machinery manufacturer, the implementation of ISOBUS is often seen as a time-consuming and expensive challenge. For this raison the authors built a modular simulation-based demonstrator to show the companies mentioned before the simplicity of integrating ISOBUS in farming systems and the efficiency of this technology to conduct smart farming. The present paper describes the mechanism by which the real ISOBUS Terminal can control virtual agricultural machines modelized in a Physics engine.

Development

Two ISOBUS fonctionalities can be tested with the present demonstrator: Universal Terminal (UT) (ISO 11783, 2018) and Task Controller geo-based (TC-GEO) (ISO 11783, 2015). While the first makes the control of a fleet of machines with one single terminal possible, the second enables variable rate application of crop protection products or fertilizers. (Figure 4)

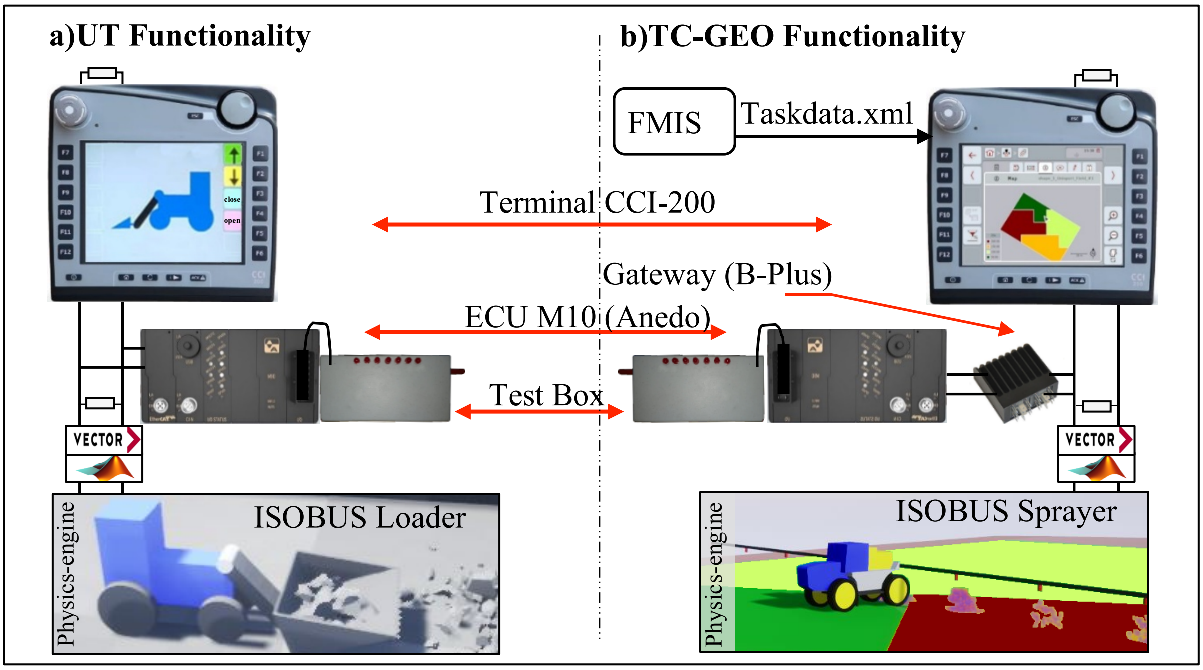

Figure 4 Simulation-based UT- and TC-GEO ISOBUS demonstrator

The present demonstrator has two main parts: an actual ISOBUS Terminal and a simulated ISOBUS-compliant machine – front loader or sprayer (Figure 4). Real and virtual ISOBUS nodes are connected using a Vector CANCARDXLe PC-interface, the CANOE software (Vector Informatik GmbH) and Matlab/Simulink 18a. Thanks to a physics engine coupled to

Simulink via UDP communication, it is possible to visualize the processed area like ground movements (Figure 1a) or agrochemicals flow (Figure 1b).
As a transitional step before implementing ISOBUS on actual agricultural machines, a test box connected to the Universal Terminal via ECU M10 can simulate the behaviour of a VT compatible implement. Additionnaly, to provide the test box with TC-GEO functionalities, a B-Plus gateway should be plugged between the ISOBUS Terminal and the ECU. (Figure 4)

The development of the demonstrator can be summarized in 5 steps:

- Development of ISOBUS Object Pools with Jetter's ISO-DESIGNER
- Configuration of the virtual ISOBUS-network with Vector's CANOE
- Matlab/Simulink Modelling of the agricultural machine, using Simmechanics, the Vector-Simulink-Toolbox and UDP-communication blocs
- Physics engine Modelling of the agricultural machine
- ECU-programming with Codesys (in case of using the test box)

Results

The first VT- and TC-GEO simulations agreed well with our expectations. Namely, operating a virtual UT- and TC-GEO compliant ISOBUS agricultural machine requires the same procedures as for a real machine. Using the demonstrators's actual ISOBUS terminal , the user can fill the bucket of the virtual loader and can spray on the virtual field at a variable rate controlled by the prescription map imported previously. (taskdata.xml imported from the Farm Management Information System into the terminal). In terms of Human Machine Interface, the virtual environment is quite responsive to the user inputs. The same user can clearly identify the processed area and the process variations - flow of agrochemicals or of loaded material - which depend on the machine parameters.

Conclusions

The use of a modular and easy to use simulation-based demonstrator is a promising approach to demonstrate to small- and medium-scale companies, being a farmer or an agriculture machinery manufacturer, how ISOBUS could be applied to their farms or their products respectively. While Hardware in the Loop (HiL) permits to create user-scenarios close to their real-life counterparts, the use of Physics-engines enables a realistic and precise simulation of the agricultural machine. In the future, new features will be implemented in order to cover a wider range of scenarios. In the coming weeks, the demonstrator will be updated to enable sensor-based Variable Rate Application.

Acknowledgements

We acknowledge the support of the companies making this work possible, most importantly by Anedo providing the CCI200 and the ECU and by B-Plus providing the ISOBUS gateway. Thanks go as well to CC-ISOBUS e.V. and LACOS GmbH for very helpful personal communications. It has to be mentioned that some contributions to this work could have only been made thanks to the European Union's program giving students the possibility to realize an Erasmus+ placement.

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MAPPING OF INTRA-PLOT VARIABILITY OF COVER CROP BIOMASS USING SOIL RESISTIVITY MEASUREMENTS AND MULTI-TEMPORAL SATELLITE IMAGES

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In France, the regulation requires the establishment of cover crop during periods where the bare soil surfaces present the conditions conducive to drainage and a risk of nitrate leaching, particularly in the vulnerable nitrates zone which represent ~75% of the agricultural area allocated to the cultivation of seasonal crops (Justes et al, 2012). Sustainable and reasoned management of agricultural surfaces requires the monitoring of key vegetation descriptors (*e.g.,* leaf area index, crop height or biomass that can be derived from satellite images, Claverie et al, 2012; Fieuzal & Baup, 2016), which can be used as a control indicator of advantages of the establishment of the cover crop. In this context, the present study aims at estimating the production of cover crop biomass at the intra-plot spatial scale (spatial resolution of 20 m), on the basis of soil resistivity measurements combined or not with multi-temporal satellite images regularly acquired by Sentinel-2.

On a study site located in south-western France, an experimental device was conducted on a network of six plots to collect a dataset making it possible to characterize the variability of cover crop. Time series of images were acquired from November 2017 to March 2018 throughout the growth of the cover crop, together with biomass measurements collected just before the destruction by burial of the vegetation. The spatial sampling takes both advantage of soil resistivity mapping (collected at three depths and representing the following soil layers: 0-50, 0-100 and 0-170 cm) and satellite images to identify zones with variable vegetation status (through the temporal behaviour of the NDVI). The first results presented here focuses on one of the six monitored plots used for training a statistical algorithm (*i.e.,* multiple linear regressions) by considering satellite images or soil resistivity measurements as input variables, or by combining these two types of information.

On the considered plot, two cover crop species, namely faba bean and phacelia, were sown after the cultivation of wheat. The values of fresh biomass range from 661 to 1673 $g.m^{-2}$. The vegetation being mainly composed by water (for at least 81%), the amount of dry biomass reaches values between 115 and 270 $g.m^{-2}$. Several cases are tested in order to estimate the dry biomass and to obtain decametric maps of cover crop. For the sake of conciseness, only three examples are presented hereinafter considering the following input variables: (*i*) the soil resistivity measurements, (*ii*) three satellite images acquired throughout the cover crop growing (determinate through an analysis of the variance) or, (*iii*) the combination of the last satellite image acquired before the destruction of the vegetation with soil resistivity measurements.

The statistical performances obtained when the estimations of the dry biomass are based on soil resistivity measurements (Case 1 on Figure 1) are associated to a $R^2 = 0.61$ and RMSE = 30 $g.m^{-2}$ (that is, a level of error lower than the standard deviation on measurements, close to 50 $g.m^{-2}$). Such level of accuracy is slightly improved when the estimations of biomass are based on NDVI derived from the three selected images (among the nine images acquired throughout the growth of the cover crop), as evidence by the values of $R^2 = 0.64$ and RMSE = 29 $g.m^{-2}$ (Case 2 on Figure 1). The combination of satellite and soil measurements allows the performance to reach a R^2 of 0.72, while the level of error is close to 26 $g.m^{-2}$ (corresponding to a relative value of 15%, Case 3 on Figure 1). Finally, the last case is retained to map the dry biomass on the monitored plot (Figure 1 on the right). The proposed approach allows reproducing the intra-plot spatial variability, and patterns either with low or high values of dry biomass are clearly observable.

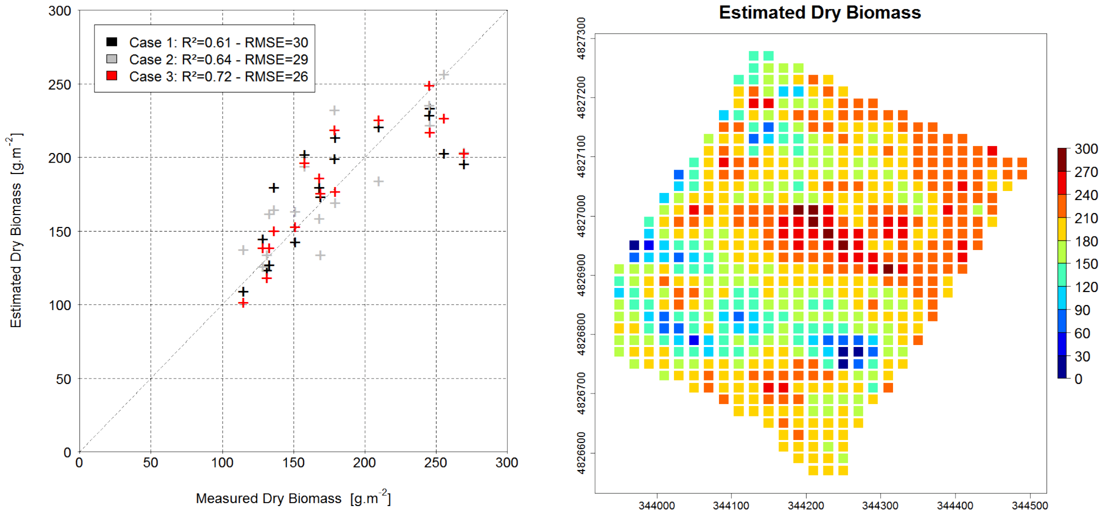

Figure 5: Comparison between the cover crop dry biomass collected on the monitored plot and values estimated by considering the three tested cases (on the left), together with the map of dry biomass estimated using the best case (on the right).

Those first results appear promising and the proposed approach will be extended to the other monitored plots, in order to identify a consistent cal/val procedure. Furthermore, the robustness of those preliminary results will be addressed by testing the presented statistical algorithm on an additional experimental dataset. Indeed, a network of plots has been surveyed throughout the growth of cover crop during the successive agricultural season (*i.e.,* from November 2018 to March 2019).

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ADVANCED TECHNOLOGIES FOR EFFICIENT CROP MANAGEMENT (ATEC)

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Crop yields have increased over the last 50 years since the Green Revolution through advances in crop breeding and changes in agronomic management including larger applications of nitrogenous fertilisers. There is now concern that yield increases are stagnating and climate change may result in increased seasonal variation in production. Farmers are under increasing pressure to manage agricultural systems in a more environmentally friendly manner with decreased inputs whilst maintaining high levels of production on a tighter budget (Chen et al., 2014; Ray et al., 2015; Asseng et al., 2015). This combination of pressures means we must find new ways to manage and target inputs where they will have the greatest impact on maximising potential yield. Precision agriculture techniques utilise sub-field scale information to support crop management decisions relating to yield and could be vital tools in addressing the challenges stated above. Advances in satellite Earth observation (EO) platforms such as the ESA Sentinel satellite systems with sensors at high spatial and temporal resolutions along with easier and cheaper availability and developments in low-cost unmanned aerial vehicles (UAVs) means that remote sensing is providing more opportunities for intensive and timely crop monitoring (Clevers et al., 2017; Delloye et al., 2018).

The ATEC projects main aims are to enhance the sustainable and efficient production of two major crops – wheat and potatoes. The project uses a combination of trial plot and field scale studies in Scotland to consider the capability of assessing nitrogen stress using EO satellites, UAV-mounted sensors and ground-based measurements. Multispectral, RGB and thermal sensors will be evaluated for their ability to retrieve information on nutrient deficiency and scaling from satellite to UAV will be assessed. Ground based measurements will not only be used in validation of the sensor outputs but will allow an in depth understanding of the soil and physiological factors driving yield development. These multi-scale observations will be used in conjunction with a crop growth model that simulates the essential soil-plant-atmosphere processes impacting crop development and yield formation. We are also engaging with local farmers to evaluate and refine our data products and provide a feedback loop into the projects development ensuring fit-for-purpose outputs.

The initial assessment of sensor and processing chain capabilities is showing accurate retrieval of plant health indicators including plant height, vegetation cover (Fig. 1) and chlorophyll content which has been fully validated with in-field measurements.

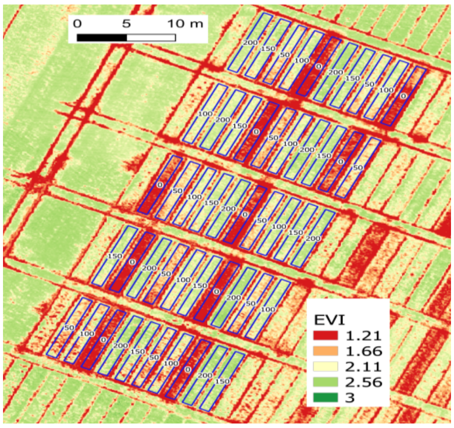

Figure 6: Enhanced vegetation index (EVI) of winter wheat trial plots treated with varying nitrogen fertiliser levels (0, 50, 100, 150 and 200kg N ha^{-1}).

We have been exploring relationships between ground measurements and observations from our UAV sensors and, in doing so, we demonstrate our capacity to upscale: from points to fields and from ground to satellite. From this work recommendations for appropriate bands for inclusion in predicting leaf chlorophyll and leaf area index are been developed. In order to further understand the physiological mechanisms behind the readings from the sensors extensive monitoring of the soil nitrogen supply has allowed the development of techniques to monitor N supply to the crop and this is being developed to understand the important factor to monitor for detecting N deficiency. We further present some preliminary output from the project covering the range of our activities.

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ROBOTTI - AN AUTONOMOUS TOOL CARRIER

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The tendency in the design of agricultural machines has been governed by improving operational efficiency by increasing working widths and operational speed while consequently increasing the tractive requirements. However, increasing productivity does not necessarily correlate with improvements in quality (Lal 1993; Nawaz et al. 2013).
During the last decades, technological improvements have increased the use of automation in multiple industries such as the automotive and manufacturing industries. This development has similarly enabled the possibility for new innovative solutions relying on automation and robotics in the agri-tech industry. By increasing autonomy in agriculture, laborious tasks can be performed with minimal human interaction. Hereby, the focus on soil preservation, crop establishment and nursing can be addressed without the constraint of limited resources of time.

This study concerns the *Robotti*, an autonomous tool carrier designed for performing field operations in arable farming. The objectives were to study the design of the Robotti with respect to weight distribution, tractive performance and vertical stress in the soil as a consequence of applying the Robotti in the field. Measurements were conducted to determine the tractive capabilities of Robotti and compare these with the tractive requirements associated with of a number of the typical field operations such as mechanical weeding, spraying and seeding using a mechanical seed drill as shown in Figure 1.

Figure 1. Robotti, the autonomous tool carrier performing a seeding operation.

A unique feature is the compatibility with existing tools. This was achieved by implementing a cat. 2 three-point hitch and PTO which enables the possibility for performing autonomous field operations using a wide range of tools within the maximum working width of 3 m.

Due to the location of the three-point hitch centred on the main-frame in the front-end of the machine, the vertical load of a given tool is acting between the front and rear wheels of the Robotti. This causes the load of the robot and tool to be distributed on each wheel. Hereby, the weight of the tool contributes to the resulting wheel loads and thereby increases the possible traction on all wheels. Contrary to, a load exerted on the three-point hitch behind the rear axle of a tractor will consequently load the rear wheels and unload the front wheels. In order to comply with uneven terrain, a revolute joint is connecting the main-frame with one of the two driving modules. This additional degree of freedom maintains the required soil-tyre contact during field operations. The design causes the weight of the tool to be distributed on all tyres, though not equally when loaded.

Robotti was designed to perform field operations while limiting the soil structural impact by reducing the weight. This was investigated in terms of the vertical contact stresses and the vertical stresses in the plane perpendicular to the driving direction below the heaviest tyre of the Robotti. The calculation relies on the principle proposed by Söhne (1953) and performed using *SoilFlex* (Keller et al. 2007).

The maximum draught force capabilities of the Robotti was measured on a horizontal paved surface as a function of velocity. The required traction of the seed drill (Figure 1) and a number of typical field operations as presented in (Hunt 2008, Table 2.6) were compared with the measured available traction of the Robotti. It was found that the light operations such as seeding using a seed drill[2] (1.4 kN at 5-8 kmh^{-1}), spike tooth harrowing and shallow cultivation that requires respectively 0.3-0.9 kN and 0.6-1.2 kN per unit width at 4.8 kmh^{-1} were all suitable tools for the Robotti. Though, the available traction force does not currently allow for operations as mouldboard or chisel ploughing which requires an available traction up to 16.6 kN per unit width at 4.8 kmh^{-1}.

In the future work, more studies of the tool traction requirement are to be performed numerically and experimentally. In addition to the test conducted on the paved surface, drawbar pull tests in the field are needed in order to better understand and predict the performance of the robot under different field conditions.

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MULTI-OPERATING REMOTE CONTROLLABLE SYSTEM FOR A NON-TRIPPED AIR VEHICLE

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It is necessary to evaluate the physical, chemical and biological aspects of the soil, to obtain management that contemplate sustainability (Santos et al., 2017). For the knowledge and management of these characteristics, it is necessary to access the soil information where the crop will be implanted. The main technology used for this is soil fertility maps, which help the farmer to make the necessary decisions and interventions (Bernardi et al., 2014).

In order to solve this factor, in recent years they have suggested new technologies such as image evaluation using satellite and manned aircraft and electric resistivity (Adamchuk et al., 2004). All of these are able to generate data based on the characteristics of the soil, but in the image evaluation, despite the high efficiency in the area unit evaluated, there is no direct contact with the soil, which greatly reduces the accuracy of the results and the diagnosis; (Rabello et al., 2014). The technological advances of the techniques of sampling have much to improve to reach the point of being more accurate and accessible in a shorter time interval (Bernardi et al., 2015).

The objective of this work was to develop a multi-operational system of remote activation, attachable to unmanned aerial vehicle composed of at least: evaluation, an electrical conductivity implement, a collection implement and / or a combination thereof.

The operation process of this multi-operating remote-activation system involves an earlier georeferential study determining the sample meshes. The system coupled to the unmanned aerial vehicle is powered for small sample collection and makes site-specific readings such as electrical conductivity. Soil / water / fluid / vegetation analyzes will be performed simultaneously to efficient collections. When finished, the system is guided to the starting point. The invention may also, for example, take the collected samples in order to carry out complementary analyzes in a given plant. All data are submitted to geo-statistical studies in order to deliver the site map, such as soil fertility.

The development of the prototype and patent deposit with the following claims: A multi-operational remote actuation system coupled to an unmanned aerial vehicle, characterized in that at least one electrical conductivity implement has at least one upper evaluation platform and or the combination thereof.

Figure 7: Multi-operating system for analyzing soil

The present invention relates to a multi-operational remote system with a minimum implement for collecting and / or analyzing soil / water / fluids / vegetation, preferably an upper evaluation platform an Electrical Conductivity Implement, a data collection Implement.

The implements are coupled to unmanned aerial vehicles (Fig. 1). It thus involves a group of interrelated inventions in a way that constitutes a single inventive concept.

They are appropriately applied in industry and the environment. Thus, the multi-operational system can be used in production areas, pasture areas, degraded and reclaimed areas, forest areas and any other type of soil where information on its physical, chemical and / or biological characteristics is required.

In this way, the system is effective mainly for the analysis of extensive and difficult to access areas, such as areas of more than 30 hectares that are planted, which are analyzed annually of soil and soil fertility maps before of each crop. Or even areas such as rivers, dams and contaminated soils.

The prototyping and development of the multi-operational platform of remote activation attachable to non-crewed air vehicle may be used for collection of samples and / or for analysis of soils, as well as of fluids, animals or vegetation and will assist the farmer to make decisions and the necessary interventions contributing to greater efficiency in crop management and cost reduction.

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AGRICULTURAL MACHINERY CHAIR: DESIGN AN INNOVATIVE TEACHING SOLUTION TO ANSWER TO NEW INDUSTRIAL CHALLENGES

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INTRODUCTION

AgroSup Dijon is a French public Institution of Higher Education for agronomic sciences, food and the environment. It is the only French public institution accredited to issue graduate level (Master and Doctoral degrees) in Agricultural Machinery and Precision Farming with a team of academics specialised in agricultural equipment and innovative technologies dedicated to Precision Agriculture.
Close ties to industry offer our graduates the opportunity to develop their professional skills. Our programs combine hands-on learning with relevant classroom work.
However, times are changing for the agricultural machinery branch. International trade is an everyday fact, for most companies. Companies need to upgrade new skills on digital farming, AgTech and agroecology. A double revolution, digital and agroecology, is underway and so, a broad cross-section of new skills is required to train future leaders, managers, teachers, doctors and other professionals.

OBJECTIVES. AN INDUSTRIAL CHAIR DEDICATED TO TRAINING

To meet this new challenge and consolidate its leadership position, AgroSup Dijon must constantly renew its educational strategy by exploring innovative pedagogical practices while remaining close to industrial companies including recruitment and training. Thus, we have started to develop a new educational tool; an industrial chair called 'Tech Agro Sup' and dedicated to training; that is the aim of this presentation. Nevertheless, the success of AgroSup Dijon depends on the availability of private funds through the support of industrial partners.

Action plan: let us work together to promote the most up-to-date training requirements.
The 3 topics addressed by the chair are:

1. A showcase to highlight our higher educational map based on the development of precision agriculture combining agro-ecological transition with digital revolution. This allows companies to work with us to attract new graduates and researchers in agricultural engineering and related sectors, as well as to improve the skills of those working in the industry through ongoing professional development and the most up-to-date technical training.
2. A partnership with agricultural equipment firms. These firms decide to support the project via a sponsorship. These firms have a key role to play in the success of this ambitious project to attract and train young people in emerging technology by knowledge sharing.
3. A sharing of our International networks. Our relationship with universities in Italy, Ireland and more recently Germany (Rhineland-Palatinate Land) means the corporate contributors (Fig. 1) can recruit young talent from other countries that they may export their product to.

Working with industrial companies and foreign universities, the ambition is to become a European leader of training, exchanges and expertise in agricultural equipment and precision agriculture in 5 years. Various proposals have been explored and the most relevant is presented below (Fig. 1).

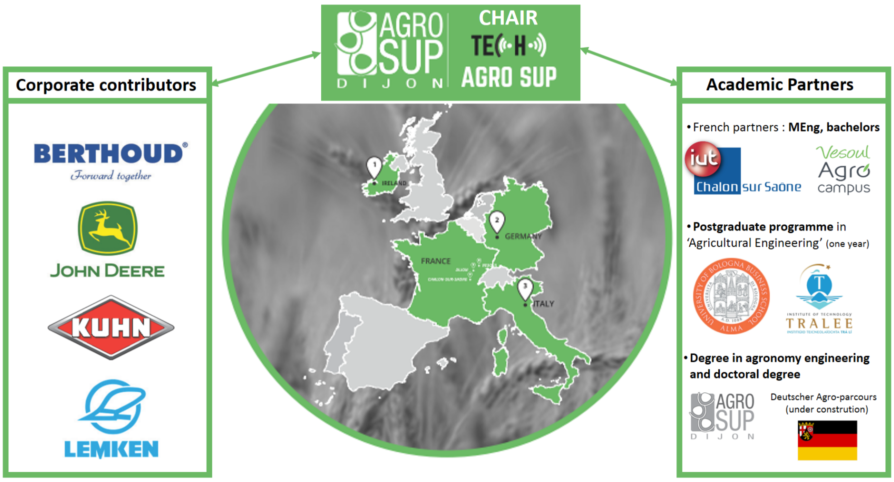

Figure 1: Launched in 2018, the Tech Agro Sup Chair encourages industrial partnership in the agricultural machinery branch and sharing knowledge between corporate contributors and international academic partners to train and recruit young talents

Ongoing action: Postgraduate programme in international agricultural engineering.
The Institute of Technology of Chalon-sur-Saône, Vesoul Agrocampus and Agrosup Dijon in France, the Institute of Technology of Tralee in Ireland as well as the University of Bologna in Italy will offer as an add-on to the current level 7 degree in international agricultural engineering.
It will begin in September 2019 and the course is 1 year in total, with an initial intake of 15 students. The main objective is to equip students with highly specialized competences and solid transversal skills all embedded in an international dimension. The classes will be in English. Students will originate from a bachelor degree in Agriculture Equipment or a BSc in Agricultural Mechanization. They will have skills in agriculture, mechanical engineering, agriculture equipment science and techniques.
Students will move across the three countries rotating each quarter in one of the Partner Institutions, including a 3 months internship experience. The 1st quarter will take place in Ireland (Module 1: design & Control), followed by Italy (Module 2: Performances & testing) and France (Precision farming &Agribotics). The final quarter will be work placement.
At the end of the programme, students will get the necessary professional qualifications for playing important roles in the main industries operating in the sector.

CONCLUSION
To promote the agricultural machinery branch, its activities and its occupations, it is necessary to attract more young people in our higher education and to work in close collaboration with industrialists who require continually updating their skills and competencies. Thus, AgroSup Dijon developed the Tech Agro Sup Chair, based on sponsorship. Whether you are a manufacturer, a research institute or a university and if you are interesting to contribute to train future international leaders in innovative technologies for agricultural equipment, do not hesitate:

JOIN US!

YIELD PREDICTION USING MOBILE TERRESTRIAL LASER SCANNING

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Yield prediction provides valuable information to plan the harvest campaign, fruit storage and sales. Traditionally, yield estimation has been carried out by manual counting of randomly selected samples, without addressing spatial variability within the orchard. To obtain a precise estimation it is necessary to sample a relatively large number of trees, which is unfeasible with manual counting. To solve this issue, this work proposes the use of a Mobile Terrestrial Laser Scanner (MTLS) for fruit detection and yield prediction.
Experimental test were carried out in a commercial Fuji apple orchard. The row of threes was scanned from the two sides (east and west). The measurement equipment consisted of an MTLS comprised of a LiDAR sensor, and a real-time kinematics global navigation satellite system (RTK-GNSS) connected to a rugged laptop. The LiDAR sensor used was a Puck VLP-16 (Velodyne LIDAR Inc., San José, CA, USA), which provides a 3D point cloud with calibrated reflectance values of the measured scene.
The fruit detection algorithm implemented in this work is divided into four steps: (1) Reflectance thresholding, which delete those points presenting a reflectance lower than 60%; (2) Connected Points Clustering using DBSCAN; (3) Fruit separation, which uses a support vector machine (SVM) to predict the number of fruits that contains each cluster; (4) False positive removal, also based on a trained SVM.
From detections obtained with this algorithm, the yield was predicted using a linear model (obtained with training data) that relates the number of detections and the actual number of fruits.

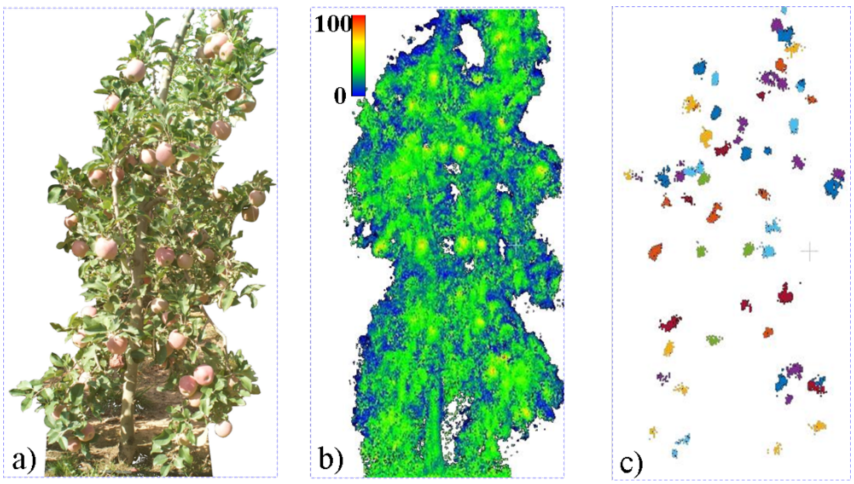

Figure 8: Illustration of a selected tree from the dataset. a) RGB image. b) 3D point cloud obtained using the MTLS. c) Fruit detections.

Three different trials were evaluated: east (*E*) side scanning, west (*W*) side scanning and merging data from both scanned sides (*E*+*W*). As it was expected, fruit detection results showed lower detection rates when only scanning from one tree side, presenting detection rates of 38.3% and 48.5% for east and west sides, respectively. However, the detection rate increased up to 75.8% when using *E*+*W* data. Similarly, yield prediction results showed higher errors when using data from only one tree side, obtaining a RMSE of 15.2% and 15.3%

(east and west, respectively). The prediction improved significantly when using data from both tree sides (E+W), presenting a RMSE of 5.4%.
From these results it is concluded that MTLS has potential in yield prediction in fruit orchards. Although fruit detection rates are moderately successful, the system was able to predict the actual number of fruits with low estimation errors. Only using data from one tree side increases the prediction error, but it has de advantage of reducing a 50% the scanning time, which may be interesting depending on the application and the interest of the farmer. Future works will extend this study to other fruit varieties.

Acknowledgements
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THE USE OF 'DRONE DATAFLOW' IN AGRONOMIC FIELD EXPERIMENTS

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Collection of plant phenotypic data from field plot experiments is very important in plant breeding and in field experiments where the aim is to test new products and/or optimize current management practices. Modern plant phenotyping relies on a couple of rapidly developing pillars: (i) non-destructive measurements to be able to follow a trait over time, (ii) high-throughput measurements, to be able to screen at similar conditions many genotypes (Costa et al., 2019). The phenotypic data from field experiments is usually a mix between visual characteristics, destructive plant sampling and final harvest of the plots. There exists several publications on how to use sensors to collect phenotypic data from field experiments. One method is the use of cameras mounted on an unmanned aerial vehicle (UAV).
The aim of this abstract is to show how the Drone dataflow MATLAB toolbox (Mortensen et al., 2019) can be used to extract Normalized Difference Vegetation Index (NDVI) from individual plots and study the plot border effects. A field plot experiment with winter wheat crop with different 10 nitrogen application strategies with four repetitions each served as experimental base. Images were collected using an eBee fixed wing UAV (Sensefly.com, Lausanne, Switzerland) coupled with the Parrot sequoia multispectral camera (Micasense.com, Seattle, U.S.) to acquire multispectral images during the spring growing season at Aarhus University, Department of Agroecology, Forsøgsvej 1, 4200 Slagelse. Images were taken on the May 2, May 16, May 23 and May 29 2018.

The workflow is described in 'Drone dataflow - A MATLAB toolbox for processing images captured by a UAV'. NDVI is given by (ρ_{NIR}-ρ_{Red}/ρ_{NIR}+ρ_{Red}), where ρ_{NIR} *and* ρ_{Red} is the reflectance in the near infrared and red band, respectively, measured by the multispectral camera. The NDVI was used, however, workflow generalized to several other crop index as well. Four selected plots in the first replicate of the plot experiment were used as example of how reduction of the plots affect NDVI.
As an example, the average NDVI within one plot increased from 0.760 to 0.805 when the plot was reduced by 0.24 meters on each of the four sides (Table 1). The minimum NDVI value increased 0.1 and the standard deviation was lowered by 0.04. In another plot, the NDVI values increased from 0.463 to 0.478.
The effect of reducing the plot area was as expected, independent from the selected nitrogen application strategies or replicates. This shows a general effect of reducing the plot area on NDVI. The reason is the border effect of each plot characterized by the outer plants in each plots that has no competition from the border side. This will inevitably cause a faster or slower growth and development of the plant dependent on the current circumstances.

Table 1: Average NDVI values for whole plots and plots reduced by 6, 12, 18 and 24 cm on all sides. Treatments A, B, C and D are different nitrogen application strategies. Measurements were taken May 2, May 16, May 23 and May 29.

Treatment	Whole plot	Reduced 6 cm	Reduced 12 cm	Reduced 18 cm	Reduced 24 cm
			May 02		
A	0.452	0.460	0.466	0.466	0.469
B	0.582	0.596	0.608	0.609	0.617

C	0.637	0.651	0.664	0.665	0.673
D	0.730	0.746	0.759	0.760	0.769
			May 16		
A	0.463	0.470	0.475	0.475	0.478
B	0.760	0.777	0.793	0.794	0.805
C	0.780	0.796	0.810	0.811	0.820
D	0.838	0.854	0.866	0.867	0.874
			May 23		
A	0.440	0.445	0.448	0.450	0.450
B	0.752	0.768	0.781	0.783	0.792
C	0.797	0.811	0.822	0.823	0.830
D	0.838	0.846	0.852	0.853	0.856
			May 29		
A	0.574	0.581	0.586	0.587	0.590
B	0.811	0.825	0.838	0.839	0.848
C	0.849	0.860	0.868	0.869	0.874
D	0.869	0.870	0.885	0.885	0.889

In traditional agricultural field plot experiments and phenotyping field plot experiments where different treatments, cultivars, or inputs are tested, the effect of reducing the plot size will of course depend on the variation in the measurements itself. In the current example with NDVI measurements as the dependent variable and nitrogen and replicates as independent variables there was not statistical difference in NDVI from the nitrogen application strategies when replicates was kept as a random effect. The effect of reducing the plot area on NDVI was therefore lower than the effect of nitrogen application strategies and replicates. The missing significant effect should not stop us from testing the effect of reducing the plot area on the measured variable and the availability of 'Drone dataflow' makes it easy and simple to calculate.

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EVALUATION OF A NOVEL THERMAL IMAGING SYSTEM FOR THE DETECTION OF CROP WATER STATUS IN COTTON

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Drought stress is a major constraint to crop productivity (Hsiao et al., 1973) and affects cotton (Gossypium hirsutum L.) development to different extents based on the intensity, the duration of the stress event, and the growth stage when the stress occurs (Snider et al., 2015). Efficient irrigation scheduling methods are important to increase economic productivity in today's agriculture. Farmers are commonly basing their irrigation decisions on visual signs of drought stress such as wilting. However, these irrigation practices usually lead to penalized yields, representing inefficient irrigation scheduling approaches. In fact, Vories et al. (2006) estimated incorrect irrigation timing in cotton can result in yield losses between 150-750 $/acre. In recent years, improvements in irrigation scheduling approaches have been used to achieve higher yields and better irrigation water use efficiency (Vellidis et al., 2016).

Thermal imagery of the crop canopy has shown to be an accurate indicator of crop water status. In cotton, canopy temperature has been successfully deployed as an irrigation scheduling tool. Novel thermal imaging systems, being able to capture near-continuous canopy temperature from a fixed position, will allow farmers to capture spatial variability in plant water status on a large scale. Using these systems, canopy temperature-based irrigation management zones (IMZs) could be defined in real-time, enabling efficient use of variable rate irrigation technologies.

The objective of the current study was to validate a novel thermal imaging system (SmartField™ Sentinel) for the detection of canopy temperature and crop water status using established methods of quantifying crop water status, including empirically-derived CWSI, IRT sensors, soil water tension, and leaf water potential. To this end, a split plot randomized complete block design study consisting of a split plot randomized complete block design with three cultivars and three different irrigation treatments, Dryland (no irrigation), 100% of crop evapotranspiration (ET_C) supplied (well-watered), and 125% of ET_C (overirrigated) was conducted at the Stripling Irrigation Research Park, GA during the 2018 growing season.

The Sentinel thermal imaging system (TIS) (Figure 1) was mounted on an extendable 15-meter pole, and a total of 27 SmartCrop infrared thermometers (IRTs) and 27 soil moisture sensors from the University of Georgia Smart Sensor Array (UGA SSA) were also installed in the experimental area. Crop water status (predawn and midday leaf water potential) and crop response measurements (growth and physiology) were collected weekly for each plot, starting at cotton squaring. Different CWSIs were derived from thermal images and IRT temperature data for every sampling date. In addition, soil moisture data were collected and analysed on the same dates. Because of the limited drought stress periods verified during the 2018 growing season, no significant cultivar, irrigation or cultivar by irrigation interaction effects were observed for any physiological parameter on any given date, including predawn and midday leaf water potential, cotton growth (mainstem height, nodes and IPAR), or single-leaf gas exchange (net photosynthesis, midday stomatal conductance, and intrinsic water use efficiency). Consequently, defining a relationship between Sentinel-based CWSI and leaf water potential was not possible.

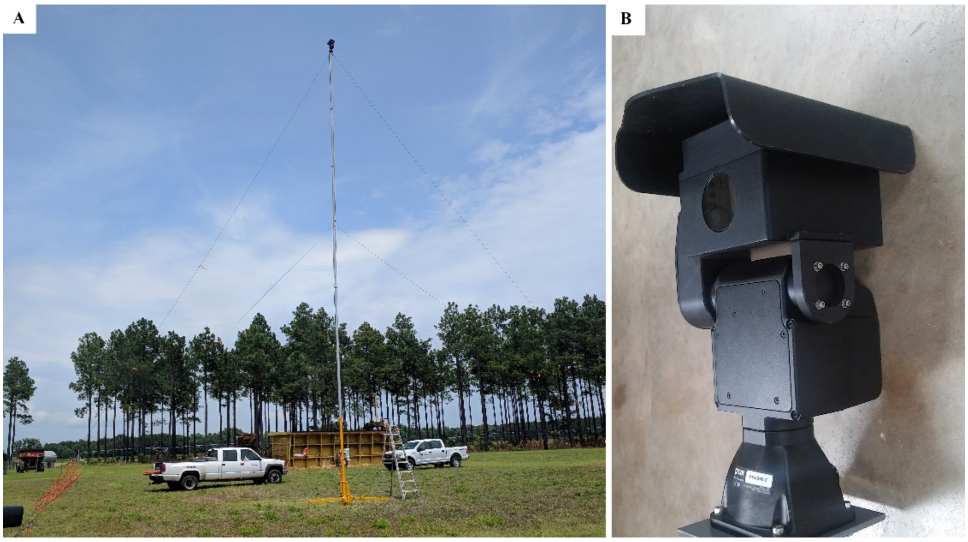

Figure 1: The Sentinel TIS (camera and pneumatic tower) after the installation (A) and lateral view of the Sentinel TIS (B).

A strong, linear relationship (well-watered baseline) between canopy-air temperature to vapor pressure deficit was observed for both the Sentinel camera (r^2=0.66) and IRTs (r^2=0.77). Moreover, the IRT-based well-watered baseline and CWSI were found to agree with a previously published relationship (r^2=0.987; Chastain et al., 2016), indicating that a general baseline could be defined and used as an irrigation scheduling tool. Sentinel TIS-based and SmartCrop-based CWSI values were strongly related (r^2=0.84) and the accuracy in canopy temperature estimates was maintained at camera-plot distances up to 170 meters. In addition, the Sentinel CWSI agreed with soil water deficit values (r^2=0.59), indicating the camera may be sensitive to early stages of soil water depletion.

Since the Sentinel TIS was related with both IRTs and soil moisture sensors, we concluded the camera could be used to investigate changes in water status even before visible consequences of water stress are observed. The deployment of this camera on a large scale would allow farmers to apply appropriate rates only where and when the crop needs it, increasing yields and water use efficiency.

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UPSCALING THERMAL AERIAL IMAGERY FOR HIGH-RESOLUTION EVAPOTRANSPIRATION ESTIMATIONS

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Remotely sensed multispectral and thermal imagery can provide high precision water status maps in orchards through stress indices, which are a very useful tool for irrigation monitoring and deficit irrigation strategies especially in areas where water resources are limited. Stress indices are also a powerful tool for breeders working on water stress phenotyping. The required data can be obtained from sensors carried onboard satellites, airplanes or unmanned aerial vehicles.
The spatial resolution of thermal images acquired by most commercial satellites are larger than an individual field in most agricultural regions, and thus, these images have limited applications for site-specific agricultural applications (Mahlein, 2016; Godwa, 2008). In order to improve thermal imagery resolutions, new methodologies have been developed to sharpen low-resolution thermal data combining low resolution thermal imagery and spatial information from high resolution multispectral images. That is the case of Guzinsky et al (2019) who, based on machine learning algorithms, were able to augment from 1000m to 20m the resolution of Sentinel-3 satellites images by using images acquired by high resolution optical sensors on the Sentinel-2 satellites. This methodology opens a window to monitoring of evapotranspiration, crop water stress and water use at field scale through thermal satellite sensors.
The application of sharpening methods to other types of sensors, such as those mounted on airplanes, has not yet been evaluated. Increase the image resolution up to leaf size could be very interesting to perform very high precision studies, avoiding the errors induced by plant-soil mixed pixels. Mixed pixels present a great source of error in the study of woody crops.

The main objective of this study is to evaluate the suitability of sharpened thermal images to perform water stress estimations in fruit crops. The secondary objectives are (i) to measure the errors related to the flight height, and (ii) to assess the errors induced by intra-pixel variability.
The sharpening method was evaluated through aerial images taken at different heights (therefore of different spatial resolutions), which were upscaled to 0.30m of spatial resolution. The data sharpening method used in this study is based on Data Mining Sharpener (DMS) introduced by Gao et al. (2012).

The study area is an apple plot located at IRTA experimental farm (Mollerusa, Lérida, Spain). Half of the apple trees in the plot were well watered, while the rest were submitted to moderate water stress.
Thermal and multispectral flights have been carried out at different heights, with which to obtain real thermal data of different resolution that can be compared with the estimates obtained by sharpening. The cameras used were a FLIR thermal camera and a 4 spectral bands SpecTerra DMSC-2K multispectral camera (450, 550, 675 and 780nm). The flights were performed with a manned plane flying at 1800m, 800m, 400m and 300m in height. The corresponding spatial resolutions obtained were 2.40m, 1.20m, 0.60m and 0.30m for the thermal data, while only 0.30m multispectral data was used.

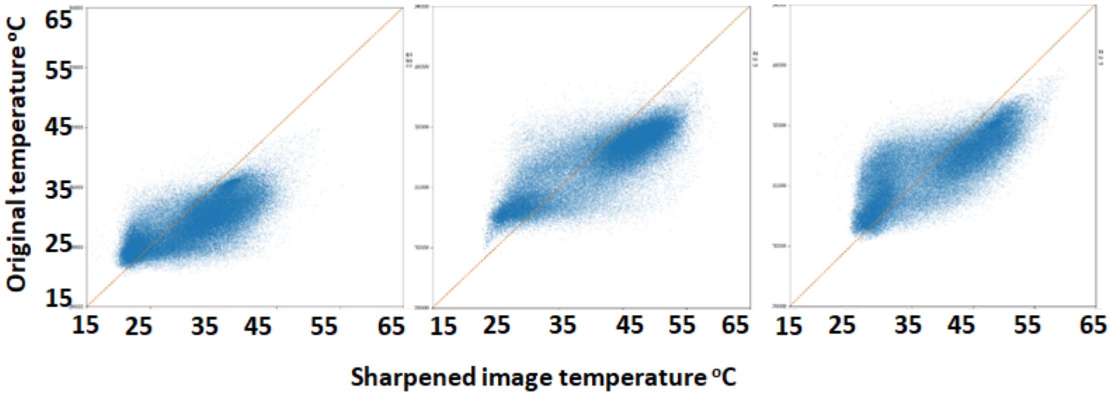

Figure 9: Scaterplots from 0.60 to 0.30m

The results have shown a high correlation in the sharpened images when the pixel size ratio (original *vs* sharpened) was 4 times, while this error increased drastically when the ratio was 64 times. Measured errors were greater on the higher temperature pixels.

On the other hand, the intra-pixel variability resulted in an increment in errors, which were more evident in the lower temperature pixels.

Although there are significant advancements in thermal technology, compared to commercial off-the-shelf optical sensors used in plans or UAVs, thermal cameras are still more expensive and have lower resolution.

The application of sharpening methods, through the fusion of images at different scales, made able to increase thermal image and resolution and allow access to data quickly and inexpensively. The methods of sharpening with aerial images open the door to other types of studies of greater precision and resolution.

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AN INVESTIGATION INTO OPTIMAL ON-FARM FIELD TRIAL DESIGNS

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Precision agriculture (PA) is a site-specific crop and field management concept that uses information-based agriculture strategies, such as variable-rate inputs, to increase profitability. To improve its efficiency and encourage adoption of site-specific management practices, new technologies have been introduced (Schepers et al, 2008). Since the year 2000, academic and commercial agriculture research has brought forth several PA innovations, such as yield monitoring system (e.g. Mahasneh et al, 2000), variable rate application of inputs (e.g. Khosla et al, 2002), and management zone determination (e.g. Fleming et al, 2000). Additionally, to accommodate the expansion in farming size and capacity, Kyveryga et al. (2018) provided us with a brief overview of how to plan, design, and conduct on-farm replicated strip trials.

In recent years, agronomic researchers began using GPS-based precision agriculture technology, especially variability rate technology, to run large-scale, on-farm field trials. A research infrastructure is being created to enable the annual running of hundreds of farm trials all over the world and, by extension, rigorous quantitative and data-centered analyses. The large-scale, on-farm trials follow many traditional small-plot trial protocols, including the division of the field into plots, and random assignment of the treatments to plots. These are recognized as automated on-farm "checkerboard" field trials.

In on-farm checkerboard trials, researchers prefer smaller plots for the benefit of more observations on one field. Having more observations is important because the advice given to producers is based on the experimental results, and such advice would be of greater value with more observations. In this paper, the optimal plot length was investigated, with the minimum width of experimental plots being fixed due to the size of the farming equipment. While shorter plot length in the experimental design results in additional observations, there is a tradeoff between the measurement accuracy of the data from a single plot and the number of plots in one experiment. In order to weigh the tradeoff between the reliability of the data from one plot and the number of observations possible in one field Monte-Carlo simulations were conducted to compare the economically optimal rates of fertilization (EOR) derived from the estimated yield on an experimental field, with variable plot length and determine the optimal plot length, as well as the optimal number of treatments.

The main results of this poster can be summarized as follows: 1) using 6 treatment levels is recommended for most trials, 2) the shortest plot is the best option in most fields, 3) the increase in yield monitor accuracy improves the accuracy of estimation significantly, 4) checkerboard trials are shown to produce more profitable estimations than strip trials.

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MAPPING YIELD AND QUALITY OF CITRUS USING SELF-PROPELLED PLATFORM WITH IN-FIELD SORTING.

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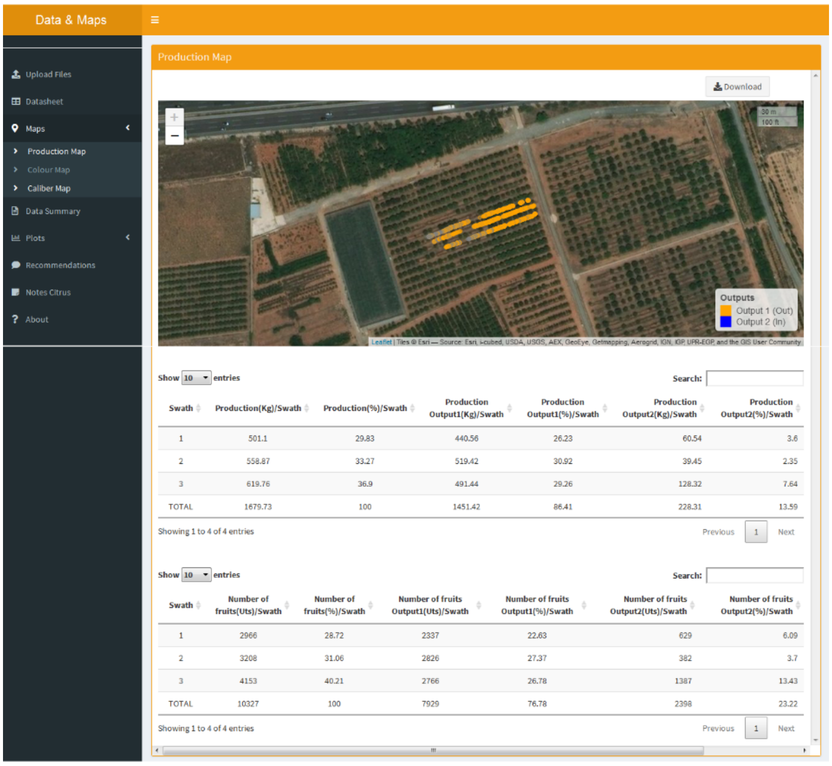
The use of new technologies the modern agriculture allows growers to obtain essential information for the management and optimal decision-making in the orchard. One of the main advantages of the use of new technologies is the possibility of associating the data with very specific crop locations, even at the individual plant level. This way, it is possible to carry out the agricultural operations in a precise way just where it is needed. However, to achieve effectiveness, it is necessary to present the information in a useful and understandable way to farmers. One of the most effective ways to present crop information is through maps.
There are several Geographic Information System (*GIS*) programs available (e.g. *QGIS*, *AFS, ArcGIS, Trimble Ag*) that are commonly used for these purposes. *GIS* software needs a spatial database in order to georeference the information in maps. This database is created at the moment of obtaining the properties of the crop by a sensor or set of sensors. To compose the database internally, the properties of the crop are linked to the spatial coordinates obtained from an integrated global navigation satellite system (*GNSS*). A main drawback of this kind of closed systems is that the measurements captured by other sensors are difficult to integrate and use to generate combined maps.

The aim of this work is to develop an open-concept web-based application using *R* programming language, capable of generating agricultural maps that show crop monitoring information captured from the field using different sensors and sources. A key advantage of this application is the internal creation of a database that links all the properties measured by any independent sensor with the spatial information provided by a *GNSS* without the need to integrate of all these components in a set. The application relates the information coming from each sensor in the database by means of a timestamp method. Each sensor has to generate a file that associates the captured measurements with the moment they are captured. To link the information of the different files in a single database, an application has been developed using the R language. This language was preferred due to its high potential for processing, data mining and computational analysis of large amounts of information.

From the information contained in the combined database, the web application allows the representation of the different properties measured in the crop, the statistical analysis of the data, the creation of graphics and crop maps, and the automatic generation of reports in the application web. Depending on the specific monitoring system, the maps could include yield prediction, vegetative status, pest monitoring, etc…
The application allows the crop information to be shown on orographic maps at the plant, swath (or row) and orchard levels. Complementary to the maps, informative tables summarise quantitative information of the crop and complete reports generated. Moreover, the spatial distribution of the information according to the different variables can be analysed statistically at the different scales to help in making further decisions on crop management.

The application has been tested using data collected by a self-propelled harvest-assist platform developed at IVIA, in a citrus orchard located at IVIA. The quality of all the fruit collected was monitored using a computer vision system mounted on the platform. The external properties of the fruit, such as the diameter, the area, the weight and the colour index were obtained from the images in real time by the computer vision system during the harvest. The geo-location data was obtained through a *GNSS* receiver installed on the prototype.

Once the data has been processed, information of the production in kilograms and in percent could be displayed in maps and tables according to one or more variables selected and combined through the controls of the application. Figure 1 shows an example of a map representing fruit quality, separating fruit that reached a high quality and were destined for the fresh market (output 1) and fruit of lower quality that should be sent to the industry (output 2). In this case, the quality attribute was weight, since small fruit do not reach commercial standards.



Swath	Production(Kg)/Swath	Production(%)/Swath	Production Output1(Kg)/Swath	Production Output1(%)/Swath	Production Output2(Kg)/Swath	Production Output2(%)/Swath
1	501.1	29.83	440.56	26.23	60.54	3.6
2	558.87	33.27	519.42	30.92	39.45	2.35
3	619.76	36.9	491.44	29.26	128.32	7.64
TOTAL	1679.73	100	1451.42	86.41	228.31	13.59

Swath	Number of fruits(Uts)/Swath	Number of fruits(%)/Swath	Number of fruits Output1(Uts)/Swath	Number of fruits Output1(%)/Swath	Number of fruits Output2(Uts)/Swath	Number of fruits Output2(%)/Swath
1	2966	28.72	2337	22.63	629	6.09
2	3208	31.06	2826	27.37	382	3.7
3	4153	40.21	2766	26.78	1387	13.43
TOTAL	10327	100	7929	76.78	2398	23.22

Figure 1: Screenshots of the agricultural mapping application

This mapping application represents an improvement over other mapping methods that need to be loaded with the properties measured by a sensor associated to a geo-location data. Thus the integration with other information captured by other sensors relative to the same crop is difficult. On the contrary, this application can integrate the spatial information with the one provided by any sensor only using a timestamp. This web application can be used as a tool for management and support for the optimal decision making of the orchard in order to increase the efficiency of management in the field and to achieve the production objectives and the traceability of the fruit.

TECHNOLOGY ADOPTION ACROSS DIFFERENT TYPES OF FARMING IN SWISS PLANT PRODUCTION

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Precision agriculture (PA) comprises optimized handling with variability and uncertainties within agricultural fields by using e.g. sensors, enhanced machinery or information systems (Zhang et al., 2002, Gebbers & Adamchuk, 2010). Main aims are an increasing profitability and sustainability of production, a reduction of adverse environmental impacts as well as improved social aspects of farming (Gebbers & Adamchuk, 2010). Therefore, technology use of farmers is influenced by various factors such as operator age, farm size or farm specialization. However, influencing factors are not always consistent and vary depending on the investigated technology and country (Pierpaoli et al., 2013, Konrad et al., 2019). The structural change in agriculture has led to increasing farm sizes in recent decades. Yet, the use of robotics and sensor technologies could bring competitive advantage to smaller farms (Shibusawa, 2002, King, 2017). With regard to farm size and diversity, Swiss agriculture differs significantly from other developed countries with an average farm size of less than 20 ha. The preservation of a sustainable and diversified agriculture is reinforced by strong financial support from the Federal Government in Switzerland to promote sustainable agriculture including e.g. the maintenance of the cultural landscape (Pierpaoli et al., 2013, BFS, 2018). The present work aimed to assess the status quo of technology use in Swiss' agriculture as an example for diverse, small-scale agriculture in Central Europe.

The work was part of a bigger study evaluating the state of mechanization and automation in Swiss plant production and livestock farms. Postal questionnaires were sent to farmers during Months 1-3 2018. In this study, we focused on the uptake of Driver Assistant Systems (DAS) and Electronic Measuring Systems (EMS) using two questions from 854 completed returned questionnaires related to plant production. The considered farm types were arable farming, fodder production, vegetable, grape, fruit and strawberry. Finally, two subgroups were defined; adopter which are those who have ticked at least one answer option of the respective question, except "none", and non-adopter, which only chose "none".

Our results show that technology use depends on the type of technology as well as the farm type. The majority of the participating farmers in Switzerland use neither DAS nor EMS with 63% and 83%, respectively. Among the adopters, the most frequent used Driver Assistant Systems in our study was 'cruise control' followed by the use of 'rear-view cameras' as well as 'headland management' and 'parallel driving aids'. The most frequent activities in which Electronic Measuring Systems are used were 'precision seeding' and 'moisture measurement of the harvest product'. The adoption of the other possible DAS and EMS were below 10%. Regardless of the farm type, the use of technologies decreased from DAS to EMS. Thus, more farmers use DAS compared to EMS as shown in Figure 1. However, the farm type vegetable was the only farm type having more DAS adopters than non-adopters. Our results are consistent with the general picture that a large proportion of European farmers do not use Precision Farming technologies as for example shown in a study of Reichardt & Jürgens (2009) across German crop farmers (Reichardt & Jürgens, 2009). The differences in the use of DAS and EMS could be possibly explained by the level of difficulty of usage. DAS such as 'cruise control' or 'rear-view cameras' are part of the basic equipment of new machines whereas more knowledge and acquisition costs are needed for the application of EMS. The high adoption of the farm type vegetable could be due to the fact that vegetable farming is very labour-intensive and the harvest products have a high production value which makes the purchase of e.g. machines more profitable.

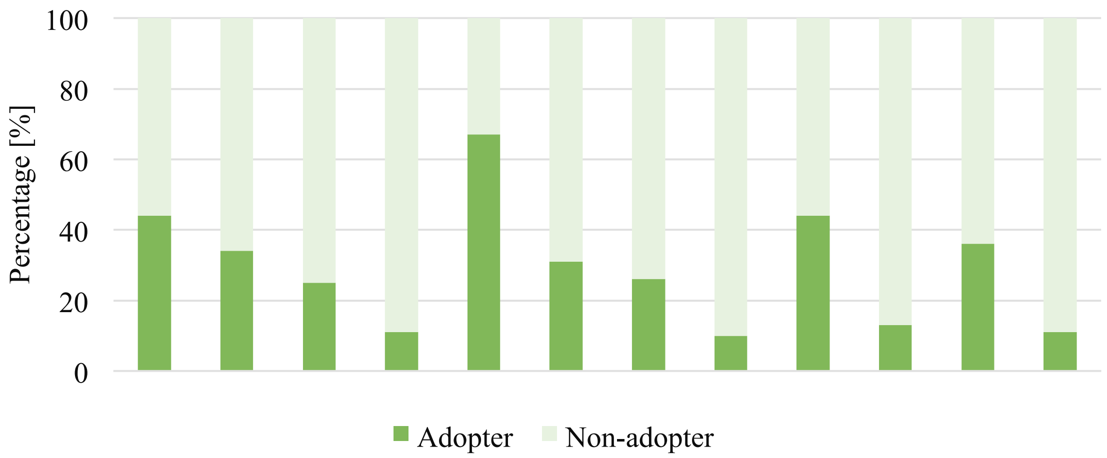

Figure 1. Adopters and non-adopters of Driver Assistant Systems (DAS) and Electronic Measuring Systems (EMS) for different farm types.

Further, especially in greenhouse production the use of automatic control management of e.g. humidity, fertilization and temperature is already well-established (Roldán et al., 2017). In summary, we conclude that the technology uptake varies across (i) the type of farming and (ii) the type of technology. The use of technologies by farmers is an important step towards Smart Farming. Thus, it should be investigated if and how new technologies could also be valuable for small farms. For this purpose, potential drivers correlated with technology adoption in Swiss' farm should be examined. This would allow more detailed conclusions on influencing factors in the adoption process and the results could support policy makers, extension services and research.

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PREDICTING LONG TERM COMPACTION WITH SOIL MAP UNITS

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Introduction

Soil compaction is a common soil degradation process that is associated with commercial agriculture (Saffit-Hdadi et al., 2009; Hamza and Anderson, 2005). Soil compaction due to agricultural traffic has been modelled using strain/stress functions and soil properties such as moisture content and texture (Alexandrou and Earl, 1998; Imhoff et al., 2004). The risk/soil sensitivity to compaction has been used to prevent and manage this problem. The role of soil surface properties in compaction have been well studied, but soil sensitivity to compaction at depth is less understood (Jones et al., 2003). Soil water content, bulk density and texture, and their interrelations; management practices; and seasonal climate all influence soil compaction at depth.

The objective of this study was to relate below-surface soil compaction due to 40 years of continuous cropping to soil map properties. Our hypothesis was that long-term compaction is related to the below-surface soil moisture regime and limiting layer depth, which confines soil material and increases soil strength magnitude. Prediction of limiting layer depth using soil maps will guide precision tillage and planting.

a) b)

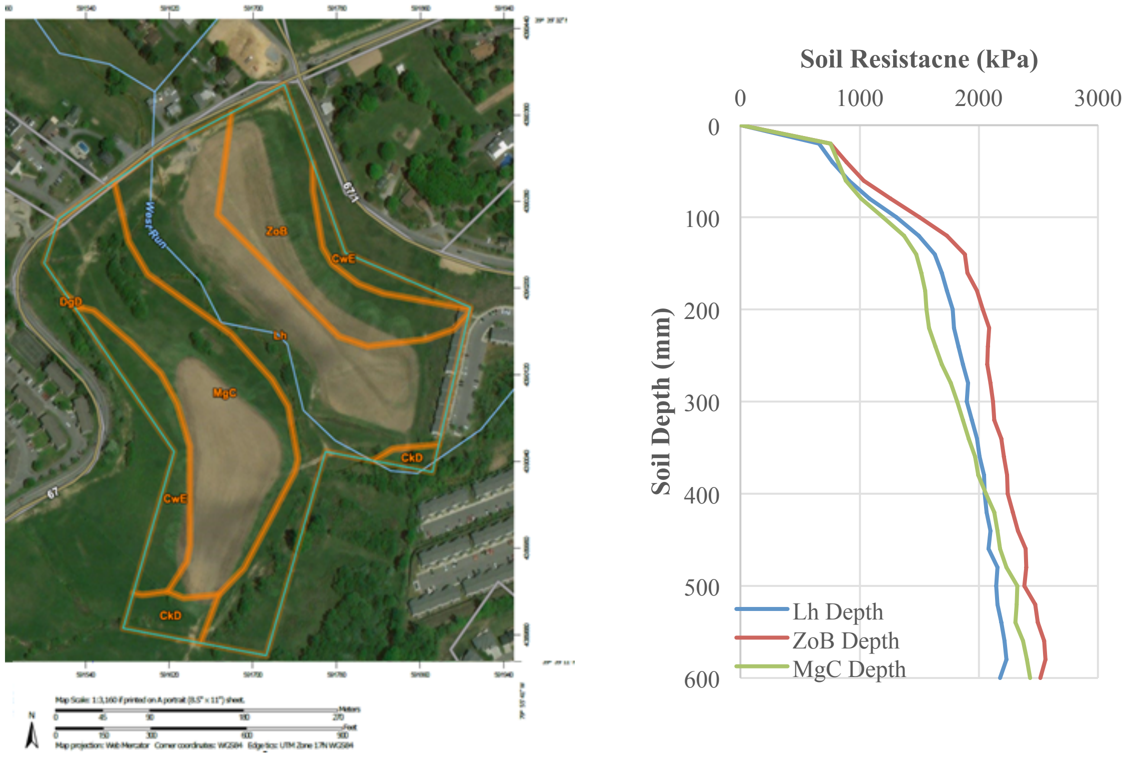

Figure 1a. Soils map and for soil resistance for the soils at the study site: a) Soils map; b) Profile soil resistance

Methods

The 10 ha study site was located at West Virginia University's Animal Research Farm (Fig. 1a). The study area contains three soil map units: Lobdell-Holly (Lh), Monongahela (MgC) and Zoar (ZoB). Most area is covered by Lb (48%), with MgC at 35% and ZoB at 21%.

Summarizing soil map units properties, although they were all silt loam some difference were described in the soil survey. Lobdell-Holly (Lh) occupied an area of 4.8 ha, with a slope of 3 to 8 %, presented a restrictive feature below 200 cm, and a depth to water table of 61-107 cm. Monongahela (MgC) occupied 3.5 ha, with a slope of 8 to 15 %, depth to water table between 45-76 cm, and with a fragipan at 45-76 cm. Fiinally, ZoB occupied 2.1 ha with a slope between 3 and 8 %, restrictive layer below 200 cm, and a depth to the water table of 33 to 61 cm. Compaction was assessed using a logging penetrometer, measuring resistance from 0 to 60 cm depth on a 10 x 10 m grid pattern.

Results

There were significant differences in soil compaction with depth. Measurements were made at field capacity, and no correction was needed. On average, soil resistance (kPA) ranged from 723 at the surface to over 2300 at 60 cm (Fig. 1b). There was a significant map unit by depth interaction on soil resistance. Surface soil (0-16 cm) resistance, corresponding to the depth of disking, exhibited significant between-soil differences, with ZoB exhibiting higher resistance. Below 16 cm (16-60 cm), though the rate of increase in resistance with depth was not different between Lh and ZoB, ZoB always exhibited higher resistance. The highest rate of resistance increase with depth was observed in MgC, likely due to the fragipan. Management related compaction (0-40 cm) followed the order MgC < Lh < ZoB. Zoar exhibited highest susceptibility to compaction.

Conclusions

Reviewing the soil survey, the main differences between soils were slope, depth to water table and fragipan absence/presence. The shallow depth to water table, which would generate a higher moisture content and increase the possibility of subsurface compaction, would explain the greater compaction sensitivity of ZoB soil. The previous study indicates that under the conditions of this study, it would be possible to design site-specific soil tillage management systems to decrease long-term compaction risk.

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DEVELOPMENT OF A DECISION SUPPORT SYSTEM FOR PRECISION NITROGEN FERTILIZATION OF VEGETABLE CROPS BASED ON DATA ASSIMILATION OF CROP MODELS AND REMOTELY SENSED DATA

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In Flanders, Belgium, each year 1.4 million tons of vegetables are produced in the open air, accounting for 6% of the total production value of the Flemish agricultural sector (Vrints et al. 2015). Open air vegetable farming is a resource intensive task, using high amounts of fertilizers and pesticides. Nowadays, nitrogen fertilization in vegetable crops is applied with a start dose and eventually one or multiple side-dresses. The amount of nitrogen farmers apply is based on advice from extension services which make use of the KNS-system (Vlaamse Landmaatschappij 2014). However, the used target values in the expert system are fixed to ensure no nitrogen deficiencies during growth, but do not include information about the current crop development or predicted growth and nitrogen uptake. Consequently, nitrogen applications are often too high compared to the actual nitrogen uptake. This results in excessive nitrate residues which may leach out to the ground and surface waters. Therefore, the aim of this study is to combine remote sensing with a crop growth model to elaborate a decision support system (DSS) for a more optimal N fertilization.

For simulating vegetable growth a dynamic crop model is elaborated which simulates biomass accumulation and respiration on an hourly basis combined with a quasi-2D extension of the WAVE model to simulate daily water flux and nitrogen processes in the soil (Vanclooster et al. 1994; Van Loon et al. 2011). To satisfy the current practices of a start and side-dress application, it is important to have accurate long-term predictions of soil processes and crop development. However, most processes in crop simulation models are driven by the weather conditions, which are inherently difficult to predict accurately on the long run. Therefore, a hybrid prediction method is developed for the DSS. First, a dataset of simulated data based on historical weather series is created on which subsequently, a nonlinear mixed model is fit, with the year as random variable to account for random variation in the climate. Next, crop development in a new year is predicted based on the current simulation state variables and the estimated mixed model. This allows the DSS to set dynamic target values for fertilization based upon current and expected crop development as well as simulated historic behavior to account for climatic uncertainty.

However, mechanistic models for the prediction of crop growth are subject to many sources of errors, like the spatial scale of assumed homogeneous input parameters such as soil properties, weather, and crop development (Jin et al. 2018). All these errors contribute to inaccurate growth prediction, resulting in inaccurate fertilization advice. Model performance will be worst for scenarios which were not covered by the initial calibration dataset. However, recent developments in crop monitoring using imaging sensors on UAV's and field robots allow to quantify multiple key crop parameters such as LAI, green crop cover, biomass, nitrogen content, and plant height in a cost-efficient way. Beside these, important soil parameters can be measured using a soil scanner, such as pH, CEC, organic matter content and EC. These data sources can subsequently be combined with the simulation state parameters by using data assimilation techniques to increase model accuracy (Jin et al., 2018) and thus provide more accurate fertilization advice. This process is facilitated when data acquisition moments are optimized using a parameter identifiability analysis (Galvanin et al. 2013; De Swaef et al. 2019). Further, remotely sensed data can also be used to identify heterogeneous zones within a field. These have different development expectations and thus require different fertilization management strategies.

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SITE-SPECIFIC NITROGEN MANAGEMENT IN WINTER WHEAT BY CONSIDERING THE MINERALIZED NITROGEN IN SOIL

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For the planning of nitrogen fertilization rates, the mineralized nitrogen (Nmin) level in soil (Nmin = NO3--N + NH4+-N) has to be taken into account. Therefore, samples are taken in spring to evaluate the amount of Nmin in soil. In the new German ordinance of fertilization (DüV, 2017) the amount of Nmin in soil has to be considered for the fertilization balance. For winter wheat crops 100 % of the amount of Nmin in the layer 0-60 cm respectively 50 % of the amount of Nmin in the layer 60-90 cm has to be considered in the region of Anhalt-Bitterfeld (Germany). Farmers have the opportunity to take samples from their own fields or use data from official sampling results in their region. To reach an acceptable result, public authorities recommend as a standard of "good practice" to draw one Nmin sample on every field and a minimum of two samples for heterogeneous fields. Alternatively, the Nmin average of an entire region can be used for planning nitrogen fertilization rates (DüV, 2017). This method of course avoids the enormously high costs of a spatially high-resolution Nmin analysis. But in a sense of site-specific nitrogen application, this method is a very imprecise approach. The questions asked in this study are (i) what is the impact of soil Nmin to yield and (ii) how strong do values of Nmin vary within a field spatially and temporary?

To determine the variance of Nmin values of a field, a site specific sampling was carried out on a 52-hectare field trial of the Martin-Luther-University in Saxony-Anhalt (Germany) in 2018 and 2019. 75 points were sampled 2018 on a core area of 34 hectares of a winter wheat field and analysed in two layers (0-30 cm and 30-60 cm). Thus the average sampling area for one point was nearly a half hectare. To evaluate a pattern in time, exactly the same test points were sampled in 2019 in the layers 0-30 cm, 30-60 cm and additionally in 60-90 cm on winter rape. The sampling period in both years was by the end of February before the first nitrogen fertilization. In order to identify the impact of soil Nmin, in a next step different nitrogen levels were fertilized by fully considering the Nmin level in soil, as requested in the German ordinance of fertilization (DüV, 2017). On the same field also standard parcels were realised with a uniform N treatment by considering the mean Nmin value of the whole field. So differing N fertilization levels can be compared with a uniform, non-differentiated N strategy. The results show very high variations of Nmin values with no impact on yield in 2018. In every fertilization level the yield differed from 45.5 to 47.2 dt per hectare. This result is not representative as 2018 was an extremely dry year and nitrogen therefore was not the limiting factor. So it doesn´t make sense to draw some logical conclusions according to the impact of Nmin on yield for this year. More interesting is the second question how Nmin values are varying spatially and over time. In 2019, the Nmin level "exploded" for various reasons. Firstly, there were no or low Nmin flux (leaching) during the dry winter season and secondly the N-withdrawal was very low due to a poor yield in 2018.

Descriptive statistics of the Nmin values in both years are shown in Table 1. The mean level is much higher in 2019 in all layers compared to 2018. Also the range is considerably higher in 2019, especially in layer 30-60 cm. In most cases the mode shows much lower values than the median or mean. This could imply that on a regular sampling basis with only a few points per hectare, the probability could increase to under- or overestimate the real mean value. To identify a possible correlation of these different variables, in the second part of Table 1 a correlation matrix is shown. No relevant correlations could be found, except from 0-30 cm 2018 to 30-60 cm 2018 with a value of 0.43. The high positive correlation of 0.92 between 0-

30 cm 2019 and 30-60 cm 2018 does not make any sense and looks like a random effect. There are obviously no or even weak correlations between layers within and between years.

Table 1: Descriptive statistics on Nmin values in 2018 and 2019 on field trial 7212

year	2018	2019	2018	2019	2018	2019	2019
layer	0-30 cm	0-30 cm	30-60 cm	30-60 cm	0-60 cm	0-60 cm	60-90 cm
				Nmin (kg/ha)			
mean	38	44	65	101	103	145	71
minimum	16	21	26	31	45	57	14
maximum	120	105	141	256	193	319	148
median	35	42	61	94	97	139	67
mode	29	29	38	112	99	122	62
variance	252	311	721	2284	1343	3098	923
SD	16	18	27	48	37	56	30
CV	0.42	0.40	0.42	0.47	0.36	0.38	0.43
25 % quantile	29	33	40	65	73	108	50
75 % quantile	44	50	85	126	127	174	91
10 % quantile	23	29	34	49	58	84	33
90 % quantile	59	67	98	162	158	220	110
Correlation matrix							
0-30 cm 2018	1	0,23	0,43	0,10	x[1]	0,16	-0,09
0-30 cm 2019		1	0,92	0,30	0,09	x[1]	-0,10
30-60 cm 2018			1	0,12	x[1]	0,10	0,20
30-60 cm 2019				1	0,13	x[1]	0,01
0-60 cm 2018					1	0,14	0,11
0-60 cm 2019						1	-0,02
60-90 cm 2019							1

[1] auto correlated values

In general, the high variance of Nmin on a field shows that only one value over a whole field or region does not allow a precise site-specific nitrogen management. Especially for the first application rate in spring, where it is not possible to use crop sensor technology, the accurate knowledge of site-specific Nmin values would be helpful. KOLBE (2005) found highly significant correlations between Nmin content and grain yield respectively other plant growth related variables on a whole field level. Therefore, it is highly interesting how far the local Nmin content influences the site-specific yield. Moreover, it is absolutely necessary to investigate further research in sensor-based detection methods for soil Nmin to generate low cost and contemporary datasets for site-specific nitrogen application.

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SEED AND EAR MAIZE YIELD ASSESSMENT BY DRONE-MOUNTED CAMERA SIMULATING VENμS BANDS

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Maize (Zea mays L.) is grown in most countries around the world (Araus et al., 2012). It is one of the most important crops, serving as a source of food, fuel and animal feed (Yin et al., 2015). Developing climate resilient crop genotypes is imperative to ensure global food security. Improvements through breeding involve phenotyping and trait assessments, especially the assessment of yield potential in drought-affected field-grown plants (Andrade-Sanchez et al., 2014). While numerous studies have tested mapping canopy vegetation traits through low altitude aerial phenotyping, few have explored maize grain yield assessment (Sankaran et al., 2015). Here we demonstrate the capacity of unmanned aerial vehicle (UAV) spectral measurements to assess maize performance in breeding trials. The aims were to identify the most suitable development stage for maize yield prediction and to spectrally differentiate between maize development stages. A UAV mounted Tetracam MiniMCA12 camera simulating Vegetation and Environmental New micro Spacecraft (VENμS) bands (Hermann et al., 2011), was used to obtain imagery throughout the growing season. Spectral data analysis was performed by partial least square regression (PLS-R) to predict yield and by PLS discriminant analysis (PLS-DA) to classify spectral data according to the development stages and the irrigation treatments. All PLS models were calibrated, cross-validated, and independently validated. The PLS-R models' quality was assessed by coefficient of determination (R^2) and root mean square error (RMSE) while the PLS-DA models were assessed by total accuracy of confusion matrices. The reproductive 2 (R2) development stage resulted in grain yield and ear weight PLS-R validation models with R^2 values of 0.73 and 0.49 and with RMSE of independent validation values of 2.07 and 3.41 t ha^{-1}, respectively. The classification models of seven development stages resulted in independent validation total accuracies of 90.9 % and 96.3 % for deficit and full irrigation, respectively. The two irrigation treatments were discriminated by PLS-DA models resulting in independent validation total accuracies of 91 % or higher for five development stages relevant to yield prediction. Irrigation status and development stage detection are useful for selecting the relevant yield prediction model (Figure 1). Based on the current data set, it was concluded that the best development stage for applying yield prediction is R2 and that the development stage can be spectrally determined in two irrigation levels. This work also demonstrates the potential of VENμS for precision agriculture.

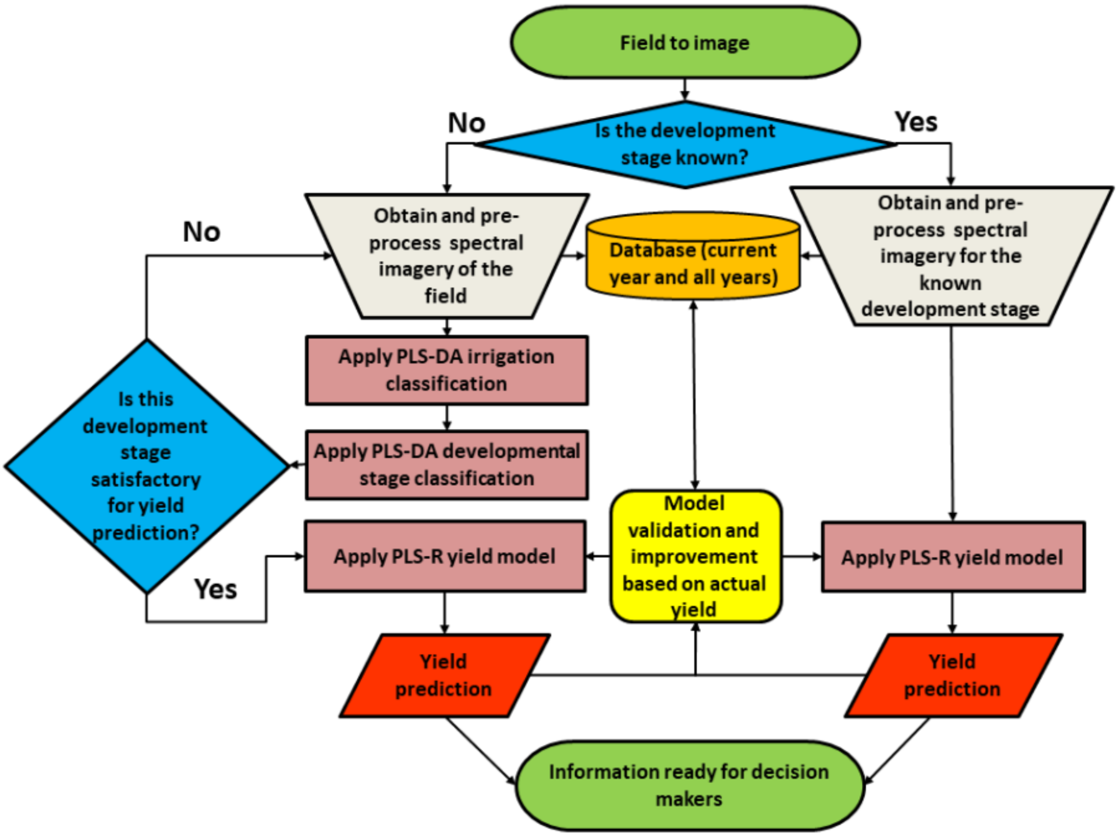

Figure 1: Yield prediction analysis steps for a field with either a known or unknown development stage when spectral data are obtained

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USER-ORIENTED, WEB-BASED GIS APPLICATION FOR LIQUID MANURE FERTILIZATION

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In Germany, administrative specifications must be strictly observed for N (nitrogen) and P (phosphorus) fertilization. There are several factors need to be taken into account when calculating nutrient fertilizer levels. The main calculation factor for the nutrient amounts for N, P and K (potassium) is the expected yield respectively a 3-year yield average. Furthermore, the soil nutrient contents have to be considered when calculating the P and K fertilizer quantities. Possible remaining harvest residues (for example, straw from the previous harvest) including the P and K values within these residues have to be subtracted from the current P and K fertilizer values. (see Fig. 1)

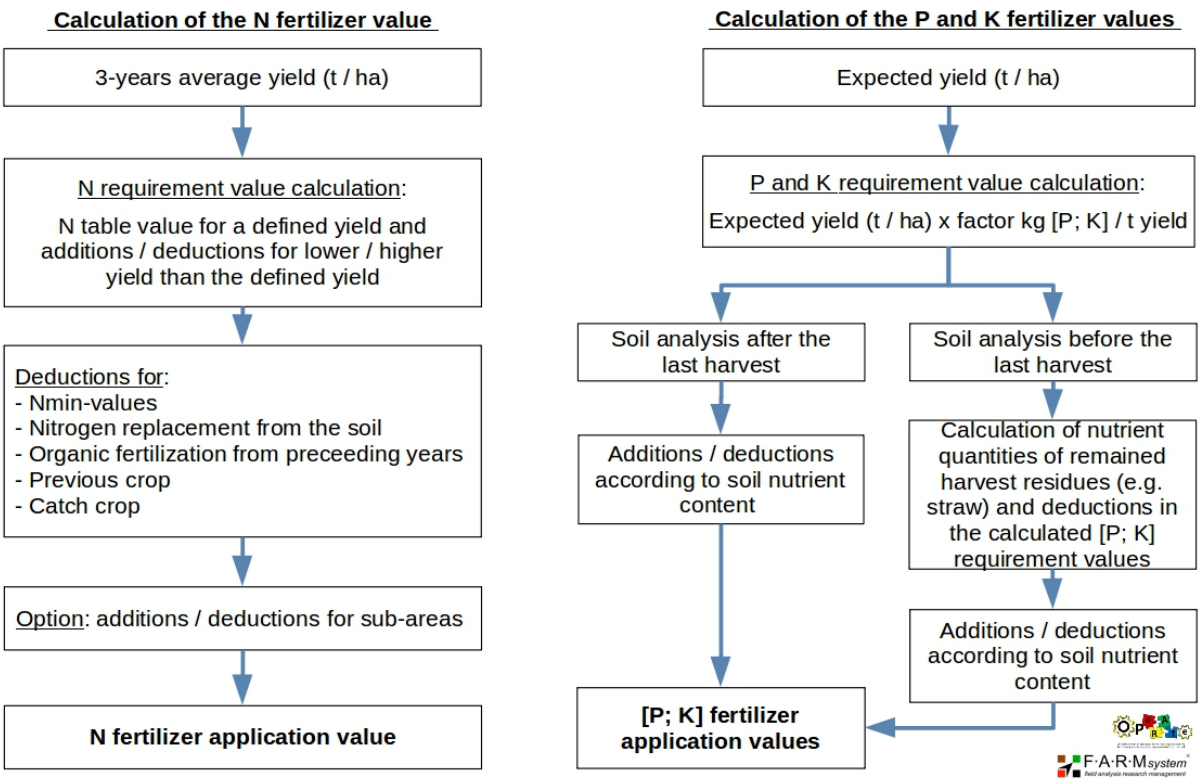

Figure 10: Schematic illustration of the procedure for calculating the fertilizer quantities, considering the administrative requirements

Mineral fertilization and also liquid manure fertilization should also be carried out as needs-based fertilization, ideally on a sub-area basis. In the case of sub-area fertilization, a multitude of data sets, e.g. yield data, nutrient demand values and soil information have to be prepared and set against each other. Partially, the data have different spatial references, e.g. point data from the yield mapping of the combine harvester or polygons for the results of the soil analysis in sub-areas. For the calculation of a fertilizer quantity, these data sets has be brought to a common spatial reference. (Hinck et al., 2018)
This circumstance has to be considered for the generation of an application map. The generation process represents a possible challenge for the farmer. In order to generate an application map, the various data levels have to be visualized and set against each other. A

geographic information system (GIS) is an ideal tool for these tasks (Fotheringham and Peter, 2013). It requires a practical, user-oriented GIS solution. The user needs to be supported in data selection and input. The GIS tool must be intuitive to use and allow the farmer to create fertilizer application maps easily, quickly and transparently (Brovelli et al., 2012).
Considering the requirements for fertilization mentioned above, a specialized "*NPK fertilizer module*" has been developed within the sub-project "Data analysis for real-time optimization of distributed processes" of the research project "OPeRAte" (Anon., 2016). This module is a user-friendly, web-based GIS calculation tool for fertilizer nutrient calculation and specialized for liquid manure application map generation. A fertilizer calculation can be conducted using "maize" crop as an example. The module can be extended for other crops.
If the liquid manure application has been carried out with a slurry tanker with near infrared (NIR) sensor technology for the detection of nutrient contents, during application, the applied nutrient quantities are recorded and stored. After the application, the applied nutrient amounts are written back to the "*NPK fertilizer module*" as an "as-applied-map". Any resulting differences between the required fertilizer quantities and the applied nutrients – in particular N and P – are determined and can be made up with mineral fertilizer. All relevant data and inputs are stored for documentation of the nutrient calculation.
The main focus at the research project "OPeRAte" is the process chain development of agricultural processes using the example of "task processing liquid manure application". The challenge in an agricultural process chain can be that the data come from different sources, is available in different formats and has to be managed at different times in the process (Nordemann et al., 2018). The application map generation is already a comprehensive sub-process and shows the overall complexity of the entire process to a certain extent.

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ASSESSMENT OF INFIELD SPATIAL VARIABILITY OF AVAILABLE WATER CONTENT ON AN EXPERIMENTAL PLATFORM

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Innovative strategies and genetic engineering solutions are needed in order to manage agroecosystems more efficiently, build improved varieties and reduce inputs. In this context, phenotyping has recently become a bottleneck for the selection of high-achieving stress-tolerant genotypes. In France, the Phenome project is responding to these stakes with a network of various high throughput facilities distributed in relevant geographical locations for studies at different scales and conditions.
Phenovia is a platform managed by Terres Inovia. It is incorporated into the INRA experimental unit (EU) of Epoisses, located in Bretenière (Côte-d'Or, Bourgogne-Franche-Comté, France) approximately 10 km southwest of Dijon. The study site is a 15-ha field divided in four subplots of approximately 4 ha each where a four-year rotation is performed.
The aim of this work is to define an extractable soil water map for the platform. First, a soil depth map was estimated from exhaustive electrical resistivity measurements combined with a smaller soil thickness dataset. Second, available water content (AWC) values were computed from soil depth according to typological soil units.

Soil apparent resistivity measurements were acquired by INRA, using a specific device developed by the Geocarta company (Panissot et al, 1997, Samouëlian et al, 2005). It is a resistivity device connected to spiked wheels acting as electrodes and towed by an all-terrain quad bike. An exhaustive set of 153 000 points was available. The soil thickness dataset was made by INRA using a quad bike especially equipped for soil sampling. The aim was to measure the depth of the alluvial coarse deposit. There were 541 boreholes made although a limit of this dataset is that the measurements did not exceed 0.90 m.
A geostatistical approach was used for spatial interpolation of datasets. First, soil and resistivity maps (Figure 1a and 1.) were generated through ordinary kriging. Then Kriging with External Drift (KED) was performed (Figure 1c). This method is relevant for the spatial interpolation of a low sampled variable of interest when an auxiliary variable is exhaustively described on studied area. For this purpose, the relationship between the variable of interest (soil depth) and the auxiliary variable (soil resitivity) is modelled. The residuals (deviations from the model) are described as a random variable and kriged on the entire plot. The spatial structure of these residuals locally defines the respective importance of the variable of interest and the drift in the estimate (Bourennane et al, 2003, Chiles and Delfinger, 2012, Loiseau, 2015).
Soil Typological Units (STU) were determined in the framework of the previous CAREX project (Seger et al, 2017). Each soil type is characterized by soil horizons, whose available water contents are known. The profile AWCs (Figure 1d) were computed toa depth of 1 m by adding AWC of soil horizons (from ground to estimated soil depth) with AWC of the alluvial coarse deposit (from estimated soil depth to 1m depth).

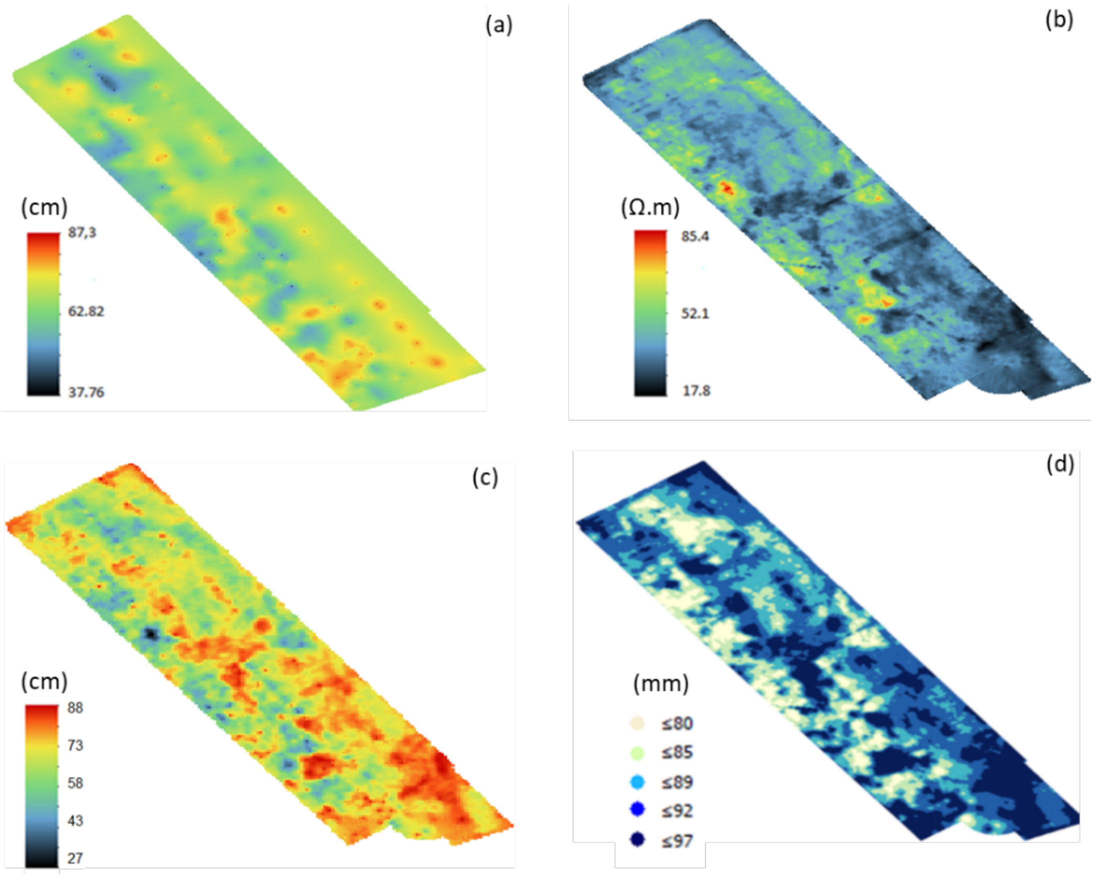

Figure 1 : Field maps of Phenovia with (a) Ordinary kriging of soil depth. (b) Soil apparent resistivity. (c) KED of soil depth with apparent resistivity as external drift. (d) Soil available water content map.

This available water content map globally meet to the expectations of the platform managers. However, it is important to remember that soil depth measurements did not exceed 0.90 m. Therefore, soil depth and AWC content could be underestimated. Complementary measurements (with manual auger) are needed to improve the quality of this map.

Further work is also needed to determine maximum or real time plant roots depths (arbitrarily set at 1 meter) and to transfer the method to other experimental sites.

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PROFIT MAXIMIZATION USING VARIABLE RATE TECHNOLOGY (VRT) IN SOYBEAN (GLYCINE MAX (L.) MERR.) IN THE SARRET REGION, HUNGARY

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Variable rate technology (VRT) in seeding (VRS) and variable rate application (VRA) of fertilizers aims to treat within-field differences occurring in agricultural lands. With the appropriate farm equipment, site-specific management can be carried out in order to define the most profitable treatment for various plants. The results of research on maize, winter wheat and sunflower experiments are available regarding VRT in Hungary, however, results for soybean (*Glycine max* (L.) Merr.) experiments are not available.
Soybean's high yields are possible only when the crop's nutritional requirements are met. Mismanagement of nitrogen or other fertilizer application prevents a grower from achieving yield potential. Variable rate technology (VRT) can be used to vary seed and fertilization rates within a field. Fertilizer variations have strong effects on yield production. Soybean grains have a nitrogen content of 40%, therefore adequate fertilization by nitrogen is required for achieving high-quality yields.

The trial is located in the Sárrét Region (N 47°08'33.32", E 18°176'32.58"), Hungary. Management zones were determined according to earlier yield maps, satellite imagery and earlier Topcon CropScan measurements. Cultivation was carried out using a Fendt 936 tractor and a Lemken diamant plough, the seedbed was prepared with the same tractor mounted with a Farmet kompaktomat 850. For fertilizing, a Fendt 720 tractor and Amazone ZA-TS spreader were used. Seeding was carried out by a Fendt 720 tractor and a Horsch Pronto 6DC precision seeding machine. Top-dressing and weed control were carried out by a Fendt 716 tractor equipped with an Amazone UX fertilizer spreader. For harvesting, a Claas Lexion 660 combine harvester was used equipped with a TopCon YieldTrakk yield monitoring system. For control and data collection, a TopCon X35 monitor was installed in the machines.
The applied treatments were: *1,* varying only seed rates: 525-615 k-seed/ha; *2,* varying nutrient rates: N: 32-54 kg in the form of Calcium ammonium nitrate (CAN 27%N), P: 84-116 kg in the form of Diammonium phosphate (DAP 18 % N:46 % P_2O_5), and K: 7-80 kg potassium (60 % K_2O); and *3,* varying seed and fertilizer rates as well. Base fertilizing was carried out on 27 March 2018. Seeding was carried out on 25 April 2018 using 15 cm row spacing. Top-dressing (FitoHorm Szója, 5 l/ha) and weed control (Corum herbicide, 1.9 l/ha) were carried out uniformly on 30 May 2018.
Fixed costs such as cultivation, soil sampling and laboratory analysis, machinery for fertilizer application, top-dressing, weed control, harvesting and costs for uniformly applied top-dressing material and weed control material were calculated for the whole field. Variable costs (fertilizers and seed) were calculated based on the size of the treatment units. All data were collected and uploaded into Topcon SGIS software. For income calculations, yield was measured. Profit was calculated automatically by SGIS software for each management unit based on the collected and uploaded data. Moisture content was also registered, therefore the actual, comparable amount of dry yield for each unit was calculable. The actual market price for soybeans was EUR 322 /t. The maturation of soybean differed, therefore moisture content of the harvested areas differed as well. The control zone was harvested with 15.19% moisture content, whereas the VRS zone moisture content was 15.9%. The VRA zone was slightly less, at 15.2%, and the driest zone was the VRS+VRA application, at 13.4%. The differences in moisture content resulted in variations in yield as well. As production was the highest in the zone where VRS and VRA were applied (4.86 t/ha), this zone produced the highest income as

well (EUR 1,564); consequently the highest profit (EUR 899.45) was realized here. Untreated control produced a significantly lower profit (EUR 704.83). Profit for the zones where only VRS or VRA was applied was even lower than the control zone's profit, EUR 598.86, and EUR 692.53, respectively. Expenses, income and profit calculations are summarized in Table 1.

Table 1. Expenses and profit calculation of soybean production in EUR at the investigated farm (calculations are related to 1 ha).

Expenses	Control	VRS	VRA	VRS+VRA
Soil sampling[1]	10	10	10	10
Cultivation+seed bed[2]	143.75	143.75	143.75	143.75
Machinery[3]	65.63	65.63	65.63	65.63
Top-dressing	20.31	20.31	20.31	20.31
Weed control	65.63	65.63	65.63	65.63
Harvesting	68.75	68.75	68.75	68.75
DAP[4]	70	77.35	74.55	77
CAN[4]	23.4	23.24	24.54	22.59
Potassium[4]	15.19	15.19	17.44	18.56
Seed[4]	176.7	173.6	176.7	172.05
Total Costs (EUR)	659.35	663.44	667.29	664.26
Moisture (%)	15.3	15.9	15.2	13.4
Yield* (kg)	4,238.24	3,921.7	4,224.67	4,858.21
Income (EUR)	1,364.18	1,262.3	1,359.82	1,563.74
Profit (EUR)	704.83	598.86	692.53	899.47

[1]Including laboratory analysis and advisory services
[2]Cost of labour (machinery, fuel, etc.)
[3]Cost of machinery for seeding, base fertilization, top-dressing and weed control
[4]Expenses are calculated for the treatment unit
*Corrected amount of yield for the treatment unit

The highest profit was reached by applying VRS and VRA to the same crop. Untreated control resulted in a significantly lower profit. The application of complex site-specific variable rate technology resulted in higher profit than individual VRS or VRA treatments using extra input materials. Reference site-specific technology for this growing region for soybean was also found, which will help advisors in the future.

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METRICS TO ANALYSE THE AGRONOME

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The opportunities from connected big data in agriculture are widely anticipated, yet large challenges remain to achieve sufficient data interoperability to provide useful insights to inform management decisions. Much of the effort in precision farming has focussed on dealing with spatial variation within fields with variable rate applications (VRA). However, it is increasingly recognised that benefits from VRA are modest in relation to the large variation in yield and profitability seen between fields and farms (Kindred *et al.*, 2017). We contend that by far the bigger opportunity from precision farming technologies and the connected digitisation of agriculture is the ability it gives farmers, advisors, industry and researchers to test decisions and to understand the drivers of variability and what to do about it (Sylvester-Bradley *et al.*, 2018).
We calculate that arable farmers in the UK face an apparent quadrillion, quadrillion ($\sim 10^{30}$) decision combinations when species, varieties, cultivation methods, dates, rates and products used in sowing and application of fertilisers, herbicides, fungicides and insecticides are considered across the range possible soil and weather conditions at key timings (Sylvester-Bradley *et al.*, 2018). Clearly not all the interactions here are important, but many must be. Variation in the outcomes of farming is huge, whether considered locally or internationally, and whether measured economically, environmentally or socially. Yet scientists currently seek to inform farmers about husbandry choices through small-plot experiments each focussing on primary effects of one or maybe two major factors. Digitisation should enable us to do far better than this.

We propose that field-scale variation in the outcomes of farming can best be considered through the concept of the 'agronome'. Fundamentally all variation must be due to differences in soils, weather, genetics, pests and multiple facets of management; or in summary Genetics x Environment x Management, including their multiple interactions. The digitisation of agriculture provides the opportunity to create the comprehensive evidence base necessary to explore the complexities of farming outcomes and optimise combinations of genetics and management for the aims and environment of each farm. However, this depends on collecting and sharing the data and metrics that most matter within interoperable frameworks utilising common ontologies. It also requires a strong incentive for farmers to engage; this can be through benchmarking, enabling farmers to visualise how their fields, crops and management compare to their peers. We have successfully demonstrated the feasibility and power of this approach in the Yield Enhancement Network (www.yen.adas.co.uk; Sylvester-Bradley *et al.*, 2014) in which over 300 farmers in UK & Northern Europe share data on wheat, oilseed, grass, pea and bean crops to learn together how yields might be improved. The YEN collates a set of important yield-related metrics, starting with the availability and capture of light energy and water. Whilst the collection, collation and integration of measures, farm and field management records, soil and weather data in the YEN has proved laborious, digital solutions are eminently feasible, and would potentially enable massive extension.

Furthermore, the wealth of sensors, technologies, tools and products now available, including smartphone digital photos, tractor-mounted sensors, UAV & airborne imagery and satellite data (both SAR & optical) provides ample opportunity to attain accurate and comparable crop measures within the season. For these sensed measures to be really useful in analysing the agronome they need to be marshalled into a common set of consistent metrics. We argue that light energy capture (or FAPAR) is the most meaningful crop metric to measure across crops.

Direct measures of biomass would be more useful still, but are currently less feasible. Where time courses of measures are available it is possible to parameterise these with a simple trapezoid function that describes the main growth phases of the crop, giving estimated dates of emergence, stem extension, flowering, onset of senescence and harvest maturity, as well as giving estimates of canopy size and light capture and (indirectly) biomass at each date. Having such metrics available when analysing variation amongst multiple crops would be invaluable in understanding the complexities of how crop performance is determined and could be better managed.

Further, a significant constraint to analysis of the agronome is that the important measures of field performance (e.g. crop yield and quality) are only collected annually, if at all. By parameterising growth curves, information on field performance can be estimated for each growth phase, enabling associations to be sought with soil, management and weather factors even where impacts on final performance may not be known, or where these are compromised by confounding factors (e.g. late drought curtailing benefits of early crop growth). So satellites could provide datasets on field performance of sufficient size to apply machine learning and artificial intelligence techniques to search out insights into the agronome.

This parameterisation approach could in principle be used with any sensor, and the ubiquity of satellite data in space and time could allow analyses of all fields everywhere. The need now is to create robust routines that integrate observations from different satellite sensors in order to obtain best possible estimates of field states as interpolated time courses. The MULTIPLY platform (www.multiply-h2020.eu) is creating such data on energy capture from both optical and SAR observations. It uses compatible radiative transfer models with data assimilation from multiple information sources (observational, prior, temporal) to optimally assimilate satellite information that are gap-free. MULTIPLY will deliver a set of internally consistent data products at different resolutions with quantified uncertainties. We have explored potential uses of such data through a 'Crop Intelligence System' which provides a dashboard and benchmarking of crop growth for farmers, plus sets of big data necessary to suitable for researchers to much more thoroughly explore the agronome.

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ACQUIRING PLANT FEATURES WITH OPTICAL SENSING DEVICES IN AN ORGANIC STRIP-CROPPING SYSTEM

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There is an increasing market for organic agriculture (Golijan & Popoviš, 2016). However, the lack of attention for biodiversity and soil fertility of current practices is a pressing issue. The SUREVEG project (CORE Organic Cofund, 2018) therefore looks at strip-cropping in organic production and its implementation in intensive farming to improve soil fertility and biodiversity throughout Europe. The aim is to enhance resilience (Wojtkowski, 2008), system sustainability, local nutrient recycling, and soil carbon storage (Wang, Li & Alva, 2010) among others. To counteract the additional labour of a multi-crop system, a robotic tool is proposed, which will operate upside down suspended from a wide-span mobile carriage. Within the project framework, a modular proof-of-concept (POC) version will be produced, combining sensing technologies with actuation in the form of a robotic arm. This POC will focus on fertilization needs, which are to be identified in real-time at the single-plant scale.
As a first approach towards facilitating field-mapping and growth registration on a single crop level, two LiDAR systems were mounted in front of a tractor, focusing on a single strip-cropping strip at a time. Performing these scans on a regular basis, which could be combined with other activities in the fields, could produce a time-dependent model of each individual plant, which allows for a comparison not only intra-strip or intra-field, but also across different fields. The point cloud data of the individual LiDARs was merged for each scanned strip, after which the points were subjected to a cost function evaluation in an effort to separate the plants from the soil. Plant clouds spanning multiple seeding locations were cut accordingly. Finally, each of the point clusters were used for a volume calculation. The procedure is visually summarised in Figure 11. It is assumed that the plant volume holds a direct relation to the current crop growth stage (Andaloro et al., 1983) and the yield.

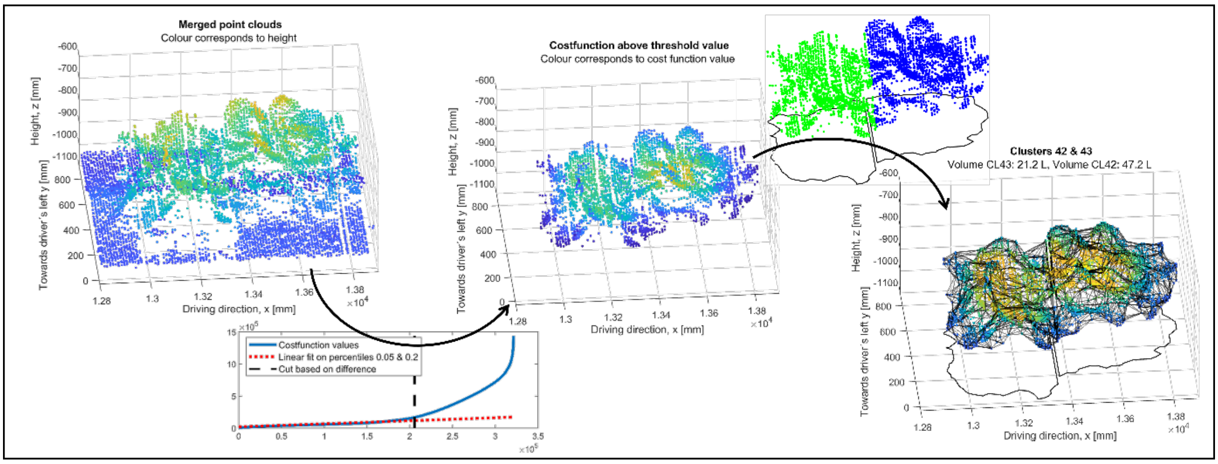

Figure 11: Summary of the developed methodology.

The aforementioned tractor set-up with the two LiDARs was used on a strip-cropping experiment field of the University of Wageningen on several strips of cabbages, which are alternated by wheat strips. Timewise the experiment was executed in the middle of the growing season (62 days after transplanting (DAT)), shortly after the mowing of the wheats. The automated GPS guidance inherent to the tractor was fixed to 2 km/h, with the LiDARs set to a scan frequency of 50 Hz and an angular resolution of 0.5°. The data was processed using Python 3 and Matlab 2018b. To separate the soil from the plant points the following cost function (Equation 1) was calculated for each point.

$$J_k = \sum_{i=1}^{N} \frac{h_i^2}{d_{ik}} \qquad \text{Equation 1}$$

The cost function value J of point$k$ looks at all the points N present in the sphere with a radius of $150mm$ immediately surrounding point$k$. The height h_i of each of these points as squared and divided by its distance d_{ik} from point k to form its contribution to the total value. In other words, the height of the points surrounding each point effectively defined its cost function value, while their proximity acts as a multiplier bonus. For the separation between soil and plants all resulting cost function values were sorted. A roughly linear slope can be identified that defines the soil points, where at some point the increase in values becomes larger. Cutting the point cloud based on the cost function value where this happens gives very promising results. As the percentage of detected soil points varied considerably for different fields, the following method was proposed to define this cut c dynamically, Equation 2.

$$c = min\{m\}, \qquad \left\{m \in \left(J_s(m) - L_{[0.05;0.2]}(m)\right) > 50000\right\} \qquad \text{Equation 2}$$

Here, the cut value c corresponded to the first point m on the sorted cost function curve J_s where the difference between the curve and the linear reference curve L exceeded a predefined threshold. The linear reference was established based on two values on the lower end of J_s which correspond to the 0.05 percentile and the 0.2 percentile. The minimal difference of 50000 was established empirically to fit the obtained data of all measured strips. For the clustering of the obtained plant points, a Euclidian segmentation with a distance of $75mm$ was used. Knowing the sowing locations, every cluster that spanned two or more is assumed to contain multiple crops. Visual inspection of the point cloud showed the separate crops to validate this assumption, allowing for average crop size estimation. After splitting the larger clusters into smaller ones to fit this estimation all clusters were subjected to a volume estimation using the boundary function in Matlab. Unfortunately the harvest of the fields that were measured occurred 3 months after the scans (at 140 and 166 DAT), which resulted in a rather poor correlation between these estimations and the actual yield. Even though the ground truth data was not present in this first approach, the algorithm generated promising results that will be very useful in upcoming experiments within the project.

In conclusion, merging the two point clouds provideed a model with surprising levels of accuracy. The growth stages of the cabbages showed a large variation intra-strip in all of the scanned fields. As the scanned fields were not harvested for another couple of months the yield data does not directly correspond to the field status as measured. The first and foremost recommendation is thus applying these methods on another field closer to the actual harvest to fine-tune the variables used. We cannot say anything about changes over time, since we only had the opportunity to execute these measurements once. Finally the clustering of plants that touch each other is something that needs to be looked into, to separate them more accurately.

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EMBEDDED VISION SYSTEM AND ALGORITHMS FOR EARLY WEED VS. CROP DISCRIMINATION. APPLICATION TO INTRA-ROW HOEING OF VEGETABLES.

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Introduction

Intra-row weed management is a critical issue with great financial and environmental consequences. Both chemical and mechanical solutions exist but their use depend on many factors such as crop type, phenological stage and ground type that hamper the use of a single weeding tool for a wide range of applications.

This work is part of a project (Challenge ROSE) that aims at developing a versatile mechanical solution to weed management in vegetable and field crops at an early growth stage. It consists of an imagery based self-guided hoeing system designed for a single row that can be mounted to a wide variety of traction vehicles. The present work aims to describe and evaluate the computer vision device and algorithms developed to detect and locate crops within the row.

Materials and Methods

Embedded vision system — The device is composed of an industrial 3 megapixels RGB camera, a pair of 20 W LED panels producing 1800 lumens each, one cutting-edge embedded AI computer Nvidia Jetson Xavier capable of delivering 32 TOPs within a 30 W thermal envelope (TDP) and two 12 V batteries. Images are acquired at a distance of 40 cm perpendicular to the ground, in an artificially light-controlled environment isolated from sunlight with a dark chamber.

Crop detection method — Image processing algorithms using Convolutional Neural Networks (CNN) are developed to discriminate crops from weeds in real-time. CNNs are versatile, accurate and robust tools for object detection in images and can run fast on Deep Learning dedicated hardware platforms. The developed system is a lightweight neural network named Tiny Yolo v3 (Redmon and Farhadi, 2018) and designed for computationally limited platforms. Inference speed of such networks are faster than state of the art ones while maintaining a descent performance for detection tasks (Huang et al., 2016). For even greater speed and energy efficiency, the implementation by (Alexey, 2017) is used as it takes full advantage of NVIDIA embedded platforms.

Database and experimental setup — Performance are evaluated on three species (i.e. maize, bean and carrot) at an early development stage (less than two weeks) with an intra-row distance ranging from 3 cm to 25 cm. Experimental setting includes (i) artificially controlled level of infestation and weed type, (ii) natural infestation and (iii) under-tunnel grown crop.

In order to obtain a great detection accuracy, the database quality is crucial. Thus, it is carefully built to match real conditions as much as possible while covering a great diversity of settings such as crop orientation, soil condition and phenological stage. The current database supports maize, carrot and bean and is populated with 1880 annotations at almost equal repartition between classes. The Neural Network is trained during approximately 60 epochs using data-augmentation as well as transfer learning to speed up the process. The split ratio between training and validation set is set to respectively 80 % and 20 %.

Results

The developed system can run at more than 30 frames per second (fps) with 416 by 416 images using no more than 30 W of power while still leaving large room for other vision tasks such as optical flow computation and tracking as the GPU is only used at 20 % of its capacity. Evaluation is carried out with the mean Average Precision metric (mAP) using a 50 % Intersection over Union threshold (IoU). Precision, recall and F1-score are given for a confidence threshold level of 25 %. Maize, bean and carrot obtain respectively a mAP score of 90.73 %, 89.37 % and 81.11 %. All crop species mixed up, precision is 0.9, recall 0.91 and F1-score 0.9. Results are good on bean and maize but the accuracy is slightly worst on carrots. This difference is due to the higher compactness, proximity and the smaller size of carrot crops contrary to others species.

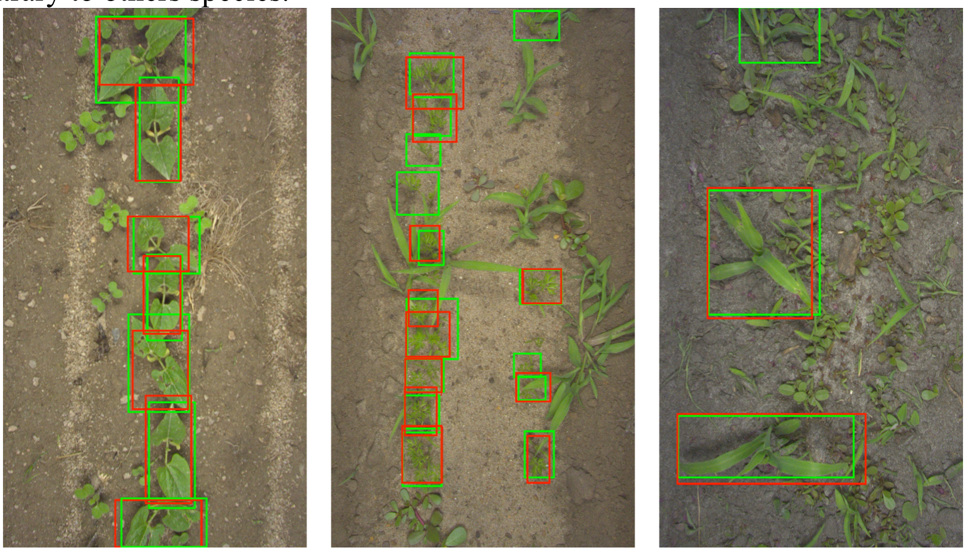

Figure 1: Detections (in red) estimated by the proposed solution and ground truth (in green) on respectively bean, carrot and maize.

Future work

In the context of the *Challenge ROSE* this method will be compared and evaluated against other methods in the same experimental setup. Moreover, the detection algorithms developed will be implemented within the autonomous weeding platform of the project and the overall hoeing efficiency will be analyzed.

Finally, the detection method will be improved to detect more details such as stems, leaves or crop orientation estimation (Cao et al., 2018) and to detect more crop specie,s such as faba bean, leek and peas.

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ESTIMATION OF RICE LAI USING SPECTRAL AND TEXTURAL INFORMATION DERIVED FROM UAV-BASED RGB IMAGERY

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Unmanned aerial vehicles (UAV) are a promising remote sensing platform with flexibility and relatively larger sensing scale for crop leaf area index (LAI) estimation. Vegetation indices and color indices (CI) derived from UAV multispectral and RGB imagery have been widely utilized for crop LAI retrieval. Texture information extracted from UAV-based RGB imagery need to be analysed for improving rice LAI estimation. Therefore, the objective of this study was to compare predictive performance between spectral and texture information (color indices and texture indices) derived from UAV-based RGB images for rice LAI estimation, and to explore the potential of improving rice LAI estimation by combing spectral and textural information from UAV RGB imagery.

The field experiment on rice was carried out in Sihong (Exp. 1, 33.37°N and 118.26°E, 2016) and Lianyungang (Exp. 2, 34.56°N and 119.32°E, 2017) of China over various nitrogen rates (Exp. 1: 0, 120, 240, 360 kg N ha^{-1}; Exp. 2: 0, 135, 270, 405 kg N ha^{-1}), rice varieties (Exp. 1: Lianjing-7, Wuyunjing-24 and Ningjing-4; Exp. 2: Lianjing-15 and Zhongdao-1) and transplanting ways (Exp. 1: manual transplanting; Exp. 2: pot- and carpet-seedling mechanical transplanting). Plant sampling were conducted on tillering (2 times), stem elongation, panicle initiation and booting stages in each experiment. Leaves of the randomly sampled rice plants (based on average hill numbers per unit area) were scanned by Li-3000c to determine the LAI in each plot and each stage. In each sampling stage, images were taken using a built-in 12.4 MP visible light (RGB) camera mounted on a UAV named DJI Phantom 3 Professional with a sensing height of 30 m under clear skies and low wind speed conditions. Camera settings were adjusted according to the lighting conditions and set to a fixed exposure for each flight. Ortho-images were generated using RGB images with GPS location information.
Actual DN values of R, G and B channel for each plot were extracted from the RGB images using the ENVI/IDL. Using normalized DNs of R, G and B channel ($r = R/(R+G+B)$, $g = G/(R+G+B)$, $b = B/(R+G+B)$), six types of CIs were calculated for each sample (GRVI (Tucker, 1979), ExG (Woebbecke et al., 1995), ExR (Meyer and Neto, 2008), ExGR (Neto, 2004), VARI (Gitelson et al., 2002) and GLI (Louhaichi et al., 2001)) . Besides, eight grey level co-occurrence matrix based textures of R, G, B channels, including mean (MEA), variance (VAR), homogeneity (HOM), contrast (CON), dissimilarity (DIS), entropy (ENT), second moment (SEM) and correlation (COR) were extracted and calculated using the ENVI/IDL for R, G, and B bands and each plot, respectively. Normalized different texture indices (NDTI=$(T_1 - T_2)/(T_1 + T_2)$), were calculated with randomly selected texture features for T_1 and T_2.
The spectral and texture information collected from two experiments were pooled together to evaluate the predictive performance for rice LAI. Simple linear regression models (LM) were built with inputs of each VI and each TI, respectively. Besides, stepwise multiple linear regression (SMLR) models were built with inputs of all the CIs, all the TIs and combination of all the CIs and TIs, respectively. The predictive capability of those models was evaluated by the coefficient of determination (R^2) and Root Mean Square Error (RMSE) through a 10-fold cross-validation procedure.

Table 1: Calibration (R^2) and validation (R^2 and RMSE) performance of the top-3 CI-based LM models, the top-3 TI-based LM models, and SLMR models with inputs of all the CIs, all the TIs and CIs + TIs, respectively.

Model	Calibration		Validation	
	Input variables	R^2	R^2	RMSE
LM (CI)	**VARI**	**0.69**	**0.70**	**1.16**
	NDI	0.66	0.67	1.22
	ExR	0.65	0.67	1.22
LM (TI)	**NDTI(MEA_R, MEA_B)**	**0.65**	**0.66**	**1.21**
	NDTI(MEA_R, MEA_G)	0.57	0.58	1.36
	NDTI(COR_R, COR_B)	0.50	0.50	1.45
SLMR	CIs	0.79	0.78	1.00
	TIs	0.84	0.82	0.88
	CIs + TIs	**0.85**	**0.85**	**0.82**

Considering the calibration results, the CI-based and TI-based LM models had a variable predictive performance for rice LAI estimation; VARI had the highest R^2 among the CIs, and 69% of the LAI can be explained; the NDTIs composed of MEA_R and MEA_B, MEA_R and MEA_G and COR_R and COR_B performed the best compared to other TIs, and NDTI (MEA_R, MEA_B) had the best calibration performance among the TIs with the R^2 of 0.65. In addition, The SMLR models were further built and evaluated with inputs of all the CIs, all the TIs and combination of CIs and TIs, respectively. The number of variables was limited as no more than 4 to avoid potential model complexity and overfitting problem. The SMLR model with inputs of TIs had a higher value of R^2 than the CIs-based SMLR model. An improved performance for LAI estimation was shown by the SMLR model with the inputs of the CIs and TIs together.

All the models were further validated and evaluated with R^2 and RMSE. For simple linear regression models, VARI had the best validation result (R^2=0.70, RMSE=1.16) among the CIs, which also performed better than the best TI (NDTI (MEA_R, MEA_B), R^2=0.66, RMSE=1.21). Moreover, the model of SMLR using spectral (CIs) and texture (TIs) had the best validation performance among all the models in this study, which improved predictive performance compared to traditional CI-based LAI estimation.

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VARIABLE RATE NITROGEN APPLICATION IN SUGAR BEET: A FLOURISH STUDY

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Increasing the use efficiency of resource inputs such as nitrogen (N) fertilizer is a major challenge in modern agriculture to simultaneously optimize the farm profitability while reducing environmental impacts. Precision farming tools such as variable rate application, facilitated by proximal or remote sensing techniques, will become more important to achieve higher N use efficiency on field and farm level. Indeed, such tools are commercially available, but they are often related to company specific calibrations, narrow time windows of application, are restricted to certain crops and are difficult to compare to other techniques or products, because of their black-box nature.

Sugar beet as an example for a commonly strongly fertilized high-value crop widespread in temperate regions is affected twofold by inappropriate N management, as N deficiency causes yield losses while excess N reduces the extractable sugar content and increases the succeptibility to pests and diseases. However, variable rate fertilization is not commonly used to optimize sugar beet N fertilization

This contribution will summarize the results from a three year study in the frame of the Flourish project using both ground- and UAV-based spectrometers to evaluate the suitability to quantify N fertilizer demand and N nutrition status in sugar beet. While the first year mainly focused on identification and calibration of the spectral indicators the two following years focused on in field experimentation using variable N inputs and its relation to biomass and sugar yield as validation parameters. Indeed the established validation experiments covered the range from reduced beet biomass production due to insufficient N fertilization to very high beet biomass production but reduced sugar extractability resulting from surplus N fertilization. Th e observations indicates that the optimal N uptake ranges between 120 to 160 kg N ha^{-1} depending on local yield potential which seemed to be different for the two investigated fields. Further we show that remote and proximal sensing approaches based on spectral information such as a simple ratio (R780/R740) can be used to differentiate deficient, sufficient and surplus N supply in sugar beets stands enabling a variable rate fertilization strategy optimizing the fertilizer application between the upper and the lower yield limitation for sugar beet cultivation.

INTEGRATED SOLUTION SYSTEMS DEVELOPMENT FOR PRECISION FERTILIZER MANAGEMENT

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The objective of precision agriculture (PA) is to increase crop production system efficiency, productivity, and profitability while reducing negative environmental impacts by employing inputs at variable rates. In the context of PA, crop yield directly reflects soil spatial variability, fertilization and irrigation. However, harvested yield data is only obtained after the season, whereas many agronomical difficulties such as nutrient deficiencies and water stress may occur during the growing season. Hence, the main impetus for this work is to develop an integrated system capable of quantifying soil spatiotemporal variations at the field level before and during the growing season in order to facilitate optimal fertilization. The final product will be a web-enabled integrated decision support system that provides near real-time solutions to farmers such as variable rate nutrient applications across spatially variable fields. We hypothesize that soil spatial variability dictates optimal nutrient inputs for prime crop production; to test these hypotheses, Site-Specific Management Units (SSMUs) should be delineated by collecting relatively large ancillary datasets (proximal soil survey, multispectral) to facilitate cost-effective sampling. There are hard theoretical questions concerning effective soil-sampling using a minimal set of points while aiming for maximal information. Such questions require rigorous mathematical modelling and involve the perspective of tradeoffs and multi-objective (Pareto) optimization. The proximal soil survey was conducted in a wheat field of 35 ha using EM38 MK2 ground conductivity meter (Geonics Ltd, Canada) that recorded apparent electrical conductivity (EC_a) and magnetic susceptibility (MS_a). We collected many 1000s points with unique geo-referencing in two modes of operation, vertical and horizontal, corresponding to two depth ranges of 0 to 1.5 m and 0 to 0.75 m, respectively. We also collected normalized difference vegetation index (NDVI) data with unmanned aerial vehicle (UAV). The pre-processing stage involves ECa and MSa data compaction, log transformation, and Ordinary Kriging interpolation to a grid at a resolution of 1m × 1m (using gstat R-package), followed by a crop to field boundaries and normalization. NDVI layer was scaled down to resolution, cropped and normalized. The field was divided into management zones (MZs) using all the ancillary data by k-means clustering of the matrix A, and the feasible search space defined by exclusion of a fixed buffer (14m) from field boundaries. We run an optimization procedure known as bi-objective evolutionary optimization algorithms with problem specific search operators. The procedure consists on conditional Latin Hypercube sampling objective function and max-min diversity function that aims to maximize the minimal pairwise geographical distances among all sampling points. The end-result known as Pareto optimization procedure that tries to obtain the non-dominated set of functions. This optimization procedure was executed in 30 parallel runs ranging from 10 to 50 points of soil sampling. Statistical measures of the sampling size were conducted using AIC which assess the degree of linear models fitness with each ancillary data channel as dependent variable, mean ordinary kriging variance, resulting from interpolation of ancillary data values at sample points and D_{KL}, derived from the ratio of ancillary data distributions in a sample, to those of the full field. Analyzing the attained efficiency fronts of different sample sizes with respect to the proposed information criteria we identify an optimal sampling-size of 22, beyond which model improvements are locally deteriorating. Upon selecting this sampling size, additional two sets of solutions were generated to address operational constraints of minimal points per management zones (MZ), and minimal distance from MZs boundaries (Fig. 1). In this study we have demonstrated that bi-objective optimization with simultaneous targets of geographic dispersion and feature space stratification is a suitable approach for sampling design, which reveals no discrepancies. The application of the integrated system in a real farm, when considering cLHS and max-min diversity as objective functions, produced many feasible solutions, mostly found on the knee-point area of the Pareto-front – offering an apt compromise between the objectives.

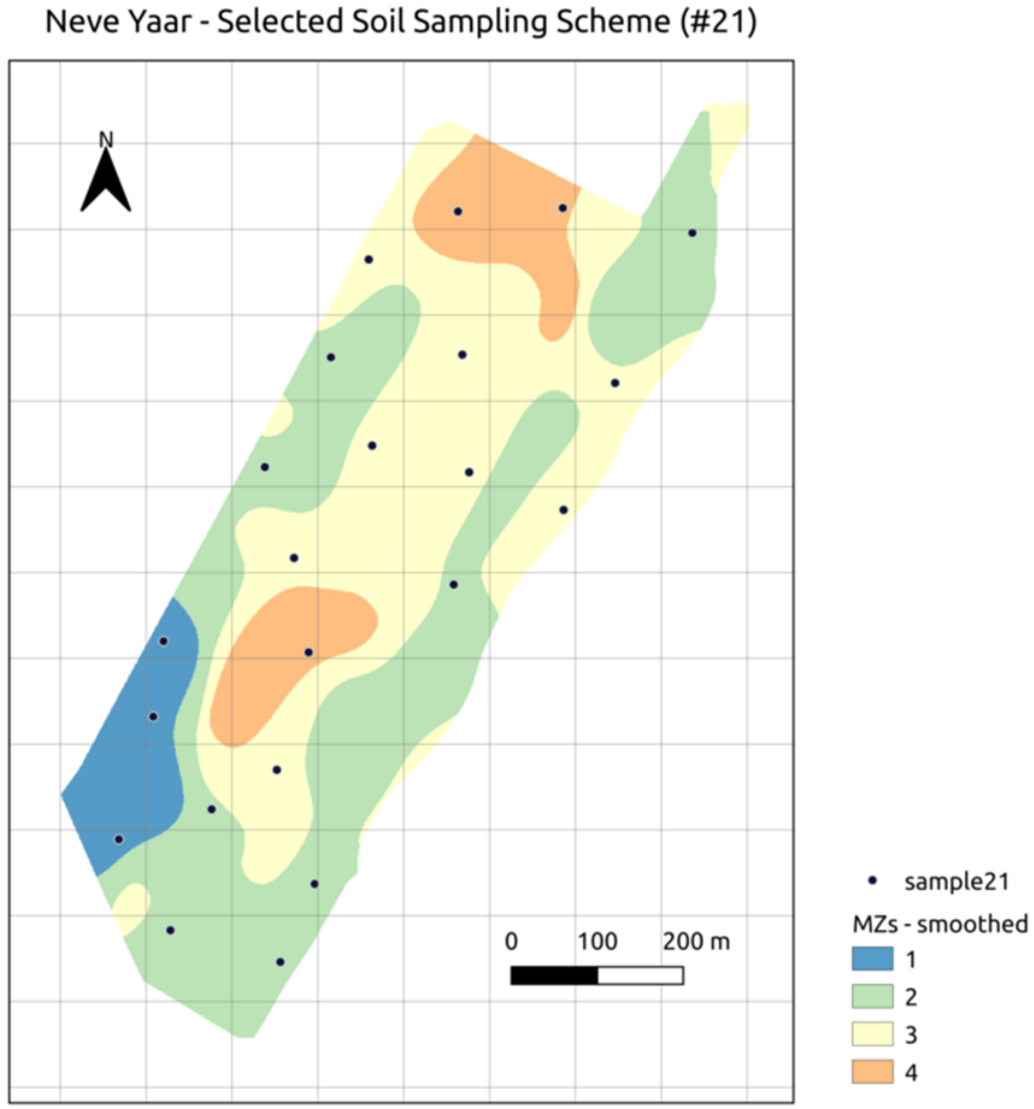

Figure 1.
Selected soil sampling plan in the field, superimposed on management zones.

R SOFTWARE CODE TO PROCESS AND EXTRACT INFORMATION FROM 3D LIDAR POINT CLOUDS

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Introduction

In the process of electronic canopy characterization, it is necessary to process efficiently point clouds obtained by means of sensors or other capturing information systems. These point clouds may have different origin but they define the main structural characteristics of the scanned crop. In the case of tree crops (vineyard, orchard crops …) the vegetation is usually organized in rows, and therefore it is necessary to extract vegetative parameters for each partial section along those rows. This information extraction procedure is crucial since in many cases large point clouds are analysed, easily containing millions of points. For this reason, a fast, easy-to-configure and precise methodology is necessary to extract such information. The work presented in this poster defines the main features of a procedure carried out with R Software code.

Point cloud data

The point cloud has to be saved in a text file. For every point, its coordinates and all its parameters are described in one row. The required information for every point is named in the next list:

UTM: Coordinate X of the point in meters.

Y UTM: Coordinate Y of the point in meters.

Z UTM: Coordinate Z (height a.s.l.) of the point in meters.

Scan Number: Number that defines the ordering of the each complete scan

Beam Number: laser beam identification corresponding to the reading (multiple beam sensors).

Beam angle: Inside of each scan, the angle of the beam for the reading

Alleyway: Number of the alleyway from where the reading was obtained

Row number: The scanned row number for the reading.

Coordinate values must be in Cartesian format. It is possible to directly use UTM (Universal Transverse Mercator coordinate system) coordinates or, as an alternative to reduce the file size, local coordinates using the same units.

Input parameters

A second file is required to run the process. This file defines the coordinates of the beginning and the end of each ROI-A (Region of interest A) that will be analysed to extract crop parameters. The analysis can be done by separate trees or by row depending on the extension of ROI-A. If the start and the end of each tree are defined, the system will analyse parameters for each tree. Once ROI-A is defined, the analysis is run according to smaller ROIs of d increments along the Y axis (ROI-B) and i increments along the Z axis (ROI-C).

Point cloud analysis process

The point cloud process is written in R Software code, under RStudio® Software. As crop parameters results, we obtain for each ROI-B and grouped for each ROI-A: width, height and cross-sectional area obtained by means of different procedures of calculation.

Results

In Table 1, we present some processing times with the proposed methodology. Depending on the size of the point cloud and the measuring precision, width and thickness of the ROIs B and C the system needs more or less time to process the results.

Table.1. Results of processing time for different point cloud analysed.

Sensor	Point cloud size (*number of points*)	Scanned crop	Measuring precision (*ROI-B, ROI-C*)	Processing time (*in seconds*)
HOKUYO UTM30-LX-EW 	15.993.805	5 rows 125 trees	0,5 m ; 0,1 m	465
			0,25 m ; 0,1 m	558
		4 rows	0,5 m ; 0,1 m	121
			0,25 m ; 0,1 m	202
			0,1 m ; 0,1 m	404
VELODYNE VLP-16 	5.222.426	5 rows 125 trees	0,5 m ; 0,1 m	200
			0,25 m ; 0,1 m	260
		4 rows	0,5 m ; 0,1 m	56
			0,25 m ; 0,1 m	102
			0,1 m ; 0,1 m	241

Conclusions

The presented code permits to process point clouds from row crops in an easy and a quick manner. The resulting parameters (width, height and sectional area) are important to characterize tree crops. Apart from the geometry of the canopy, other structural parameters related to leaf density are expected to be obtained in new and improved versions of the code. It is important to underline the ability to process a big point clouds using an open source software like R.

Acknowledgements

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MULTI-ACTOR, MULTI-CRITERIA ANALYSIS TO ADOPT SUSTAINABLE PRECISION AGRICULTURE

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Introduction

Fostering innovation in agriculture is a catalyst needed in the direction of digitizing agriculture and make it more sustainable. In the last years, several studies and European think thank pushed to put farmers at the centre of the innovation process (Di Mambro, 2017, Eip-Agri, 2019), contributing also to the dignity of this figure starting the food process and providing it for people. The introduction of innovation in farming is a complex process made by different steps in which taking decision is needed. To bring innovation and thus precision agriculture in the farming system means also to approach the ecosystem differently from the past (Lombardo et al., 2018). In this regard, MAMCA (Multi Actor Multi Criteria Analysis) software (Macharis & Baudry, 2018) is a tool to help with decision processes in multi-actor and multi-criteria situations.

Method

The MAMCA software was applied to answer the following question in three different levels of acquired technology: Is Precision Agriculture a real opportunity? For each level, there are several actors involved in an Italian Sustainable Precision Agriculture (SPA) System as farmers, providers, innovation brokers, industry, local community, research, public bodies. There are also several criteria for each actor, mainly divided in environmental, social, economic and operative criteria.

Levels are about the technology adopted in the farming system. The first level is about the introduction of auto-steering in farming, the second one considered the introduction of Variable Rate Technology (VRT) spreaders and seeders based on yield data and the third one is on the introduction of Decision Support System (DSS) in farming.

MAMCA is useful for taking decisions and considering the sustainability and the weight of each actor at the different levels. In this case, we tried to apply it to a poor system, represented as marginal agricultural lands, as a methodology to help actors in the decision process. After the problem and the alternatives have been defined, and the stakeholder analysis has been made, a definition of criteria and relative weights to build a criteria tree is needed. In MAMCA Analysis, the aim and goals of the stakeholder should be considered as criteria and weights and not, as is often done, as effects or impacts. In this case, the weight of each actor was considered equal as a pragmatic approach, in order to make it possible to respect each point of view on an equal basis. Afterwards, a set of indicators are built for each actor and a pairwise comparison of the alternatives respecting each specific criterion can be made. (Baudry et al, 2018)

Results

Results show that the MAMCA method could help to order (Macharis et al., 2012) the likely adoption of SPA from the actor point of view in marginal lands, highlighting contradictions between actors or point of contact between them. This allows to better visualize different views and to address the consequent solution that could be found also for policy makers.

Conclusions

From Figure 1 below, it is clear that different levels of acquired technologies mean different needs and different awareness of the ecosystem surrounding all the actors. It is important to take into account that new technologies acquisition is not only a cultural problem but depends also on economic availability, only partially solved thought PAC funding. The MAMCA method could help actors in understanding and supporting decisions and make the best choice.

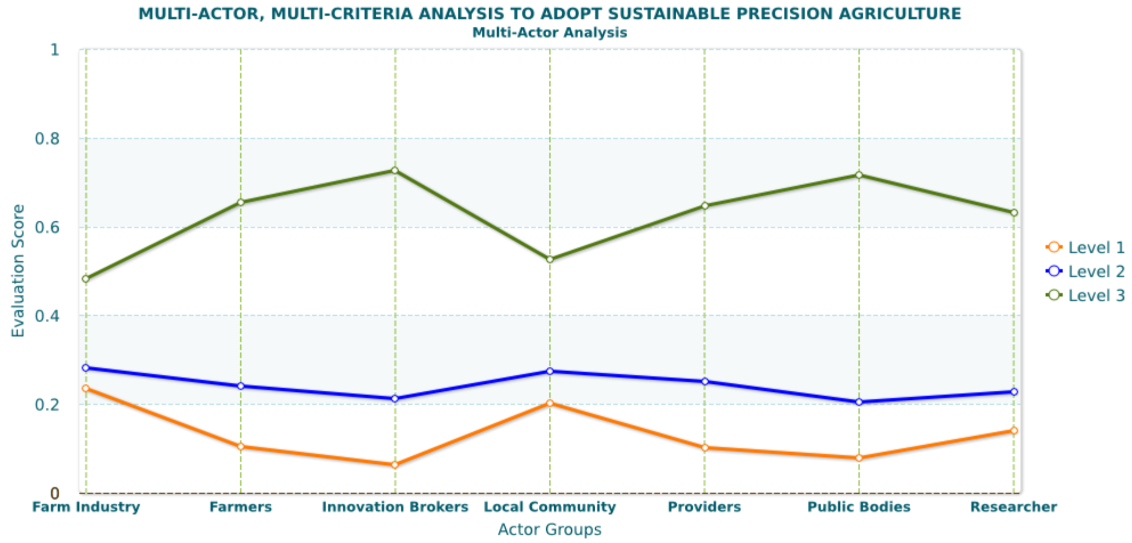

Figure 12: Multi-Actor Multi-Criteria Analysis chart for adoption of a Sustainable Precision Agriculture system

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INVERSION OF RICE PLANT POTASSIUM ACCUMULATION USING NON-NEGATIVE MATRIX FACTORIZATION WITH UAV-BASED HYPERSPECTRAL REFLECTANCE

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Introduction

Potassium (K) is a major crop nutrient, the price of potash fertilizer is high. Therefore, precise K management is important for minimizing production costs (Singh et al, 2018). K are applied as basal and panicle fertilizer and the soil is exposed before the booting stage. Thus, the soil background will affect the estimation accuracy of K nutrition using RS technology in rice>

Non-negative matrix factorization (NMF) is applied to solve the problem of BSS without the limitation of independent statical sources and the non-Gaussian distributions of sources. Li et al, (2017) found that NMF could be applied to separate the mixed spectra. In recent years, UAV have been a new technology platform for estimation of crop K nutrition (Severtson et al, 2016). However, no studies applied NMF to weaken the influence of soil background. Therefore, the objective of this study was to determine whether NMF could effectively alleviate the influence of soil background and improve the estimation accuracy of rice PKA.

Materials and Methods

Field experiments were conducted in 2017 with two rice cultivars and four K fertilization rates. Ground destructive samplings were taken along with the UAV campaigns at critical growth stages. A six-rotor aircraft (DJI M600 PRO) was used to carry a hyperspectral camera (UHD 185) to acquire the rice canopy images. NMF was applied to separate vegetation and soil spectra from the mixed spectra. The PLSR was used to establish models, validated with all data using cross-validation, and evaluated using the root mean square error (RMSE) and ratio of prediction to deviation (RPD).

Results

As the vegetation coverage increased, the red edge characteristics of the separated vegetation were more pronounced (Fig. 1). This confirmed that NMF could enhance vegetation spectral information while weakening soil spectral information.

The results based on mixed spectra showed that the calibration model had an R^2 of 0.74, and the RMSE and RPD of validation model were 3.94 g m^{-2} and 1.64 respectively (Fig. 2a, b). The results based on NMF-separated spectra showed that the calibration model had an R^2 of 0.84, and the RMSE and RPD of validation model were 3.36 g m^{-2} and 2.05 respectively (Fig. 2c, d). Compared to the mixed spectra model, the validation model RMSE decreased by 14.7%, and RPD increased by 25%.

Discussion and Conclusions

The performance of NMF-separated vegetation spectra in this study indicated that NMF could separate vegetation and soil spectra from the mixed spectra to enhance the vegetation information and weaken the influence of soil background, which was consistent with the result of Li et al, (2017) for estimating wheat AGB.

The area of the plot in this study was 30 m^2 and the soil difference was small. However, when applying the UAV to the larger field, the soil type was rich. Thus, we must take the soil differences into consideration. Ouerghemmi et al, (2016) had successfully applied NMF to separate the soil spectra from the mixed spectra using airborne image with a spatial resolution of 5 × 5m. For row crop rice (plant spacing 30 × 15 cm), whether NMF is suitable for separating vegetation spectra and improving the estimation accuracy of rice PKA remains to be further studied.

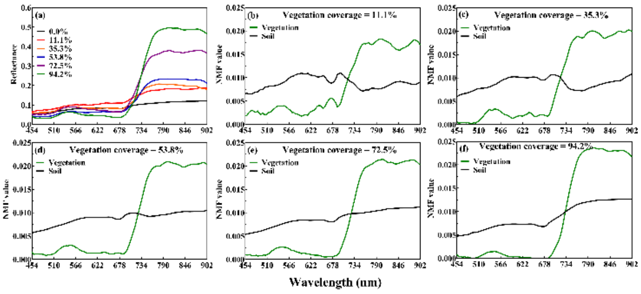

Figure 1: Reflectance of six original spectra under different vegetation coverages (a) and the separated spectra of five samples using the NMF method (b-f).

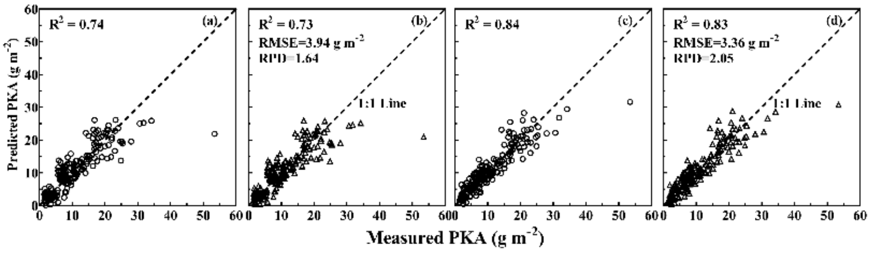

Figure 2: Calibration and 10-fold cross-validation results for predicting PKA based on the mixed spectra (a, b) and NMF-seperated vegetation spectra (c, d).

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LOW YIELDING ZONES ARE PREDOMINATLY ON THE EDGE OF FIELDS

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Understanding how spatial and temporal variations of crop yield occur within a field is a critical prerequisite to implement a spatially variable management plan. Fields are characterized by areas that have a lower temporal variability and areas that exhibit larger fluctuations across the years (Maestrini & Basso, 2018). We call the zones with low temporal variability "stable" yield zones, and depending on the level of productivity they can further be divided in "Low and Stable - LS" and "High and Stable -HS"; the areas that fluctuate are called "Unstable - U" (Basso et al., 2019).

Here we present results on within-field location of these zones with regards to their distance from the edges of the field. We posed the following research questions: 1) Are the edge of field more likely to have low and stable (LS) and unstable zones (U) than the centre of a field? 2) Are U mostly high yielding or low yielding?

To answer these two questions, we analysed a dataset composed of 1319 yield maps from 626 fields - located in four states of the Midwest of the United States. For half of the fields we had yield maps from three different years and for the rest of the fields from more than three years. The crops comprised in the dataset were in order of frequency: maize (1319 yield maps), soybean (626), and wheat (162). We defined the U zones by scaling the yield of each yield map so that it has a mean equal to 0 and standard deviation equal to 1, we then computed for each pixel the average and standard deviation between the years and defined as unstable the cells with a standard deviation larger than 1.

On average 55% of the within field area were classified as HS, whereas 32% were classified as LS and 13% as U. Using a multinomial model we calculated that the probability of a cell to be HS increased with the distance from the edge ($p<0.05$), whereas the probability of being LS or U decreased moving from the edges toward the centre of the field (Figure 1). For example at a distance of 50 m from the field edge the probability of a cell to be LS was 32%, the probability of being HS was 49%, and the probability of being U was 18% whereas at 150 m from the edge, the probability of finding a cell that was HS increased to 80%, and the probability of being U decreased to 2% and the probability of being LS to 17%.

Furthermore we found that U zones not only are located in the same position — near the edges — as the LS zones, but they also dominated by more years with low yield then years with high yield on average. We believe that the cause of the low average yield of the U zones is the left-skewness of the distribution of the yield at within field level. In fact given the long left-tail of their distribution they tend to vary more.

To support our theory we provide the following two evidences: first in our dataset the correlation between average and standard deviation (measured as Pearson-correlation) tends to increase with the skewness of the distribution of the yield, second we show that the correlation between mean and standard deviation for an independent synthetic set of samples randomly drawn from left-skewed distributions tend to be negative whereas they are positive if the samples are drawn from right-skewed distributions and they are not correlated if the underlying distribution is not skewed.

The identification of the most likely within-field position of the low-yield cells is an important insight for the management of field variability, even though the causes have not been investigated here.

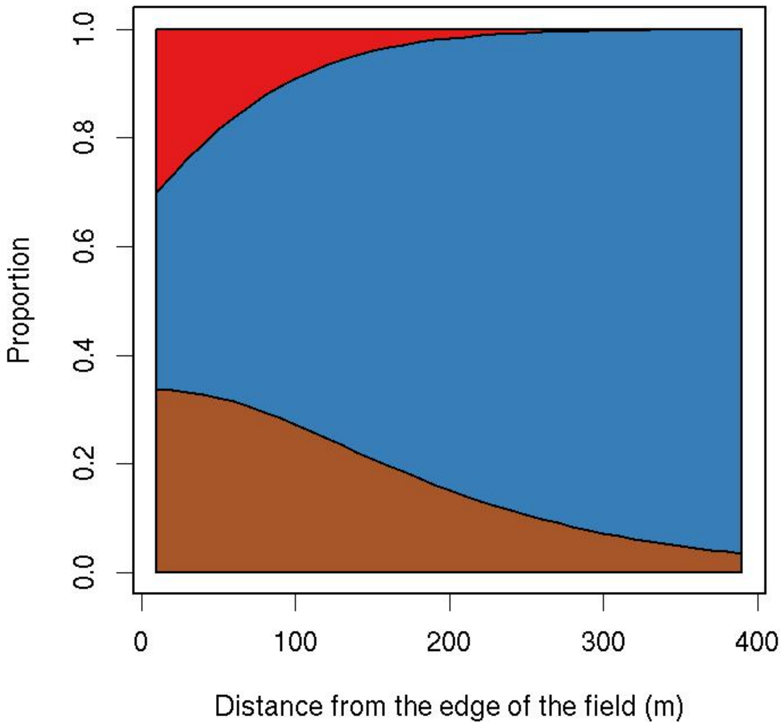

Figure 13: Proportion of the different stability classes as a function of the distance from the edges. These data represent the probability of a cell to pertain to a certain class according to a multinomial model fit to our dataset. The blue color represents the high and stable zones (HS), the brown color represents the low and stable zones (LS), and the red color the unstable (U).

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EVALUATING CROP SENSOR IN MAIZE GROWN IN SEMI-ARID CONDITION UNDER VARYING IRRIGATION AND NITROGEN LEVELS

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Optimization of nitrogen (N) management in agriculture is key to addressing economic and environmental issues associated with N fertilization. Studies have suggested different strategies for in-season N management using remote sensing that monitor differences in crop N status by evaluating relative crop response to applied N in an effort to improve N management (Scharf et al, 2011; Raun et al, 2008; Thompson et al, 2015). In-season N application practices guided by canopy sensor have been validated in fields under full irrigation or adequate rainfall for maize production (Holland & Schepers, 2010; Kitchen et al, 2010). In semi-arid conditions where there can be a complex interaction of major limiting factors, including water and N, use of crop sensor has not been adequately investigated. A field experiment was initiated in semi-arid western Nebraska in 2018 to evaluate use of crop sensor in predicting in-season maize N status and eventual yield under various irrigation and N levels.

The experimental design was randomized complete block with irrigation as the main factor and fertilizer N as the sup-plot factor with 3 replications. Irrigation treatment included irrigation levels of 0, 50, 100, and 133% of full irrigation based on evapotranspiration (I1, I2, I3, and I4) and N treatment included 0, 50, 75, 100, and 125% of full recommended N rated based on spring soil test and yield goal (N1, N2, N3, N4, and N5). Crop canopy reflectance was measured using a handheld active crop sensor and a vegetative index, Normalized Difference Red Edge (NDRE) was estimated at growth stages V6, V8, V10, and R1.

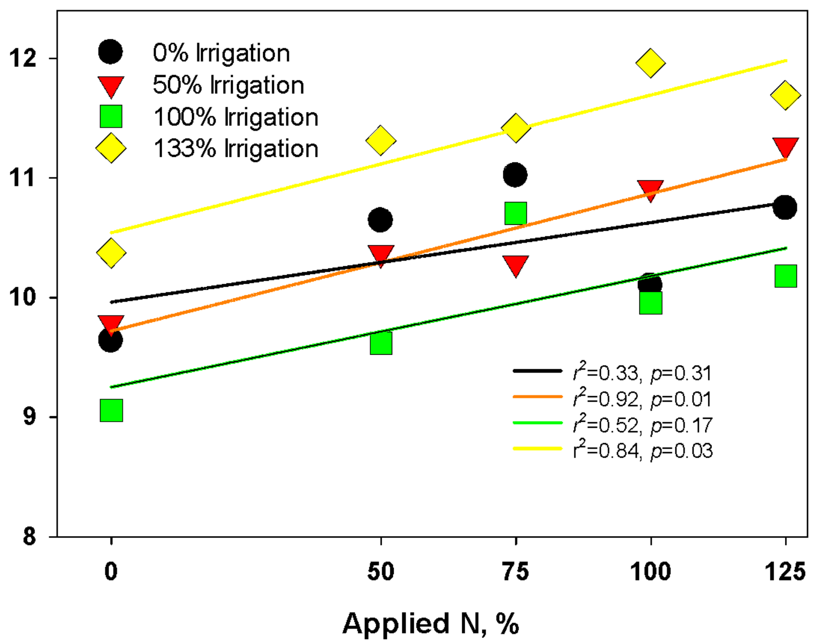

Figure 1. Single factor linear regression results for maize yield versus applied N rates (% of recommended N) at four different irrigation levels.

Maize yield was significantly correlated with applied N rate at irrigation levels I2 and I4 at p<0.05 and at I3 at p=0.17 (Figure 1). Only at those three irrigation levels, ANOVA tests were run to evaluate effects of N rates on NDRE at all growth stages. Wherever ANOVA test results were significant, NDRE were regressed against maize yield and N rate. At irrigation level I2, NDRE did not differ by N rate at any growth stages. At irrigation level I3, NDRE differed by N rate at growth stage V10. At irrigation level I4, N rate had significant effect on NDRE at growth stages V6 and V10. At irrigation level I4, NDRE was highly correlated with yield at V6 at p=0.01 and at V10 at p=0.09. This one-year data suggest that crop sensor was not effective in evaluating in-season maize N status in dry land condition (0% irrigation, I1) or in deficit irrigation (50% irrigation, I2). A passive crop sensor mounted on an unmanned aerial system (UAS) was also used to collect canopy reflectance at V10. This paper will also share data comparing active and passive sensors at all irrigation levels.

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CHARACTERISATION OF THE BIOMASS-STATUS AND THE NITROGEN-UPTAKE OF CORN AS A BASIS FOR A SENSOR-BASED, SITE-SPECIFIC FERTILIZATION

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Introduction

Many agricultural areas show more or less heterogeneous soils. This leads to different yields as well as a strongly varying removal of nutrients within a site. A uniform fertilization on the entire field results in an undersupply of nutrients in high-yield areas as well as an oversupply in low-yield areas. Both under- and oversupply are ecologically and economically disadvantageous. A possible way to solve this problem is the sensor-based and site-specific fertilization, which is successfully in practice in winter wheat (Link et al. 2002, Philips et al. 2004, Maidl 2011). Behind winter wheat, corn occupies the second largest share on arable land in Germany. Moreover, there is often a connection between corn cultivation and high doses of organic fertilizer, whose nutrient availability is difficult to estimate. Although there is a great potential for improving nitrogen efficiency, there are currently no site-specific measurement- and nitrogen fertilizing algorithms available for corn like for winter wheat.

Material and Methods

In 2018, experiments for fertilizing corn were conducted at three different trial sites of the Technical University of Munich, each with different yield potentials. The two factor trials differentiated between nitrogen (N) amount (0-250 kg N/ha) and scheduling of the inputs of N fertilizer (at planting and at a plant height of 20 cm and 50 cm, respectively).
Eleven times during the vegetation period, plant samples were collected and reflectance measurements were conducted in parallel. Dry matter yield, nitrogen content, N-uptake and height of the plant samples were determined. The reflectance measurements were conducted with a handheld spectrometer. It operated within a measurement range from 350 to 1050 nm at a resolution of 3.2 nm.

Results

At very early stages of plant development (20 cm plant height), only small coefficients of determination of the correlations (R^2 <0.2) between biomass growth, N-content, N-uptake and yield of the corn plants for silage or grain use were observed. With increasing plant height, the R^2-values of the corresponding regressions increased. At a plant height of 50 cm, there were R^2-values of 0.5 and 0.6 for the relations between biomass growth as well as N content in the biomass and yield of corn for silage use. Between N-uptake and silage yield, very high R^2-values of 0.7 were calculated. From the reflectance data, the following vegetation indices (VI) known from the literature were calculated: REIP, NDVI, IR/R, IR/G, IRI 1 (740/730), IRI 2 (740/720), SAVI, NDI 1 (750/780), NDI 2 (780/740), SR 1 (740/780), SR 2 (780/740) and YARA ALS. Figure 1 shows quadratic regressions for the first three sampling dates between the VI SR 2 (780/740) and the N-uptake into the above-ground biomass.

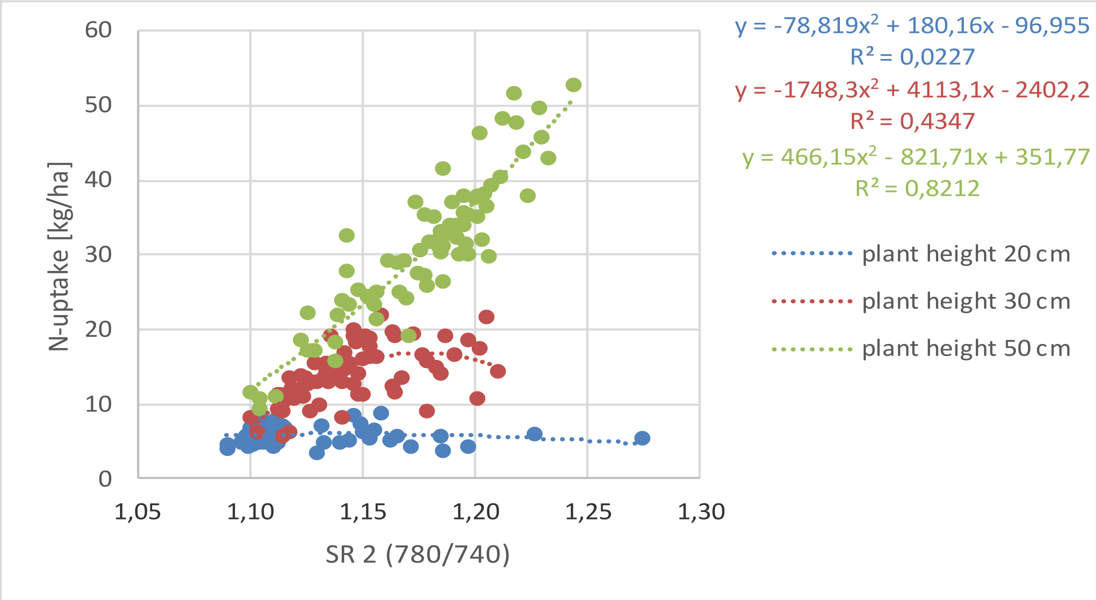

Figure 1. Correlations between VI SR 2 (780/740) and N-uptake into the biomass at early growth stages (3 sites, 2018)

Capturing the development of small corn plants was not possible with reflection measurements. With progressing plant development, the R^2-values of the regressions between the VIs calculated from reflection measurements and the biomass as well as N-uptake increased. In the example at hand (Figure 1), the coefficients of determination between SR 2 and N-uptake increased from R^2=0.022 at a plant height of 20 cm to 0.43 at 30 cm and eventually to a very high value of R^2=0.82 at a plant height of 50 cm. In addition, Figure 1 clearly shows the growth stage dependency of the relationship between VI and the N-uptake.

Conclusions

The results of the trials showed that a base N fertilization at planting was necessary for reaching high yields. To some extent and without yield loss, it was also possible to give additional fertilizer up to a plant height of 50 cm. The optical measurements of biomass formation and N-uptake by reflection were of high accuracy from a plant height of 30 cm and above. Thus, the prerequisites for a site-specific sensor-based N-fertilization were, besides winter wheat, also given for corn.

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FIELD EVALUATION OF COMMERCIALLY AVAILABLE SMALL UNMANNED AERIAL APPLICATION SYSTEMS

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The aerial application of pest control products in the United States is conducted primarily by piloted aircrafts over large acre farms with minimal physical obstacles. The objectives of this research were to develop aerial application technologies for conducting pest control operations in cropping systems not easily accessible to manned aircrafts. Corollary to these objectives, we conducted research to characterize spray pattern uniformity, effective swath, and spray droplet spectra for three commercially available small unmanned aerial application systems (UAASs). Using three UAAS aircrafts (model HSE V6A, DJI Agras MG-1 and HSE V8A), a spray mixture of tap water and a fluorescent dye was applied at three different application heights (2, 3, and 4 m) and four different ground speeds (1, 3, 5, and 7 m/s) over the center line of an 11-m long x 1 mm diameter cotton string, suspended 1 m above the ground. Each experiment was replicated four times. Cognizant of weather conditions that could likely influence the results, we sought to minimize the weather effects by orienting the string perpendicular to the wind, regardless of wind direction, during each spray application. Fluorometric assessment of spray deposits on cotton strings and spray droplets captured on water sensitive paper samplers described spray pattern and droplet spectra, respectively. Using a custom software, effective swath was determined by choosing the widest swath with a coefficient of variation (CV) less than 25%. The CV is an index of the uniformity of spray deposit across the swath width and represents the degree of variation in deposition from the mean (Whitney & Kuhlman, 1983). Spray droplet spectra measured were $D_{v0.5}$, the percent area coverage and the spray rate. The $D_{v0.5}$ is the droplet diameter (µm) where 50% of the spray volume is contained in droplets smaller than this value and is commonly called the volume median diameter (VMD). Data were analyzed using the PROC GLM procedure (SAS, 2012). Graphical illustrations were conducted using the JMP® software (SAS, 2018). Data indicate that the UAAS platforms predominated in significantly influencing effective swath. Neither application height nor ground speed significantly affected effective swath. The effect of application height and ground speed on effective swath is presented in Figures 1 and 2, respectively. This study demonstrated that the HSE V8A platform provided the best effective swath with an average value of 10.1 m. Despite the acceptable swath obtained for the HSE platform, the droplet spectrum generated by this aircraft is relatively small ($D_{v0.5} < 200$ µm) and is likely to be driftable. Whether or not these droplets were driftable were not investigated in this study, however, research data indicate that there is a strong correlation between droplet size and drift. It is likely that operational factors such as application height and ground speed could have contributed to the smaller droplet size. Nevertheless, the nozzle type, the nozzle orifice, the spray pressure and flow rate are more important determinants of spray droplet spectrum. Results reported here will provide guidance to aerial applicators on how best to enhance deposition of pest control products on cropping systems using remotely piloted aerial delivery vehicles.

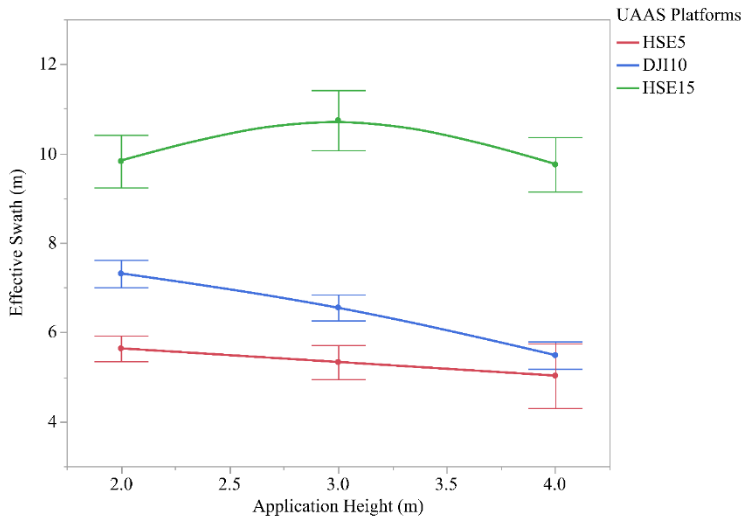

Figure 14. The effect of application height on effective swath for three UAASs. HSE5 is the 5L HSE V6A, DJI10 is the 10L DJI Agras MG-1, and HSE 15 is the 15L HSE V8A. The main effect of the UAAS platforms on effective swath was highly significant, while application height did not significantly influence effective swath.

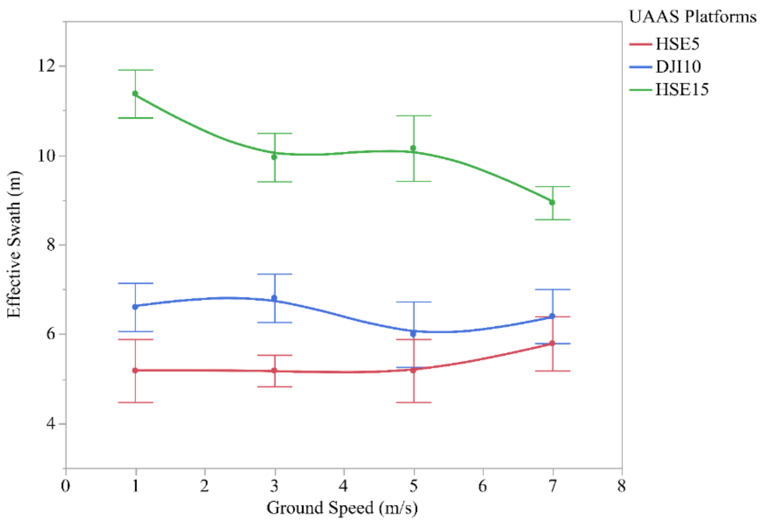

Figure 15. The effect of ground speed on effective swath for three UAASs. HSE5 is the 5L HSE V6A, DJI10 is the 10L DJI Agras MG-1, and HSE 15 is the 15L HSE V8A. The main effect of the UAAS platforms on effective swath was highly significant, while ground speed did not significantly influence effective swath.

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SATELLITES REVEAL NITROGEN LOSS

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By using new satellite technology, this project aims to reveal the amount of nitrogen uptake by catch crops and, thereby, enable a more precise prediction of the nitrogen need for the following crop. The method will be implemented in Denmark through a unique fertilizer planning platform used by almost all Danish farmers. Catch crops retain nitrogen during autumn and winter and release it for the following crop. Therefore, the total need of the following crop will be dependent on the amount of retained nitrogen. For this reason and, since catch crops are a substantial part of the Danish regulation, nitrogen leaching in Denmark could be significantly reduced by predicting the nitrogen uptake in catch crops. In 2018, the claim for mandatory catch crops was about 15 percent of the total agricultural area and will be 25 percent in 2021. Firstly, the most suitable spectral bands for measuring nitrogen uptake in catch crops will be found. Secondly, the project aims to establish a relationship between the satellite measurements and the amount of nitrogen in catch crops. The method includes selecting 40 fields each year, where nitrogen uptake is measured in the plant material. Satellite data from the same fields enable establishment of a relation between the satellite index and nitrogen uptake. As a supplement, soil samples will be taken in the same fields in the following spring, which will measure N-min (mineral nitrogen). Preliminary results with only 13 data points show a positive relationship between normalized difference vegetation index (NDVI) of catch crops in the autumn 2017 and the nitrate content (25-50 cm) in February 2018 ($R^2 = 0.40$). Most of the catch crops in Denmark are fodder radish which is destroyed by ploughing or by frost. The hypothesis is that, higher NDVI reflects higher nitrogen uptake, and more nitrogen is available as nitrate in February. Measurements were also done in oilseed rape fields, and with only 13 data points a negative relationship was found between NDVI in autumn and N-min (0-100 cm) in February ($R^2 =0.52$). This may reflect that high nitrogen uptakes will reduce nitrogen content in the soil, since oilseed rape is not destroyed by frost. Autumn 2018 is the first year to measure nitrogen in the plant material. The vision is to implement the method to run automatically in the fertilizer planning system in the whole of Denmark without any extra input from the farmer.

In autumn 2018, *SEGES*, under the sponsorship of the GUDP project SAT-N, took plant cuts to measure the nitrogen uptake in 17 different fields with catch crops and 18 different winter rape fields. The catch crops in Denmark were well-established in many fields and have absorbed a considerably larger amount of nitrogen than normal**.** In October 2018, there was an exponential correlation found between plant uptake of nitrogen (kg N ha^{-1}) and measured NDVI in catch crops ($R^2= 0.51$) (Figure 1). NDVI is calculated as follows: NDVI= (NIR − Red) / (NIR + Red), where 'NIR' and 'Red' is the spectral reflectance measurements attained in the visible and near-infrared regions. The NDVI values acquired in this study are the average NDVI values in a specific 10x10 area of a field. NDVI becomes saturated at a high biomass, indicated by NDVI values around 0.8 or higher, therefore the correlation is limited by the NDVI values above 0.8. This occurs because the red light used in NDVI is heavily absorbed by the chlorophyll and the wavelength, which causes difficulty in reaching further down the plant cover than the top leaf layers. This limitation is prevalent in Figure 1, as most NDVI values are greater than 0.8. Furthermore, the variation in NDVI before the saturation point could be due to the type of catch crop or location.

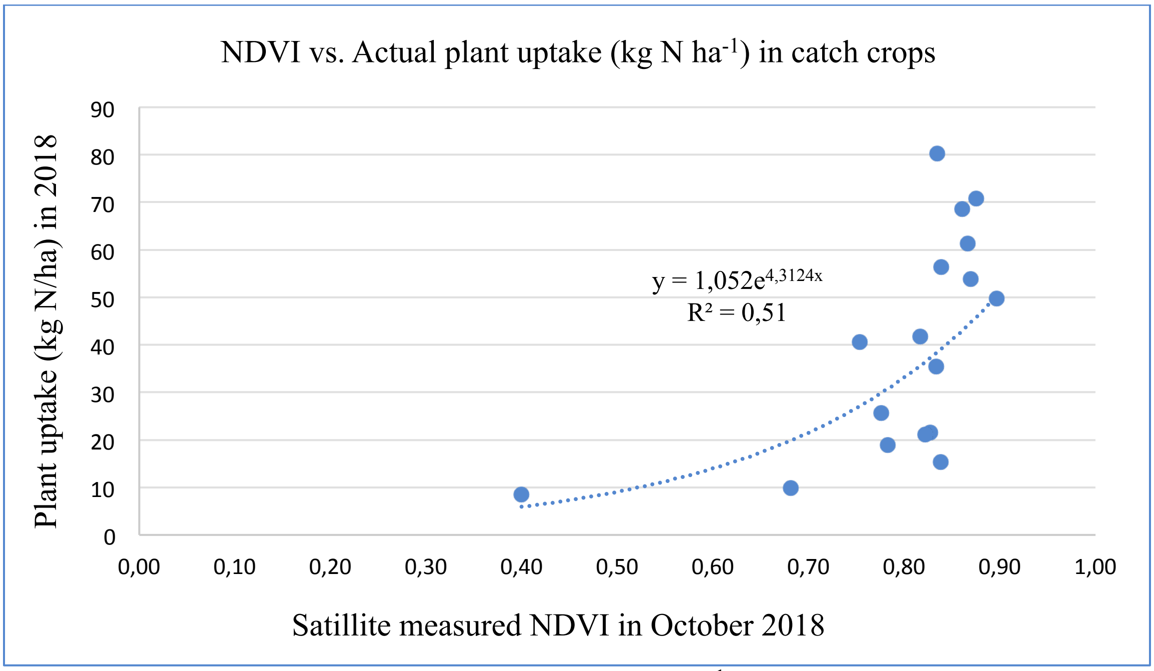

Figure 1. Correlation between plant uptake in kg N ha^{-1} and satellite measured NDVI in October 2018 in catch crops.

No correlation was found between uptake of nitrogen in winter rape and NDVI. Furthermore, in 2019, there was no correlation between measured N-min (0-100 cm) in catch crops and winter rapes, in February, and NDVI in the fall. As previously stated, Denmark had well-developed catch crops in the autumn of 2018, which should attribute to a greater amount of nitrogen in 2019. For heavy catch crops, *SEGES* expected after-effects that were 5-10 kg nitrogen larger than normal, however this varies based on runoff in the autumn. Therefore, the lack of correlation between N-min and NDVI in 2019 could be due to a high precipitation in autumn of 2018 causing leaching of nitrogen not taken up by the crops in autumn.

Conclusions

There is great potential for using NDVI as a measurement parameter for whether a field is vegetated and capable of retaining nutrients. However, NDVI is limited at measurements around 0.8 and greater and, therefore, introduces uncertainty. NDVI is most accurate in the first growth stages, before the plant has excessive foliage. More studies are required to evaluate the use of NDVI to predict field conditions. Due to the uncertainty in the NDVI values, it is evident that more measurements are required before obtaining a concrete conclusion regarding the correlation between plant uptake of nitrogen or N-min and measured NDVI.

EFFICIENCY IN THE USE OF ELECTRONIC PROGRAM OF MAPPING FOR SAMPLING OF GEOREGREATED PEST

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The current scenario of intense technological changes and innovations aimed at agriculture includes precision agriculture, which allows, through georeferenced monitoring and geostatistical techniques, the deepening of the dynamics of the temporal space of pest insects in different areas with crops of interest economic (Liebhold et al., 1993). The integration of these technological innovations into integrated pest management (IPM) can contribute to the elaboration of protocols for pest monitoring, as well as to more efficient and localized control, reducing the cost of production and the load of pesticides in the environment.

Integrated Pest Management is the management system that in the context associates the environment and population dynamics of the species uses all appropriate techniques and methods as compatible as possible and keeps the population of the pest at levels below those capable of causing economic damage (Domiciano, 2010). The adoption of precision agriculture in the control of pest insects is an alternative to traditional agriculture, which currently causes environmental impacts and unnecessary costs to the producer. Thus, since the precision agriculture system makes use of several tools for its employability, the Integrated Pest Management is characterized by the use of several techniques that are employed harmonically in order to solve a specific problem (Kogan, 1998).

Manual spreadsheets used to record times during insect pest sampling in agricultural field monitoring does not allow insect means of pests per point automatically, exposure of manual spreadsheets is exposed to climatic weather, making sampling in the working period more difficult I enjoy. Electronic spreadsheet using a georeferencing system for sampling, with a series of operational control tools, pest species adjustment and population levels for each phenological stage of the crop, allows autonomy in the number of pest mean automatically, providing statistical plots of each georeferenced point.

The objective of the experiment was to compare the method used to record the amount of pests obtained during sampling. And what their efficiency related to the time for the accomplishment of the monitoring. The experiment was carried out in the experimental field of the agricultural Suzano located in the city of Jataí - Goiás, from January to April. 2019. A comparative test was performed using two methods to record pest sampling during monitoring in the agricultural field. Method 1 spreadsheet manual, method 2 spreadsheet The experimental field has size of 400 ha with 100 georeferenced points. Were realized 10 with the spreadsheets and 10 with the spreadsheet both in the same area. After data collection, manual spreadsheet information is tabulated, averages of infestation are calculated, and infestation charts are plotted against the level of control, which are passed on to farmers and consultants to make a decision about the control.

In the spreadsheet with software in tablet with the spreadsheets are already inserted and the process of setting the levels of control through the sampling and possible to inform on each level. In the data collection process, the spreadsheet already warns of the need to apply insecticides or not and also presents other tools that help decision-making by the producer and consultant, who can follow in real time the information collected through the data platform. According to the Graph 1, it is possible to observe that during all of the months using the Manual and electronic spreadsheets there was a significant difference the spreadsheet allowed to perform the sampling in the monitoring of pests in less time of work. The use of spreadsheets reduced the collection and processing time of insect sampling by 50% in the agricultural field. Providing the farmer accurate information on each point georeferenced according to the average obtained and autonomy to use pesticide or not.

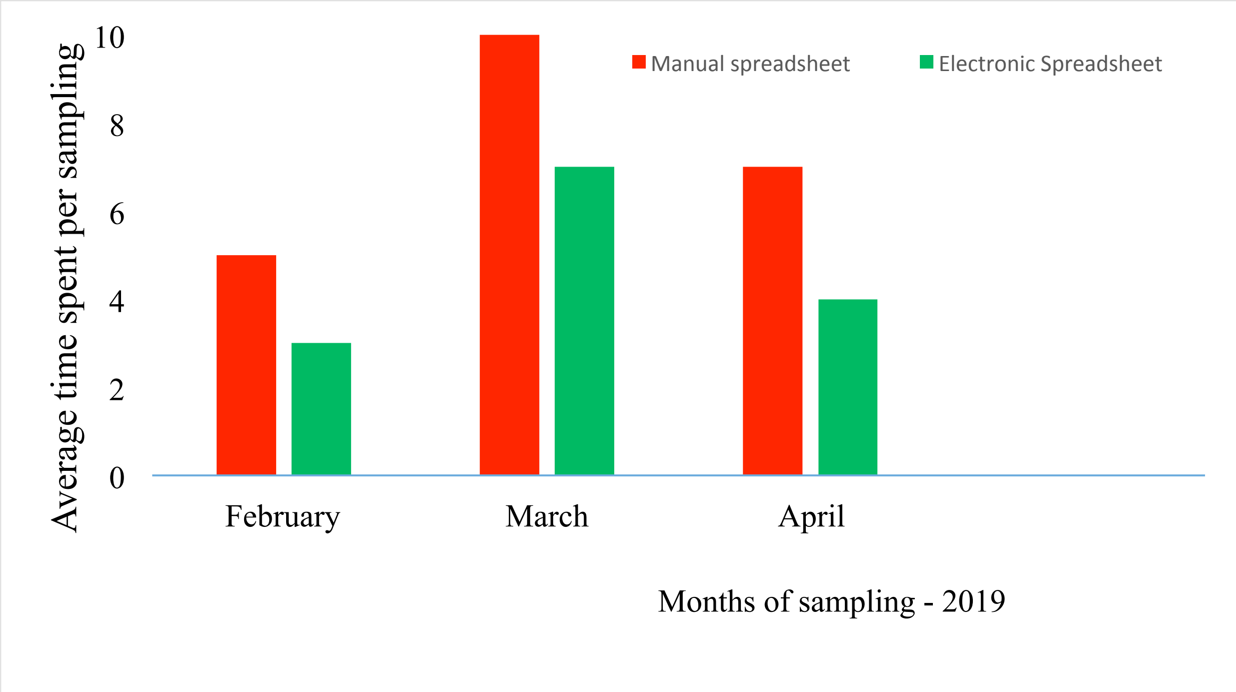

Figure 1. Use of manual spreadsheets and electronic spreadsheets in the experimental field of agricultural Suzano located in the city of Jataí - Goiás.

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USE OF HIGH-RESOLUTION DRONE IMAGES TO QUANTIFY SOIL EROSION

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Introduction

Soil erosion is considered to be one of the most important causes of land degradation. Most classical erosion measurement methods are time-consuming and expensive but new technologies provide innovative tools for conducting soil erosion survey.
The objective of this project was to evaluate the use of high-resolution drone images to quantify rill erosion and to compare this approach with the classical method and a reference system.

Methods

The volume of an artificial 30 m long rill was quantified i) with a Riegl VZ10006 terrestrial laser scanner (reference system), ii) with a ruler (i.e. the length, the depth and the width of the rill were measured manually) and iii) with drone images taken at different resolutions (0.25; 1; 2; 4 cm/pixel). To estimate the volume of the rill from the drone images, an orthophoto and a digital surface model (DSM) were obtained using the Pix4D software. A digital terrain model (DTM) without the rills was generated from the DSM using ndimage library from Python. The subtraction of the two models provided a differential depth model (DDM) allowing the calculation of the eroded volume. This DDM was also used to automatically identify erosion rills from large areas.

Results

In comparison to the terrestrial laser scanner estimates, the quantification based on the ruler method overestimated the volume of the rill by 39 % while the method based on drone images underestimated the volume by 6 to 15 %. For this last method, the best compromise between maximum accuracy and a reasonable amount of data was the 2 cm/pixel resolution technique (red rectangle, Figure 1).

Conclusions

In conclusion, this project demonstrated the potential of the drone method to quickly and automatically quantify the volume of the rills. In addition, the drone deliverables constitute useful tools for farmers, farm consultants and soil managers to understand soil erosion processes. The use of these different models coupled with the orthophoto enabled (i) the description of water flows on open land with the help of the DSM and (ii) the evaluation of erosion risks associated with different farming practices. Finally, this drone approach allowed the identification of the spatial causes of erosion (roads, plough rills).

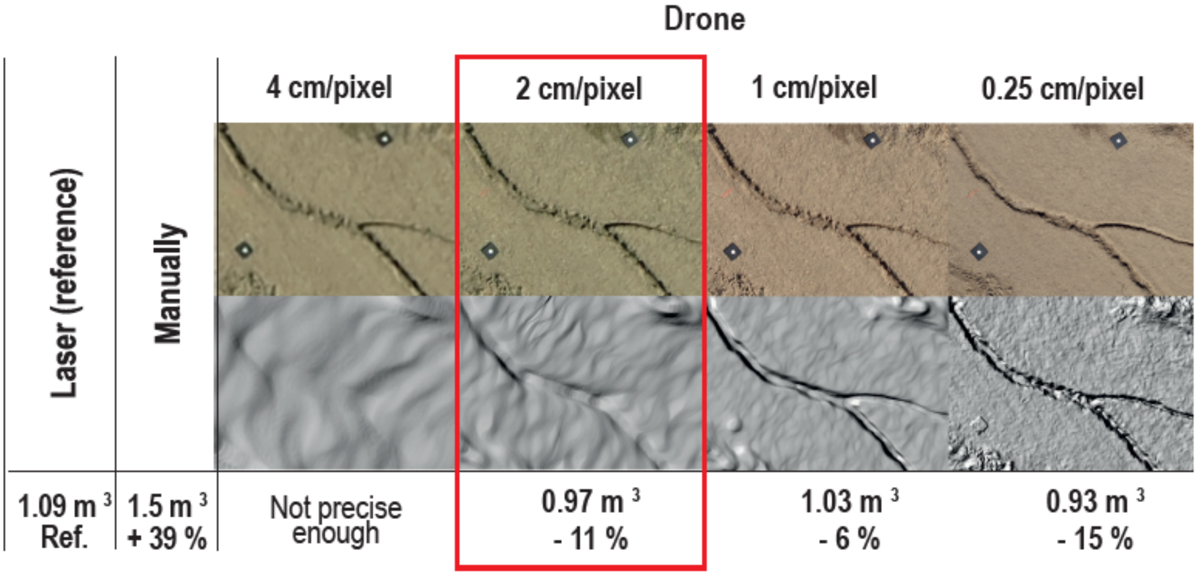

Figure 16: Artificial rill erosion volume estimates in m^3 from three different measurement methods. For the drone method, images were taken at different resolutions (0.25; 1; 2; 4 cm/pixel). The top images = orthophoto, the images at the bottom = digital surface model

COMPOSITION OF LEGUME SPECIES IN MIXED LEGUME-GRASS PASTURE USING HYPERSPECTRAL IMAGING

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Since the improvement of nutritional value and the reduction of the amount of fertilization are expected in mixed legume-grass compared to a pure grass pasture, it is important to grasp the precise proportion of the legume species to realize labor-saving production. Previous researches showed the effectiveness of hyperspectral imaging (HSI) to detect the composition of each grass species in pasture (Suzuki et al, 2008). Because of the specific growth characteristic of legumes as ground-hugging vegetation, however, there is a technical challenge that must be addressed: detecting legume species that are often hidden beneath the grass canopy. To address this issue, this research investigated the performance of two un-mixing mapping algorithms—Mixture Tuned Matched Filtering (MTMF) and Spectral Feature Fitting (SFF) — to estimate the degree of legume composition over a range of vertical strata of pasture vegetation. In order to evaluate the effectiveness of each mapping method, the hyperspectral data was acquired in each environment with known and unknown spectra of each composing species in pasture, using hyperspectral sensor (Headwall Photonics, Nano-Hyperspec) mounted on Drone (DJI Matrice-600). Canopy cover values for each species were calculated after all end member species were mapped. Therefore, an accuracy of detecting results was evaluated at the plot scale by comparing the R2 and the root mean square error (RMSE). As a result, we demonstrated that both methods have an ability to detect relative canopy density of a legume species in a vertically stratified pasture.

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ARTIFICIAL NEURAL NETWORKS CAN ESTIMATE CORN FOLIAR AREA WITH PROXIMAL REMOTE SENSING

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Introduction

The leaf area index (LAI) is defined as the ratio between the leaf area of a plant population and the soil area occupied by it (Müller et al., 2005). The leaf area index (LAI) is a fundamental physiological variable for maize crop, however, it is one of the most difficult to measure or estimate (Breda, 2003). In this context, the (LAI) can be used to develop management strategies that minimize the risks of productivity reduction.

Direct and indirect methods have been proposed to quantify the (LAI). The destructive harvesting of plants is the most accurate direct method to quantify the leaf area, however, is limited to small plants (pastures) and limited areas (by the demand of labor) (Colaizzi et al., 2017). Thus, arises the need to explore new learning techniques to estimate the (LAI) independent of the conditions of each environment. Artificial neural networks have the ability to learn the patterns of a data set during the training process, thus providing consistent predictions or generalization capabilities in test suites (Savegnago et al., 2011). Assumes that the (RNA) can be used to estimate the leaf area of the maize crop. Therefore, the objective of this study was to estimate the leaf area of the maize crop using (RNA) with different topologies, activations functions and varying the number of neurons of the hidden layers.

Materials and Methods

The experiment was conducted at the farm, in the City of Jaboticabal State of São Paulo, Brazil, located around the coordinates 21° 14' S and 48°16' W. The variables analyzed were height (cm), stem diameter (mm), leaf area (cm^2), vegetation indexes NDVI, IRVI and NDRE. To acquire the NDRE index, a remote active proximal OPTRX ® sensor (AGLEADER, 2202, South River Side Drive Ames, IOWA 50010, USA) was used to 0.6 m from the plant canopy and for NDVI and IRVI indexes the GREENSEEKER™ 505 hand-held optical sensor was used (N-Tech Industries, Ukiah, CA). A total of 160 samples were collected manually in the crop in different growth stages V4, V6, V7 and V10. For the steps of training and validation of RNA, 80% of the samples were used for training (T), and 20% was used for validation (V).

The accuracy and accuracy of the proposed MLP neural network model were evaluated by calculating the absolute percentage error (MAPE) and the coefficient of determination (R2).

Results

In general, using all variables as input information for training and validation of (RNA) the best values of accuracy and accuracy. The performance for the training and validation of the resultant topology presented MAPE of (14.61% and 13.14) and R^2 of (0.93 and 0.91) respectively. Data collection to estimate leaf area demand time and labor, although RNA obtains accuracy and precision, to obtain all these variables and feed the input layer on a large scale, it becomes unfeasible.

The Vegetation Index (NDRE) was considered high performance for the stages of training and validation, obtaining the MAPE values of (29.74% and 14.60%) and R^2 of (0.73 and 0.89)

respectively. Therefore, the validation step of the NDRE index was like validation using all variables with minimal differences MAPE (1.46%) and R^2 (0.02).
One advantage of using the NDRE index is that the values can be easily obtained in the crop because it is collected with sensors being considered a non-destructive sampling, making it viable for large-scale applications.
Analyzing the results of the vegetation indices (NDVI and IRVI) used as the basis of information to compose the input layers of (RNA) presented an unsatisfactory performance for estimation of the leaf area with low accuracy and precision, thus not being recommended as information to compose the input layers of the (RNA).

Table 1: Results of training and validations of different topologies of artificial neural networks.

Variables of Input	R2				MAPE			
	Hyperbolic		Logistics		Hyperbolic		Logistics	
	T	V	T	V	T	V	T	V
All Variables	0.96	0.88	0.92	0.91	12.17	14.68	17.12	13.49
NDVI	0.72	0.89	0.44	0.58	64.09	40.65	75.88	53.64
NDRE	0.45	0.63	0.73	0.89	50.46	29.74	29.93	14.58
IRVI	0.46	0.65	0.45	0.60	78.14	49.74	74.15	50.08

T.: Training, V.: Validation, R2: Coefficient of determination, MAPE: Average error of absolute percentage.

The following conclusions are included in the study: the use of artificial neural networks provided satisfactory performance to estimate the leaf area of maize crop using de NDRE.

Acknowledgements
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STATISTICAL MODELING FOR ON-FARM EXPERIMENTATION USING PRECISION AGRICULTURAL TECHNOLOGY

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On-farm, large-scale agronomic field trials were conducted using precision technology to facilitate trial implementation by enabling the automation of treatment assignments. Automation of changing input rates and monitoring associated plot yields provided data for the estimation of yield responses as functions of input treatments and field characteristics, which are useful for developing environmentally and economically optimal crop management prescriptions. The analysis of this type of on-farm agronomic trial data is powered by new developments of methods to estimate spatially restricted predictive models. The spatial variability within the field, which is usually linked to the variability of soil properties and topography, should be taken into account when comparing input rates under different conditions. In these experiments, we fit yield response functions with different nitrogen fertilization (N) and seeding (S) rates, applied with spatial precision during sowing. The performances of several statistical and machine learning methods, used to fit predictive models, were analyzed, using site characteristic variables in the predictor, with and without accounting for spatial autocorrelation.

We evaluated the relative accuracy of five algorithms to estimate site-specific response functions relating grain yield to (N, S) treatment values: Generalized Additive regression (GAM, Tibshirani 1990), Generalized Boosted regression (GB, Elith et al., 2008), Random Forest regression (RF, Breiman, 2001), and Partial Least Squares regression (PLS, Abdi, 2010). A multiple linear regression was also used as a reference model. All algorithms were adjusted, with and without spatially correlated residuals, and with and without soil covariates. Spatially correlated errors for linear models (West et al., 2014) and ordinary kriging on model residuals for machine learning methods (Li et al., 2011) were taken into account. Ten-fold cross-validation was used to assess the predictive accuracy of each model strategy in terms of the root of the mean square prediction error (RMSPE).

All statistical models produced small errors when predicting grain yield, both from input-rate treatment levels and site covariates. Although variability among fields was high, the results showed that PLS and GB performed better than GAM, RF, and all were preferred to LM as a method to estimate yield response function. For both PLS and GB, the prediction errors of models including spatial autocorrelation were at least 10% smaller than of those models that did not account for spatiality. When site soil and topographic covariates were included, the spatially restricted PLS was the best tool to estimate site-specific yield response functions (Table 2).

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Table 2: Prediction error (expressed as percentage of mean) of five statistical and machine learning methods to fit regressions of plot yield to the applied Nitrogen and Seed Rates

Field	LM	GAM	GB	PLS	RF	Explanatory Variables
						Nitrogen and Seed doses
Corn 1	2.0	2.6	1.8 *	1.8 *	1.8 *	N [140, 160, 180, 200]; S [30,34,38,42 t]
Corn 2	2.0	2.7	1.7 *	1.8 *	1.8 *	N [160, 180, 200, 220]; S [28, 32, 36, 40 t]
Corn 3	3.5	3.7	2.6 *	2.5 *	2.8 *	N [140, 160, 180, 200]; S [30, 34, 38, 42 t]
Corn 4	3.9	4.0	3.1 *	3.4 *	3.4 *	N [160, 180, 200, 220]; S [28, 32, 36, 40 t]
Wheat 5	3.0	4.5 *	4.3 *	4.1 *	4.4 *	N [80, 125, 170]
Wheat 6	3.4	5.4 *	4.1 *	4.8 *	4.1 *	N [80, 125, 170]
Wheat 7	8.8	6.9 *	4.4 *	4.7 *	4.4 *	N [80, 125, 170]
Corn 8	9.5	9.7	6.2 *	5.8 *	7.1 *	N [165, 190, 215,240]; S [30,34,38 t]
Wheat 9	7.8	8.9	7.6 *	8.6	7.6 *	N [97, 125, 170]
Corn 10	17.9	19.3	11.6 *	11.7 *	12.9 *	N [140, 160, 180, 200]; S [27,31,35,39 t]
Mean	6.2	6.8	4.8	4.9	5.0	
						Nitrogen and Seed Rates plus site variables
Corn 1	2.1	2.6	2.0	1.8 *	2.0	ELV, EC_{05}, EC_1
Corn 2	1.9	2.6	1.9	1.8 *	1.9	ELV, EC_{05}, EC_1
Corn 3	3.5	3.8	2.9 *	2.6 *	3.3 *	ELV, EC_{05}, EC_1
Corn 4	3.4	3.9	3.3	3.3 *	3.5	ELV, EC_{05}, EC_1
Wheat 5	4.1	5.9	4.4 *	3.7 *	4.4 *	ELV, EC_{09}, Soil depth
Wheat 6	2.8	4.8	5.0	3.9 *	4.9	ELV, EC_{09}, Soil depth
Wheat 7	6.9	6.2	5.2 *	4.1 *	5.9 *	ELV, EC_{09}, Soil depth
Corn 8	10.0	9.8	7.3 *	5.9 *	8.4 *	ELV
Wheat 9	9.8	9.2	8.9	8.6	8.5	ELV, EC_{09}, Soil depth
Corn 10	15.6	18.9	11.5	12.0 *	13.9 *	ELV, EC_{05}, EC_1
Mean	5.6	6.5	5.4	4.8	5.7	

LM: Linear Regression; GAM: Generalized additive regression; GB: Generalized Boosted regression; PLS: Partial Least Squares regression; RF: Random Forest.
N: Nitrogen rate [$KgNha^{-1}$], S: Seed rate [$seedsha^{-1}, t = thousands$], ELV: Elevation, EC_{05}, EC_{09}, EC_1: Electroconductivity at 0.5m, 0.9m and 1m, respectively.
*Accounting for spatially correlated data improved prediction error in more than 10%.

PISUM SATIVUM L. (PEA) YIELD MODELLING USING SENTINEL-2 NDVI MAPS

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Crop yield forecast data can be an important factor for producers and agri-food companies when allocating and distributing resources for the harvesting process. The increasing presence of new technologies in agricultural management, allows a quick, reliable and relevant data production for agri-business. By using European Space Agency's Sentinel-2 satellite images, this research aimed at yield modelling pea crops (*Pisum sativum* L.) in Sorraia and Tejo's Valleys, in southern Portugal (Lat: 39.028601; Long: -8.860793). A total of 37 parcels, managed by the agri-food company DARDICO S.A., were chosen. From those, regarding the 2017 and 2018 campaigns, 13 and 24 parcels concerning the first and second year, respectively, totalized a crop area of 722.5 ha. Sowing occurred between mid-December and late January for the 2017 campaign and between early December and late February for the 2018 campaign. Information regarding final yield was obtain for each parcel, with an overall average of 6458.66 Kg/ha. Sentinel-2 images were used to generate 10 m spatial resolution Normalized Difference Vegetation Index (NDVI) maps of the region. The average NDVI value was retrieved for each parcel considering the maturity stage close to 120 days after sowing (Zajac et al., 2013). The study region is characterized by a Mediterranean climate with dry summers and rainy winters. However, 2017 was one of the driest years in 8 decades and 2018 presented an above average spring precipitation, especially in March (IPMA, 2019). All of the 37 parcels had an active irrigation system providing water to the crops if necessary.

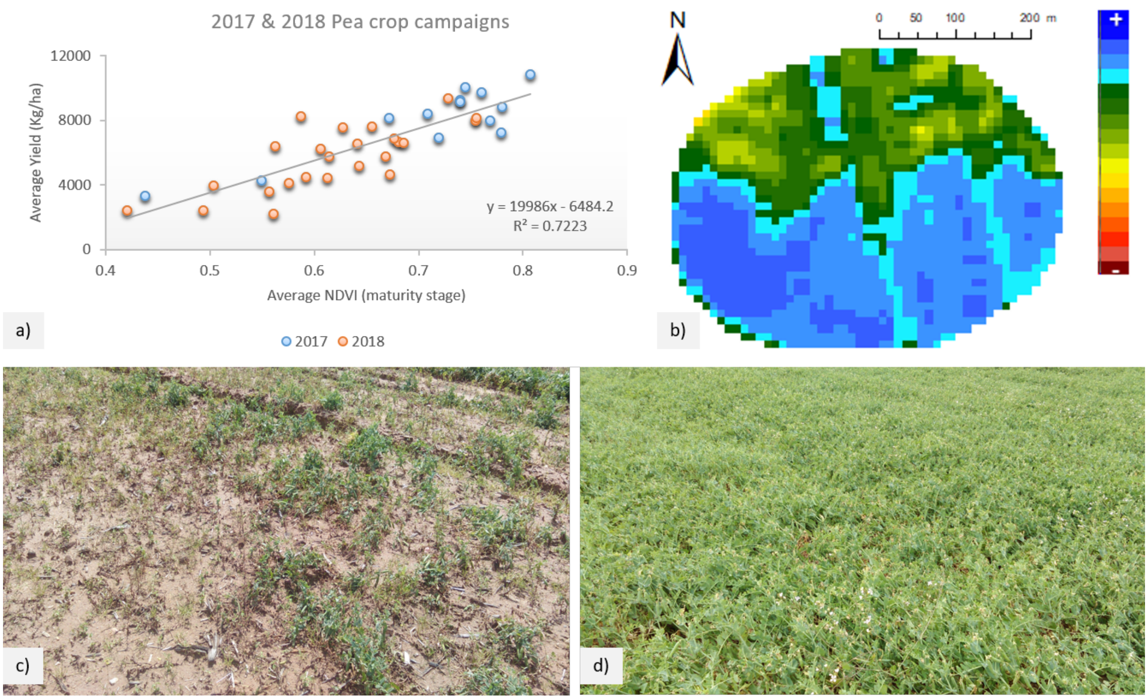

Figure 1: a) Linear regression between average NDVI (maturity stage) and average yield (Kg/ha) for each of the 37 parcels of the 2017 and 2018 pea crop campaigns in Tejo and Sorraia Valleys, Portugal; b) NDVI map of a 2018 pea crop parcel at maturity stage; c) & d) Plant development in the lower (green) and higher (blue) NDVI regions portrayed in b).

The dryer climate in 2017 was balanced by the water supply, which allowed the crops to develop in good conditions. In 2018, the heavy rain of March flooded segments of some parcels, especially in slow drain soils, making it impossible for the crops to develop in those sites, which can explain the average NDVI and yield values decrease, comparing with 2017's average values.

In Fig.1 it's possible to verify the positive relationship between the average NDVI at the maturity stage and the average yield. In general, average yield increases with higher average NDVI values. The fitted regression line achieved a R^2 of 0.7223 and can be considered statistically significant at $p<0.01$.

Using the model presented in Fig. 1, DARDICO S.A. agri-food factory can: i) predict the overall pea production (in space and time) that will arrive to the factory and better organize the factory operational processes; ii) better manage Nitrogen fertilization due to the fact that the NDVI index is highly correlated with the plant nitrogen deficiency especially on rainy years when leguminous plants have difficulties in fixing nitrogen from the air; and iii) segment harvest between fields and intra-fields in order to obtain different pea quality and different product price.

Future developments include; i) the validation and/or adjustment of the model with the 2019 pea crop campaign; ii) the consideration of weed presence and their effect in NDVI and yield values; and iii) automatic segmentation of crop parcels in order to manage different pea qualities.

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APPLICATION OF UAV MULTISPECTRAL IMAGES FOR ESTIMATION OF WINTER RAPESEED AGRONOMIC VARIABLES

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Winter oilseed rape (WOSR) is the second winter arable crop after wheat in Europe and France. A whole WOSR cycle lasts around 11 months, from august (sowing) to July of following year (seed harvest) and is divided into four critical periods: i) emergence and leaf development; ii) elongation; iii) flowering; iv) green pods to maturation.
During the vegetative cycle (emergence to flowering), several agronomic traits are usually considered as growth and health indicators, such as biomass (fresh and dry), Leaf Area Index (LAI) and nitrogen content (N). The aim of this study was to assess the relevance of multi-year and multi-site UAV images to estimate some of these variables for rapeseed crops using vegetation indices (VIs).
Two experiment sites were designed for this study to conduct three WOSR campaigns (2015, 2017 and 2018) in the context of PHENOME-EMPHASIS and RAPSODYN projects. Both experiments were carried out in Experimental farms of French Agricultural Research Institute (INRA). The first is located at Bretenière, near Dijon, with two plots in 2015 (CAN and PHE) and one plot in 2017 (CAN); the second is located at Le Rheu, near Rennes, with one plot in 2017 and 2018 (CAN).
Information about subplots, genotypes and N fertilization applications for both experimental sites are summarized in Table 1.

Table 1 : Detailed information about each experiment design

Site-year	Trial	N supply (kg/ha)	Genotype	Subplot	Microplot/date
Bretenière-2015	CAN	0,60,140	8	2	48
Bretenière-2015	PHE	0,40,100,180	1	4	16
Bretenière-2017	CAN	0, 60,140	20	4	120
Le Rheu-2017	CAN	0,40,80	20	3	120
Le Rheu-2018	CAN	0,40,80	10	3	90

Several measuring operations were planned at different key dates between February and April during vegetative stage. For each date, remote observations and field measurements were carried out. Remote observation consisted in UAV flights using Parrot® Sequoia Multispectral cameras with a spatial resolution of approximatively 5-7 cm in 4 spectral bands: 550 nm, 660 nm, 735 nm and 790 nm at an altitude of 100m. Radiometric and geometric corrections were performed for all images either directly by Airinov (Parrot® service provider) or by intern operators according to the technical instruction provided by Parrot-Airinov. All UAV output data were transformed into reflectance georeferenced orthomosaics (using Agisoft PhotoScan or Pix4D). A total of 14 data sets, including field measurements *vs* multispectral images, have been involved in this study. Field measurements included fresh above ground biomass (gr/m²) and leaf area index (m²/m²), both measured on 0.5 m² or 1 m² of canopy samples. As image data, we calculated a set of the most commonly used vegetation indices (MCARI2, MTVI, NDVI, Clrededge, MCARI and NDRE), and a new index proposed for this study:

$$NDVI_{log} = \frac{log\frac{1}{R_{PIR}} - log\frac{1}{R_R}}{log\frac{1}{R_{PIR}} + log\frac{1}{R_R}}$$

The reflectance values (0<R<1) of each spectral band were extracted and averaged for each microplot area after applying a 30-cm geographic buffer to avoid edge effects. Each field data was related to corresponding averaged images data (reflectance values) measured on the same microplot.
Data from both sites were analysed and processed by Python to establish a single, homogenized, multi-site and multi-date dataset. Within this dataset, 75% of the data was randomly selected to establish regression models between image data (VIs) and field data (biomass and LAI) and the remaining 25% was used for validation. We applied Tukey's test to assess the ability of each vegetation index against field variables to discriminate genotypes. Analysis of variance (ANOVA) were used to study the relationship between remote sensing data and field data for each site, including multiple genotypes and nutritional conditions. Finally, the LAI model was then used to compare genotype evolution kinetics of several nitrogen levels.
Remote sensing data allowed a more accurate classification of genotypes (9 classes by remote sensing *versus* 4 classes from field observations). The most appropriate model for estimating LAI (highest R^2 and smallest RMSE) was based on the NDVIlog index (RMSEP=0.28) whereas the one for estimating biomass was based on the MCARI index (RMSEP =254 g/m²). The image-based LAI values (estimated by LAI model) highlighted very well the crossover between the genotype and the nitrogen level (G X N) ($p<0.001$), contrary to the results obtained from field observations ($p>0.1$). This result could be explained by the higher number of data available by remote sensing. When comparing genotype evolution kinetics with the LAI model, there was significant differences by genotype according to nitrogen supply.

In conclusion, the UAV images provided suitable data for estimation of agronomic variables of winter rapeseed, in particular LAI and green biomass. In this study, we used a rich data set covering two different geographic sites during three non-consecutive WOSR campaigns. Therefore, the developed model based on this dataset is robust and applicable to a large number of genotypes and different levels of nitrogen supply. One of the limitations of this observation method is the availability of images at the suitable time, depending on the equipment accessibility and climatic conditions. Remote sensing data from UAV enable more frequent and exhaustive observations due to the synoptic view and provide more discriminating results than field observations, which are often long and tedious. Further studies will focus on the validation of each prediction model for new datasets, the simulation of the overall growth dynamics for new genotypes and the use of machine learning predictive models.

AGRICULTURAL DATA OWNERSHIP AND USE: DIGITAL FARMING PERSPECTIVE

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The agricultural and food value chain is entering an era of digitally enabled processes, where data can be generated during all operations related to agricultural production, post-harvest management, transportation and storage. Agriculture and food production is becoming increasingly data-driven. Smart farming in turn goes beyond primary production as it is influencing the entire food supply chain (Wolfert et al, 2017). Although the technical capabilities of precision agriculture are already well developed, the efficiency of the applications undertaken could be further enhanced by making use of the proliferating data sources. The foreseen transition to digital farming and to data-driven agricultural processes opens a variety of concerns among data originators, data providers and data users about the privacy, protection, intellectual property and use of farm-related data. This is one of the core issues for many hesitant farmers on their decision to adopt new technologies.

The increasing exchange of data constitutes a major challenge for the agri-food sector. In general, the nature of agricultural data is very diverse including land and agronomic data, livestock and fish data, climate data, machine data, financial and compliance data. According to the General Data Protection Regulation (EU) 2016/679 (GDPR), personal data means any information relating to an identified or identifiable natural person (‘data subject’). An identifiable natural person is one who can be identified, directly or indirectly. Data sharing between different stakeholders in the farming and food sector has to be performed under fair and transparent rules.

This paper is concerned with the governance i.e., data attribution (referred to as ownership), data protection, privacy, usability and security focusing exclusively on an actual case of digital farming. The study has been carried out in the framework of a newly funded research initiative by ERA-NET ICT-AGRI-2. The iFAROS project is an ambitious, 3-year project with 6 partners from 4 European countries (Belgium, Germany, Spain and Switzerland) focusing on data-driven solutions with the aim of sustaining and increasing agronomic productivity and environmental performance for small European farmers by exploiting multi-source data to optimize fertilization in wheat cultivation.

Following a structured approach, a conceptual framework for analysis was developed taking into account the joint EU Code of Conduct (CoC) (Anon. 2018) on agricultural data sharing, which was launched by a coalition of associations from the EU agri-food chain. This methodology can also be used for future studies on relevant topics. For all actors along the data value chain, a clear framework is provided on who, and under which conditions, can access and use which data. This framework is based on “Free flow of data” initiative of the EU which is part of the digital single market (DSM) strategy that looks at all elements that facilitate access, use and exchange of commercial data. The examined case is a typical example where multi-source data need to be processed and aggregated. In many cases, agricultural contractors are hired by the farmer to perform the fertilization. Furthermore, in order to develop the detailed fertilizer application prescription map envisaged by the project, the data need to be transferred to third parties for further processing (i.e., big data analytics). Consequently, there is a need to define the frame of data sharing in the entire project frame.

One important aspect of the aforementioned CoC is that the agricultural data are of economic importance for both the farmer and the whole value chain. The data transfer along the entire agricultural production chain was adapted to the activities of the iFAROS project (Fig. 1).

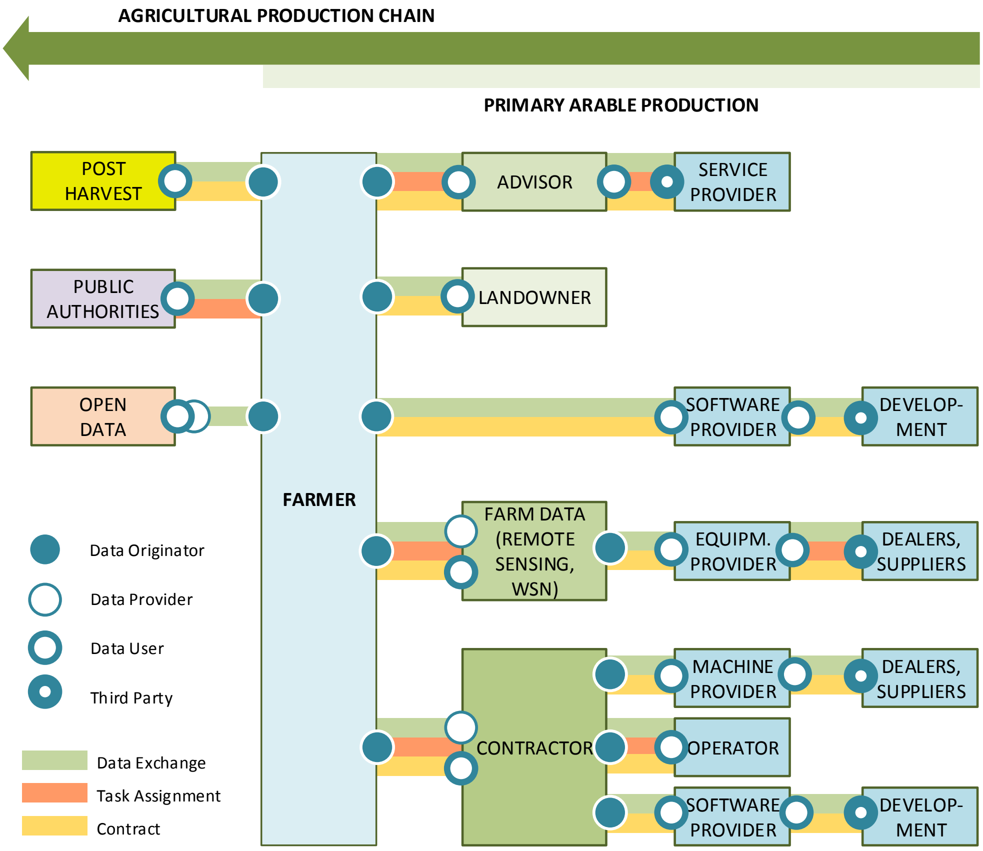

Figure 1: iFAROS – Data transfer among the parties of the agricultural production chain ("EU Code of conduct on agricultural data sharing by contractual agreement," 2018, modified).

The farmer is the main data originator but if a contractor is involved, he may also become a data originator (location, N fertiliser dose rate, fuel usage). Nevertheless, it should be clear that all data that are produced on the farm are granted to the farmer and they should determine who can access and use these data. In case the contractor involves third parties or other data users, a contractual agreement among all parties (including the farmer) should describe in detail the data collection and sharing conditions. As a strong focus of iFAROS is the multi-source data, various sources of farm data are also considered such as remote or wireless sensor network (WSN) soil data. The farmers may also seek for advice and support by software providers e.g. farm management system (FMS) vendors and/or agronomical advisers. In case the latter employ third party service providers or application developers, again a contract should define the data sharing framework. The farmer as the main data originator can always have a contractual agreement and provide data to land owners in rented fields. Furthermore, data should be provided to public authorities, since in most cases fertilization amounts are connected with EU subsidies. Finally, if desirable, the farmer may also supply farm data to open data platforms for further analytics.

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SMALL PLOT FIELD EXPERIMENTS AND PROXIMAL SOIL SENSING (GAMMA AND MID-INFRARED SPECTROSCOPY) PROVIDE RECIPROCAL SERVICES

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Introduction

High resolution soil data are an essential prerequisite for the application of precision farming techniques. Sensor-based evaluation of soil properties may replace or reduce laborious, time-consuming and expensive soil sampling with subsequent conventional measurements in the laboratory. Gamma spectrometric field measurements provide high resolution information on topsoil texture. In a previous study (Heggemann et al., 2017) we successfully calibrated site-specific texture models (linear regression) and also a study site-independent prediction model (support vector machines) that was applicable to soils from a broad range of parent materials and with widely varying soil texture.

Mid-infrared (MIR) diffuse reflectance spectroscopy is a performing tool to predict various soil fertility properties (Terhoeven-Urselmans et al., 2010). Among others, models for pH, soil texture and organic matter content were calibrated, i.e. all soil properties that are required to determine lime requirement (LR). In the ongoing project, a database calibration approach (Leenen et al., 2017) was compared with single-site calibrations.

The aim of this study was to elucidate the interaction and potential mutual benefit of plot experiments and proximal soil sensing. On the one hand, soil sensing prior to establishing a plot experiment can help to find the optimal trial design and location. On the other hand, existing experiments provide soil data within a limited area, i.e., under *ceteris paribus* conditions. The soil properties studied here are texture, organic matter content, and pH value.

Material and methods

In total, four current plot experiments were accompanied and evaluated by soil sensing activities. Conversely, routinely collected soil data from the trials were used to improve sensor signal understanding and calibrations. All plot experiments are located in Western Germany and comprise liming experiments (Heimbach: arable land; Hilberath: permanent grassland), a soil organic matter experiment (Siebeldingen: vineyard), and a long-term fertilizing trial (Rengen: grassland, since 1940). For all trials and single plots, conventional lab analyses are available for texture, organic matter content, and pH value. Gamma spectra were recorded with a tractor-mounted spectrometer (Radiation Solutions, 2* 4.2 L NaI crystals). Diffuse reflectance MIR spectra were taken in the lab using a Bruker Tensor 27 FTIR device. First pre-tests were conducted with a portable MIR spectrometer (Agilent 4300). From the gamma spectra, local prediction models were calibrated as linear regression between conventionally measured soil texture and total counts (TC) [cps], K-40 [cps], or the K-40/Th-232 ratio. To explore MIR spectra, partial least square regression was conducted using the OPUS Quant software.

Results and Discussion

As shown in a previous study (Heggemann et al., 2017), gamma spectrometry is generally capable of providing reliable soil texture data. However, transferring site-independent calibration to unknown soils partly remained disappointing. This was valid for all test sites and exemplary demonstrated for the Heimbach experiment. Limited model applicability was insofar surprising as soil parent material were periglacial slope deposits from weathered sandstones (Bunter Sandstone), a material that was even present in our 2017 site-independent calibration. At least satisfactory texture prediction was expected following the results of

Coulouma et al. (2016) on regional calibrations. Nevertheless, optimal positioning of the 48 small experimental plots (6*12 m each) within the 8 ha field could be verified according to minimized TC variability recorded on-the-go at 27 m spacing and 4 km h^{-1} (3,593 spectra). In addition, a satisfactory local calibration for the entire field was achieved by correlating stationary recorded K-40 counts with clay contents at 11 sampling points (11-21 % clay, R^2=0.88).
At the Heimbach site, clay and organic matter content as well as pH were successfully predicted from MIR spectra after local calibration (n=62; R^2=0.72, 0.82, and 0.92, respectively). Lime requirement was estimated from conventional analyses and predicted from MIR-derived soil properties; both results were closely correlated (R^2=0.86). Further, even direct prediction of lime requirement was possible (R^2=0.77; Leenen et al. 2019 unpublished, revised manuscript under review at J. Plant Nutr. Soil Sci.). Similar results were obtained for the other three plot experiments (not shown here). First pre-tests of the portable MIR spectrometer yielded promising results. Prediction of soil parameters provided similar values for the portable and the benchtop device, although the spectral range is smaller for the portable instrument. This is in line with results reported by Soriano-Disla et al. (2017). Further respective investigations are part of the running project.

Conclusion

Rapid gamma screening of soil properties at potential plot trial sites can help to substantially decrease unexplained variability in field experimentation. Reciprocally, samples and data collected in field experiments provide valuable information to further improve sensor signal comprehension and enlarge calibration basis. No additional efforts are necessary, when soil sampling and analyses are conducted in joint experiments.

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SOIL VAIRABILITY WITHIN HIGH TUNNELS

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Introduction

High-tunnel or hoophouse food production presents an opportunity for urban and non-urban agricultural production. They are structures covered by clear plastic film, heated by solar radiation, and used to protect crops from excessive weather conditions. High-tunnels can provide year round sustainable food production, especially in temperate climate regions, by extending the growing season (Wells and Loy, 1993; Lamont, 2005). These structures are internally leveled areas ranging from 4.5 x 6.5 m^2 to larger than 30 x 32 m^2. Compared with open agricultural fields and due to their small size, high tunnels have been traditionally sampled with one soil composite sample per structure, collected at one depth (Knewtson et al., 2012).

The objective of this study was to propose a soil sampling design that represents soil growing conditions within a high-tunnel. Our hypothesis was that the high-tunnel environment exhibits high spatial soil variability related to management practices, causing traditional/whole field sampling to poorly represent actual soil conditions.

Methods

The research was performed at West Virginia University's Organic Research Farm in a 22 x 8 m^2 high-tunnel. In this structure, multiple crops (tomato, carrots, peppers) were produced in 21 x 1 m^2 rows. Soil sampling was performed in quadrants with two quadrants towards the east end and two towards the west end of the structure. Soil cores were taken in 1 x 1 m^2 grid, to a depth of 20 cm. The cores were cut into 5 cm depth increments (0-5, 5-10, 10-15, and 10-15 cm). Soil samples were analysed for pH, bioavailable nutrients (phosphorus (P), magnesium, potassium), organic matter and texture.

Results

In this paper we will discuss phosphorus and sand content. Preliminary results showed differences in soil bioavailable nutrients and sand contents within the high tunnel. Significant differences in sand content between the east- and west-ends were observed at the surface 0-10cm and 10-20cm. The east-end exhibited higher sand content at 0-10 cm (310 mg kg^{-1}) and 10-20 cm (302 mg kg^{-1}), than the west-end of the high tunnel where 276 mg kg^{-1} at the 0-10 cm, and 277 mg kg^{-1} at the 10-20 cm depth were measured. At these short distances, significant differences in sand content are the effect of high tunnel construction and land levelling, and may affect irrigation performance and general high tunnel productivity due to texture's influence on storage of plant available water. Soil sampling results indicated high variability in bioavailable nutrients content at the surface (horizontal), and in depth (stratification). Table 1 presents the results obtained for bioavailable phosphorus (BP). For the traditional whole field soil sampling, BP was 130±74 ppm at 0-5 cm, 63±58 ppm at 5-10 cm, 41±70 ppm at 10-15 cm and 47±97 ppm at 15-20 cm; differences of BP obtained with quadrant sampling could be observed in Table 1. Average bioavailable nutrients estimated by traditional sampling (whole average field sample) were statistically different from quadrant sampling.

A designed soil sampling strategy provides more informative data than traditional sampling because the designed strategy accounts for bioavailable nutrient management related variability, and may help guide appropriate practices for more sustainable high-tunnel production.

Within the high-tunnel, there is a high variability in soil properties - variability that follows a spatial pattern. This observation supports the need for soil sampling protocols that improve sampling representativeness and support sustainable management. The causes of this variation range from construction to the ongoing soil management in support of several crops each year. The high variation in bioavailable nutrients due to soil type, construction, and high-tunnel crop management will require consideration of soil sampling depth and location within the high-tunnel.

Table 1. Whole Field and Quadrant Stratified Phosphorus Content.

Quadrant	**Phosphorus (ppm)**			
Depth	0-5 cm	5-10 cm	10-15 cm	15-20 cm
Whole Field Sampling	130±74 a	63±58 b	41±70 c	47±96 c
Quadrant Sampling				
#1 (East)	105±62 a	55±83 b	55±124 b	81±172 b
#2 (West)	121±59 a	49±29 b	32±22 b	39±33 b
#3 (East)	103±61 a	40±35 b	14±14 c	11±15 c
#4 (West)	184±79 a	100±46 b	55.0±38 b	45.0±33 b

Different letter in the same row (sampling depth) identify significant differences at α=0.05.

There is little published information that discusses the soil sampling required to adequately characterize the soil property variation in these food producing structures. These study results will aid fertilization practice planning for sustainable high-tunnel production.

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DESIGN AND EVALUATION OF A SELF-PROPELLED ELECTRIC PLATFORM FOR HIGH THROUGHPUT FIELD PHENOYPING IN WHEAT BREEDING TRIALS

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Keywords: Wheat; Non-destructive measurements; Precision phenotyping.

Introduction

There is general consensus among the scientific community that the challenge of feeding a growing population in a resource-limited world must be addressed by developing new crop cultivars with enhanced yield potential and stress tolerance more rapidly and more efficiently than is currently possible with conventional crop breeding techniques. High-throughput phenotyping platforms (HTPPs) have emerged in recent years to deal with this need by increasing the quality and amount of data collected during field trials of germplasm collections. One such field-based HTPP platform has been developed and evaluated at the University of Arizona (Andrade-Sanchez et al., 2014). The majority of commercial HTPPs developed to date are designed to fit in fully automated indoor facilities with robotics, precise environmental control and proximal sensing techniques that focus on measuring specific traits of individual plants in greenhouses or growth chambers. These systems are costly, only being affordable for large transnational seed companies and the most advanced public plant research institutions globally (Araus and Cairns, 2014; Deery et al., 2014). Besides their high cost, a major drawback is that these systems operate under controlled environments that differ greatly from the ambient conditions in the open field. Consequently, genotypes selected for their higher performance (e.g. yield potential) under controlled environments may not retain those traits in the field (White et al., 2012). This work describes the results of the preliminary phase of the design study of an electric-power driven platform with the ability to travel across a typical wheat breeding trial carrying a modular array of non-contact sensors.

Materials and Methods

Design requirements including size limitations, drive motor torque delivery, battery size, voltage regulation, structural stability, mechanical steering, and operational safety were evaluated and optimized. First phase of testing was under controlled conditions in laboratory with 3D printed artificial plants, which do not present phenotypic variation. In field trials, 10 wheat cultivars were chosen, of which 6 were water stress sensitive and 4 water stress tolerant. Wheat field plots had a size of 5.4 m^2 (4.5 x 1.2m) with 6 rows per plot 20 cm apart. The HTTP was designed to carry a set of sensors and imaging instrumentation able to measure and record plant architectural traits such as canopy height, Leaf Area Index (LAI), spectral reflectance (310-1100nm) and plant canopy temperature simultaneously on 6 adjacent rows (Fig. 1a). To date, we have successfully collected HTP data over part of a wheat growth cycle. The HTPP velocity was 0.27±0.09 m s^{-1} and the sensors were positioned at a height of 0.50 m over the average wheat canopy.

Results

The HTTP designed in this project moved at a constant rate and without causing plant damage over the plots (see Fig. 1.a). A set of RGB images were acquired for each plot. LAI and the Fraction of Vegetation Cover (FVC) were estimated using image segmentation and ANN (Artificial Neural Network) techniques. The comparison between actual and predicted LAI values showed a coefficient of determination (r^2) of 0.96 with *RMSE* = 1.52. Spectral information was used to calculate NDVI and PRI indices for each wheat cultivar. In addition, our team has done work to capture geometric parameters such as canopy height of the crop with LiDAR. Preliminary results of point cloud for a set of cultivar plots is shown in Fig. 1.b.

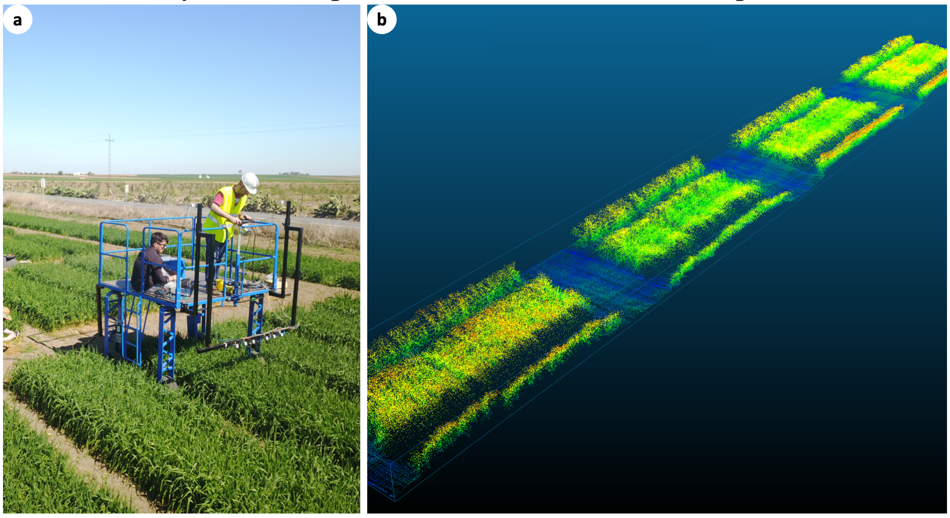

Figure 1. a) Wheat plots in Sevilla (Spain) and b) point cloud of set of plots.

Frequent deployment of the instrumented platform generates large volumes of time-series data to enable advanced data processing and analytics. HTPP-derived physiological and structural traits are highly informative and will shed light on the existing wheat yield variability under water stress conditions and provide decision support in unbiased selection to wheat breeders.

Acknowledgements

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AN ENHANCED YIELD POTENTIAL SPATIAL CLUSTERING METHOD, ACCOUNTING FOR SEASONALITY, HETEROGENEOUS MORPHOLOGY AND CLIMATE VARIABILITY: AN APPLICATION IN THE UMBRIA REGION (CENTRAL ITALY) FOR THE SMARTAGRI PROJECT.

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The SMARTAGRI project for precision farming aims at improving the efficiency of agricultural practices, including fertilization, for farms of moderate size in the heterogeneous morphological conditions typical of Central Italy. Variable rate fertilization prescription maps are generally based on the recognition of spatial patterns of temporally stable similar yield potential. These can be currently identified at low-cost by using open access, high spatial resolution multi temporal imagery, such as that provided by Landsat and Sentinel-2 satellites. For this purpose, a number of clustering algorithms have been developed, mainly based on the analysis of vegetation indices, possibly integrated by yield maps and geophysical surveys, when available.

The suitability of soil conditions for crop growth, however, is likely to depend on the interaction of a crop species and variety, with the microclimatic and soil conditions, in respect to a combination of seasonal factors limiting crop growth, such as water and nitrogen availability, thus interfering with vigor related indices. This is especially true for agricultural areas in highly heterogeneous morphological conditions, such as in large part of in Central and Southern Italy. As a consequence, we expect that, in these conditions, a clustering algorithm that takes into account such variability, may benefit by a reduction in potential confounding factors, thus resulting in higher accuracy of species and variety-specific yield pattern recognition.

In order to assess novel clustering methods that take into account the seasonal dynamic patterns of crops, weather and soils, we assembled a dataset over five cropping seasons in agricultural plots in the Umbria region (Central Italy). Meteorological data were obtained from nearby meteorological stations, and individual years for specific sites classified according to three rainfall regimes (dry, median and wet years). Crops were split in potentially irrigated (Summer crops) and non-irrigated (Winter crops). Sentinel-2 and Landsat 8 images were downloaded for every year and field, and vegetated ones retained for clustering, based on vegetation indices thresholds. Images of individual sites with non-irrigated crops were then grouped based on climatic years, resulting in three groups of images. Morphological features (catchment, slope and aspect) internal to each plot were derived from a digital elevation model (DEM). Spatial correlation between reflectance in water absorption bands on bare soil images and the DEM derived features was used to test for the appropriateness of the latter to represent topsoil moisture conditions. A k-means clustering based on vegetation indices was then applied to each group of images obtained for individual fields, in order to assess the intra-plot spatial yield patterns. The resulting spatial patterns were validated against yield maps collected in the field in different years. The methodology provided interesting results when compared to a previous clustering algorithm which did not take into account the seasonal dynamics of crops and weather.

QUINOA PLOT AND DRONE

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Introduction

Agriculture is facing various challenges worldwide, especially in recent years. There are many problems, including the well-known problem of food shortage (González et al., 2017) which constantly affects developing countries, rural economic development, and the quality of life in rural areas that depend on this activity (Liaghat 2010). Likewise, environmental problems are becoming increasingly acute (scarcity of water resources, energy sources, climate change, etc.). This challenges the agri-food system to be more efficient and innovative in processes and in the use of natural resources (Briz & De Felipe 2011). Given this context of problems that this economic activity is going through, the implementation of new technologies is proposed as alternative management, monitoring, and control of agricultural crops (Berrío et al., 2015). These technologies include the use of devices such as Unmanned Aerial Vehicles (UAV) (Sagan et al., 2019). This is how the concept of precision agriculture emerges.

In Peru, quinoa is sown in different agroclimatic zones and is classified according to the way it is sowed, the geographical location it is grown in, and the market; The following is an example: altiplano, sheltered inter-Andean valleys, high and cold areas above 4000 m, areas of the salt mines, coast and in the jungle (Fairlie, 2016). Additionally, the crop is beneficial for the rural families of the Altiplano since their production costs are low and complex infrastructure is not required for washing, drying and storage processes; it also does not need much labor for its production and it consumes only small amounts of water (Salcines, 2009).

Study

Given this general context, we have this case study in a quinoa cultivation plot in the Cabana district of Puno province, in the Puno region, administered by a community association supported by Cooperativa Agro Industrial Cabana (COOPAIN CABANA) at 4000 meters above sea level. We have data at two different times to compare the state of quinoa. Two flights were carried out with a multispectral camera, which captures the light electromagnetic spectrum in five bands: Blue, Green, Red, Near Infrared (NIR) and RedEdge on February 2nd and February 28th of 2019. Figure 01 shows the images of the quinoa plot on both dates.

The investigation done by Lupaca in her Master´s Thesis shows that the protein value offered by soil conditions in the high Andean areas has an advantage over coastal crops. However, the atmospheric variables are more stable at sea level, which leads to a high yield and a guarantee in production, which is contrastable with the difficult weather at the high Andean areas. The application of technology such as UAVs and remote sensing methods can become an advantage that balances the disadvantages of atmospheric events of quinoa crops in high Andean regions such as Puno, helping to solve the problem of food shortage with a product that has high protein value and good quality.

When Figure 1A and 1D are compared, it is apparent that not all the quinoa plots have had a homogeneous yield due to atmospheric conditions such as low temperature and hail. These conditions affect the plants and the soil. Also, Figure 1C shows that the size of the plant decreases as time passes, which is a point of study for further investigations. The images from UAVs provide real time information to make better decisions and make a good estimate of the production yield.

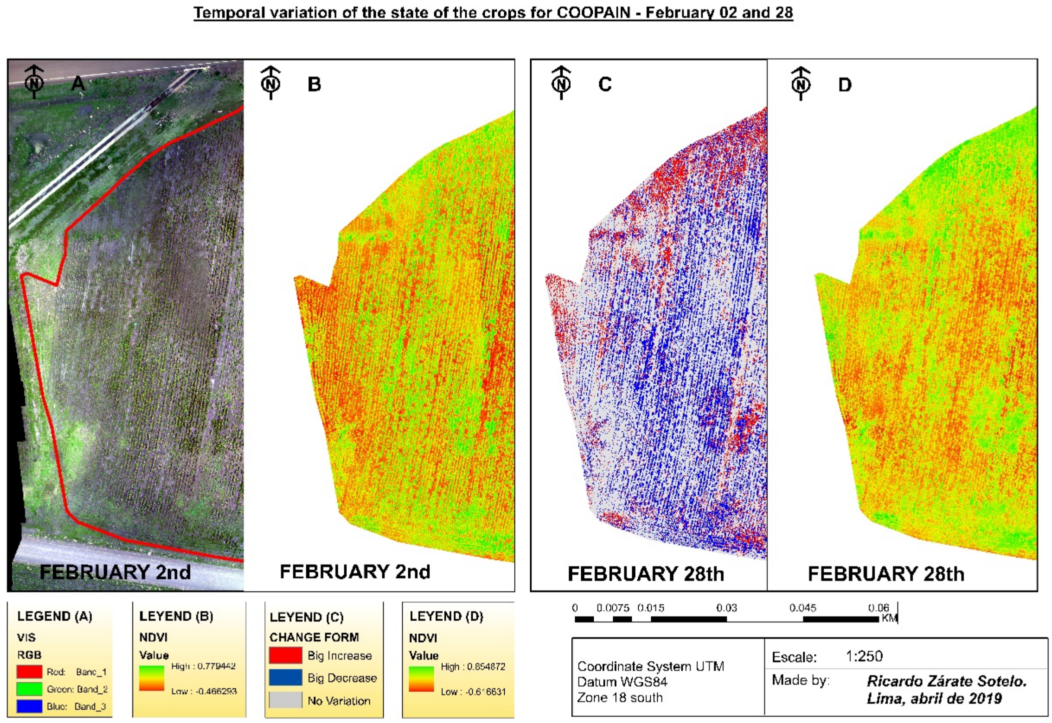

Figure 17: Map's Description and Interpretation

Figure 1 shows a RGB (Red Green Blue) of a small part of the quinoa plot. Image B is the Normalized Difference Vegetation Index (NDVI) on February 2nd. Image C shows how much the quinao plants have increase or decrease its physical shape from February 2nd to Febraury 28th. Image D shows the NDVI for Febraury 28th.

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REMOTE ESTIMATION OF GLYPHOSATE INJURY ON *ELEUSINE INDICA* THROUGH RGB IMAGES

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Symptoms of phytotoxicity by herbicides such as necrosis and chlorosis cause reduction of plant chlorophyll, affecting the reflection in the spectral regions visible to the human eye (400-700 nm), red-edge (690-730 nm) and near infrared (780-2,500 nm). Thus, it is possible to automate the process of injury evaluation through sensors based on spectral/optical responses, allowing site-specific application of herbicides (Castaldi et al., 2017; Czarnecki et al., 2017).
This study aimed to build statistical models for predicting glyphosate injury (phytotoxicity) on *Eleusine indica* (L.) using digital RGB images.
The experiment was carried out between April and August 2018, at the Instituto Federal Goiano - Campus Urutaí, GO, Brazil, geographic coordinates: 17º 27' 49" S and 48º 12' 06" W. Seeds of *E. indica* were sown in pots with 12 L capacity, filled with Red Latosol of 42% clay from an experimental area with known history. About 45 days after sowing, the plants received glyphosate in the following doses: 0%, 25%, 50%, 75%, 100%, 200%, 300% and 400% of the prescribed dose (1,440 g a.i. ha^{-1}). Each dose (treatment) was applied to four experimental units, which consisted of a pot with two plants. The applications were done with a costal sprayer equipped with XR11002 tips, pressurized with CO_2 providing constant flow rate.
At 7, 14 and 21 days after application (DAA), visual scores of injury (%) were assigned by three evaluators using the EWRC (1964) and ALAM (1974) scales. The mean scores of the three evaluators were analyzed.
After the visual evaluations, digital images of the experimental units were obtained with the RGB camera of the iPhone 6, with 8 megapixels resolution. The images were acquired under full sun, between 10:00 a.m. and 2:00 p.m., at the standard height of 0.90 m from the ground and FOV (Field Of View) angle of 90°.
The software R was used to processing images through the following steps: 1) converting RGB pixels to HSV (Hue-Saturation-Brightness) colour space, which is robust to illumination variation, where hue is represented within [0, 360º], with 0º being red, 60º yellow, 120º green, 240º blue and 300º magenta; 2) segmentation based on hue differentiation between soil (background) and plant using the method of Otsu (1979), which consists of determining a threshold for hue; 3) extracting median values of hue for plant pixels. These were used as explanatory variables in regression models of visual injury mean score.
Thresholds for hue ranging from 28 to 45 were capable of discriminating soil reasonably well. Similar results were found by Ali et al. (2013).
Figure 1 shows the decrease of visual injury according to the medians of hue for plant pixels, mainly at 7 and 14 DAA. For these data the following equations were fitted: $y = 495.02*\exp(-0.0544*x)$, with 13.67% of prediction error, and $y = 208.28*\exp(-0.0221*x)$, with 12.44% prediction error. With the confidence bands it is noticed statistical differences ($p < 0.05$) of predictions of injury at 7 and 14 DAA. It is also observed that predictions are more accurate at hue ranging from 35 to 60, that is, for plants presenting, at least, intermediate injuries. In this region the decrease is linear. At 21 DAA all the plants that received glyphosate presented injury above 80%, which explains the behaviour of the data being ‘clustered’ in hue values ranging from 35 to 55. In this case no model was fitted, though a linear decrease is also observed.

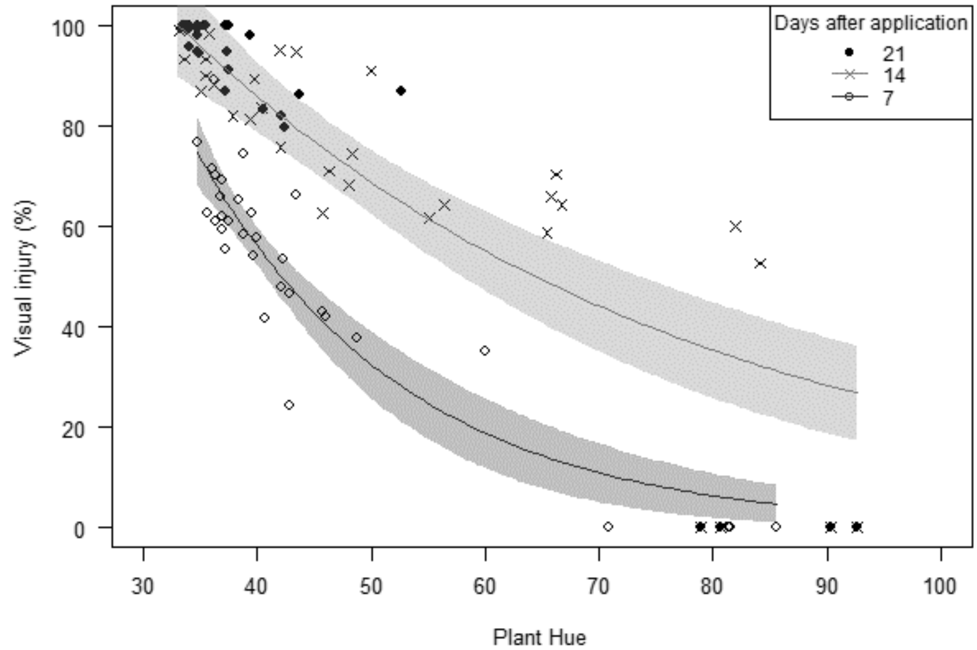

Figure 1: 95% confidence bands for the predicted values of visual injury as a function of median values of hue of *E. indica* subjected to glyphosate.

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MEXICAN CROP OBSERVATION, MANAGEMENT AND PRODUCTION ANALYSIS SERVICES SYSTEM – COMPASS

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The COMPASS project aims to develop a decision support system (DSS) for sugarcane and wheat farmers in Mexico to enhance their crop management systems. The DSS is underpinned by the concepts of the AquaCrop model. The wheat component employs within station and farmers' fields trials for model calibration in the Yaqui Valley, an irrigated agricultural area located in Northwest Mexico. Although the Yaqui Valley is one of the country's most productive breadbaskets, consisting of about 225,000 ha, local farmers still lack decision support tools for more sustainable and profitable farming practices.

The timing of sowing date and irrigation are well known practices driving yield potential in this region and even experienced farmers can benefit from the adoption of a DSS to inform their decisions. As such, the COMPASS' objectives within the wheat component are to provide farmers with a mobile application which consists of two modules. The first module will provide the optimum sowing date for a given location within Yaqui Valley as a function of the number of post-planting irrigations (usually 3-4 irrigations). This module provides an overview of the effect of the sowing date on grain yield over twenty years of historical weather data, providing farmers the opportunity to adjust their sowing dates to minimise yield loss. The second module of the DSS app is an irrigation scheduling feature which provides a probabilistic yield forecast for potential irrigation events over a 10-day window.

Planting date recommendations are made in advance of the season and therefore the simulations are unavoidably based on a representative climate ensemble. The Power Project (https://power.larc.nasa.gov/) historic weather data set was used for this which provides daily weather values on a 0.5×0.5° grid, with 9 grid squares covering the extent of the Yaqui Valley. A 20-year climate ensemble (1996-2015) was used to represent the influence of inter-seasonal variation. The Yaqui Valley was spatially classified into five main soil classes and the soil hydraulic properties of those classes were used (Moreno-Ramos, 2014). For each grid square and soil type, the 20 year simulations were performed for each possible sowing date, over the period of 15th November to 15th January, which is the planting window observed in the Yaqui Valley.

The model has been calibrated for the durum wheat cultivar cv. CIRNO C2008 using a range of combined crop-climate-soil datasets collected in the Yaqui Valley area. These data include final grain yield and within-season total biomass observations for different sowing dates and irrigation managements made within the COMPASS project (on both research station trials and farmer's fields) and pre-existing data sets from CIMMYT's extensive archive of experimental work. The crop parameters retained for the model calibration were identified following a thorough sensitivity analysis, where only the most sensitive parameters have been selected.

Figure 1 illustrates the model performance in simulating both grain yield and biomass. The calibrated model used in this study presented an overall RMSE of 1.11 and 1.57 t ha^{-1} for grain yield and biomass, respectively. The RMSE obtained in this study is similar to that obtained by Wellens et al. (2018) who simulated winter wheat grain yield using satellite data assimilation within AquaCrop.

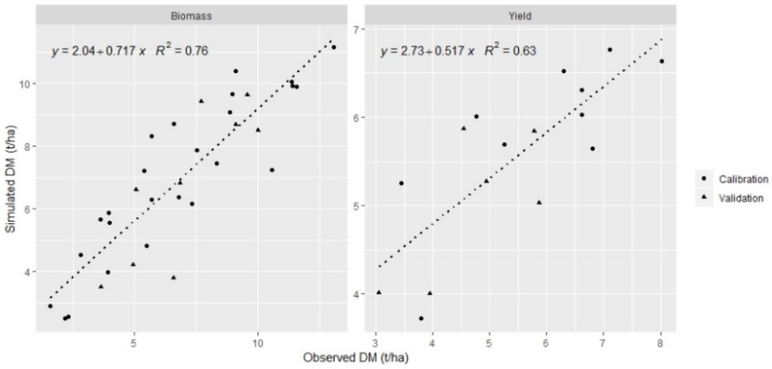

Figure 1: Model performance for the estimated and observed biomass and grain yield.

The calibrated model was applied to the whole extend of the Yaqui Valley, using 9 grid squares (0.5×0.5° grid) of historical weather data in combination with the digital soil map. The model was evaluated for each date within the sowing window. Figure 2 shows an example of the heat-map of the possible yield gaps between the optimum sowing date -15/11- and sequences dates within the sowing window (15/12 and 15/01).

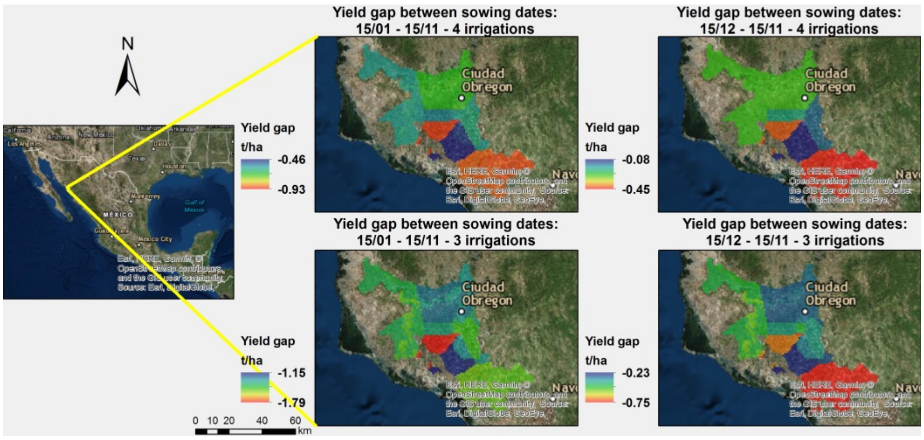

Figure 2: Heat-map for sowing date yield gap

Next steps of the project are to use satellite data to retrieve state variables (i.e. canopy cover), which will be used through data assimilation to further adjust the model to better represent the field spatial variability and developing the second module of the mobile application.

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STUDENT AMBASSADORS FOR INCREASING ON-FARM TECHNOLOGY ADOPTION

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An increasing demand for agricultural production without improving the existing farming practices would result in further degradation of natural resources and increasing greenhouse gas emissions. Intensively resource-consuming agricultural systems with high inputs cannot provide the society with a sustainable farming production. A paradigm should be shifted from the destructive practices to a holistic approach to improve sustainable production in a short - as well as a long-term (FAO, 2017). One of the areas contributing to sustainability is smart farming. Innovations in agriculture are being developed and spread resulting in the growth of more efficient agricultural practices. However, despite the recent developments in agriculture, technology adoption on farms is still low. One of the main reasons for low adoption rates among farmers is the lack of information and skills to utilise the technologies (Barnes et al, 2019).

The main objective of this study was to increase the awareness of farmers about modern agricultural technologies and improve their on-farm adoption. To deal with this problem, a study was carried out in the framework of the EIT-Food project "Education for Technology Take-Off" involving researchers, industrial partners and farmers from Germany and the UK. The first part of the methodology focused on a literature survey on problems associated with low technology adoption and identified mechanisms for increasing the adoption rates. The second part of the research was directed towards students and farms selection. In total, 12 students were recruited as student ambassadors to support 64 farmers in their activities and promote the adoption of modern agricultural technologies. The students were divided to 2 groups: 6 M.Sc. students involved in crop production, supported 6 farms in a close collaboration with the John Deere and the University of Hohenheim, whereas 6 B.Sc. students worked on animal husbandry, supported 58 farmers and supervised by the ABP Food Group and the University of Reading. The M.Sc students were employed by the John Deere for 6 months and therefore had a longer period of time with the farmers compared to the B.Sc students who were employed for 3 months.

The SWOT method of analysis was carried out for each farm separately in order to identify the particular parameters affecting the adoption of on-farm technology. In addition, a survey using standardized audit forms including 3 questions (i.e., use of specific technologies by farmers, support received from the students and effectiveness of methods used by students) was carried out among the farmers and students before and after the internships.

The analysis revealed that there was a small, but significant proportion of the farmers who did not engage with technology prior to this research. For instance, 19% of farmers were either not comfortable or extremely uncomfortable to use on-farm technologies, 14% used technology irregularly/seasonally, 9% did not use technology and 12% would not be confident in investing in technology. Only, 6% of farmers gained little or no benefit from the research. Despite using a range of support mechanisms, 20% of students reported lack of farmer interest, often citing difficulties to reach the farmer – due to lack of mobile phone signal, poor internet access and/or the farmer working long hours and being unreachable. With 19% of farmers not interested in being involved in a subsequent work, this raises a question on how to engage farmers best who do not have the confidence and/or interest in technology.

Prior to this research farmers used a range of publications/articles/brochures to stay up to date with technology, however, they would prefer support via farm-to-farm visits to be informed about best practice, discussion groups, video demonstrations, webinars, courses and weekly updates. Whilst 2 student ambassadors attempted to use videos and Skype with their farmers, the effectiveness of these methods was rated low. The farmers initially were particularly interested in attending visits to other farms, however, very few visits were organised. This is partly because of the lifetime of the project – the farmers were often too busy to attend courses, farm visits. Nevertheless, the final farmer questionnaire reflected the eagerness of the farmers to attend farm visits and training courses and workshops.
The results of the SWOT analyses were evaluated and an attempt was made to present a consolidated SWOT analysis integrating common factors influencing the adoption of technologies in 64 farms (Table 1).

Table 1: SWOT analysis of integrating common factors influencing the adoption of technologies in 64 farms in Germany and the UK

Strengths	**Weaknesses**
Regular personal contact and farm visits	Frequent change of supervisors
Good training programs	Lack of time for personal contact
Contact with competent personnel	Difficulties in email, phone communication
Coordination, evaluation mechanisms	Too short program duration
Link with agricultural companies	Poor selection of farmers
Continuous exchange of knowledge	Lack of farmers' interest
Opportunities	**Threats**
Implementation of new technologies	Desire to adopt many technologies at once
Time-saving due to technologies	A risk of misunderstanding
High interest in new technologies	Farmers' loss of faith
Frequent change of supervisors	Farmer' 'laziness'
Lack of time for personal contact	Difficulties to satisfy farmers' expectations
New relationships, improved collaboration	Farmers' decisions made on their own

The results indicated that the most effective and widely used method of engaging farmers was via 1-2-1 visits by the student ambassadors. The direct visits allowed farmers to receive tailored-made support with technology, which it was directed to their farming needs. The student ambassadors often provided additional support e.g. by organising expert visits – nutritionists, veterinarians. The farmers stated the expert visits as the most helpful support that they received. Over 80% of the farmers would be interested in taking part in the subsequent research activities and 95% would recommend to collaborate again with both industrial and research partners. The model of using B.Sc. students is restrictive – the students are only available during the summer, generally, June-September and this coincides with the busy time of harvesting. On the other hand, the John Deere format of employing M.Sc. students for an extended period of time allowed students to spend more time with the farmers building trust, confidence and knowledge in the technology.

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INCREASING THE SPEED AND UPTAKE OF INNOVATION IN THE FIELD VEGETABLE AND POTATO SECTORS: DEFINING A NEW APPROACH FOR DELIVERING COST EFFECTIVE RESEARCH (INNO-VEG)

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Introduction

This project aims to (i) evaluate the suitability of using high resolution aerial imagery to carry out measurements in field experiments and (ii) to define and implement a new approach for delivering cost effective research in the field vegetable and potato sectors. The new approach will reduce the cost of delivering research, enabling the current research funding to address a wider range of research priorities. It will also facilitate a change from predominately research organization and commercial company led research to one where farmer led research forms an important component. This approach places the farmer at the centre of the research process which helps to up-skill the industry and drive improvements in crop production efficiency by testing and implementing new approaches or products on commercial farms.

Field Experiments

In 2019, 48 field experiments have been set up across the UK, France, Belgium and the Netherlands to develop an over-arching 'Protocol' for the integration of high resolution crop data into research methodology. The 'Protocol' will be developed from a programme of 'conventional' small plot field experiments where traditional field measurements (i.e. hand harvest assessments of yield and crop quality) are being compared with remotely collected high resolution spatial crop data. Data analysis of field measurements and spatial crop data will identify whether crop sensing is sufficiently accurate to detect treatment differences in crop growth/performance at the field scale. The small plot field experiments cover a number of horticultural crop groups (including potatoes, brassicas, alliums, leafy salads, carrots, vining peas and cucurbits) and research priority areas (e.g. soil management, crop nutrition and protection) in order to generate sufficient data to evaluate the suitability of high resolution aerial imagery to assess field experiments. The experimental programme has been designed to ensure the protocol has broad relevance for field vegetable and potato research.

The use of spatial crop data to assess field experiments allows upscaling of research from small plot to field scale, which in turn allows development of a farmer led approach to research. In 2020, 14 field validation experiments across the UK, France, Belgium and the Netherlands will test the 'Protocol' developed in 2019 in field scale research experiments in order to develop a 'Framework for farmer led research'. This Framework will be tested in a further 14 farmer led field experiments in 2021. The framework will provide farmers with the information they require to set up and run field scale experiments including experimental design, application of treatments and sourcing crop sensing data. The framework will enable farmers to test new approaches, equipment or products on their own farms. This will facilitate innovation at the farm level, increasing the knowledge and profitability of individual farming businesses.

Economic Analysis

An economic cost benefit analysis on integration of high resolution aerial imagery into research experiments will be carried out as part of the project. Information will be collected from the field experiments on the cost-effectiveness of delivering research based on: (i) 'Conventional' small plot research, with in field crop assessments; (ii) Small plot research using high resolution crop imagery to replace some or all of the in-field assessments (based on the ‘Protocol’); (iii) Field scale farmer led research (based on the ‘Framework for farmer led research’). Savings related to costs and labour will be a key factor encouraging individuals and organizations to adopt a new approach to research.

Innovation Network

In addition to the field experimental work, the project also includes the set-up of a cross border (UK, France, Belgium and Netherlands) innovation network to facilitate innovation between the precision farming/sensor technology industry, research organisations and the field vegetable and potato crop sectors. The INNO-VEG Innovation Network will have a specific focus on facilitating innovation by realizing the value of crop sensing technology in the delivery of field vegetable and potato research. The Innovation Network will launch in July 2019 and will be free to join and open to any interested individuals or organizations. Dedicated ‘networking’ events will be held in the UK, France, Belgium and the Netherlands in 2020/21 to create links between stakeholders.

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VINESCOUT: A VINEYARD AUTONOMOUS ROBOT FOR ON-THE-GO ASSESSMENT OF GRAPEVINE VIGOUR AND WATER STATUS

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VineScout is an autonomous ground robot designed, built, and demonstrated in commercial vineyards. It has been developed in the context of a H2020 European project. The VineScout goal is assessing grapevine water and nutritional status. The current improvements concerning autoguidance have been the addition of a multi-beam lidar to assist in the 3D perception acquired by a stereo camera, and two ultrasonic sensors to enrich perception for headland turning. Regarding crop sensing, a multispectral camera (Bay Spec Inc., San Jose, USA) and an infrared radiometer (Apogee Instruments, Inc., Logan, Utah, USA) were mounted in the robot to measure vine vigour and plant water status.

The external dimensions of the VineScout autonomous vehicle are approximately 0.90 meters wide, 1.40 meters long, and 1.20 meters tall with the GPS antenna folded. Figure 1 displays three images of the robot front (Figure 1-left), side (Figure 1-center), and rear (Figure 1-right). The robot was powered by two electric lithium batteries of 12 V coupled to deliver 24 V, and it was also equipped with two solar panels supplying an extra power of 128 W in total. The robot dynamics were enhanced by four independent suspensions affixed to the electric motor propelling each wheel.
The VineScout robot was tested from May to November in season 2018. Navigation sensors, as well as crop sensors installed in the autonomous vehicle, were tested along various data-collection tests organized in commercial and experimental vineyards in Spain and Portugal. The goal of field-testing was, on one hand, to check the mechanical, electrical, and autonomous navigation behaviour, and on the other hand, to gather information with crop sensors under field conditions to check their data against widely accepted reference indicators (NDVI, CHL, and NBI).

Figure 1. VineScout status in November 2018: front view (left), side view (middle), and rear view during night mapping (right).

The autonomous navigation system is based on the augmented perception obtained by merging information from two sonar sensors, a binocular stereo camera, and a non-rotational multi-beam lidar rangefinder that was added to the robot in 2018 to increase robustness in

ranging measurements. The multi-beam lidar gives eleven measures at a time, covering a scanning zone of 88 degrees. The two ultrasonic sensors facing the lateral canopies assisted in the headland turning. The computer mounted in the robot is an embedded fanless processing unit, that also managed the ultrasonic sensors, the lidar, and the rest of sensors, through a multifunction I/O device. The tests to check the autonomous navigation capabilities followed the method described in Cuenca et al. (2018), for validating the new ultrasonic network model, recently installed in the robot and more adjusted to the constraints found in vineyards. The precision of autonomous guidance was checked by evaluating the deviations from the centre line between vineyard rows. Vehicle states data were saved by the robot computer along the tests. After the analysis of lateral deviations for straight guidance and headland turning, the autoguided performance was satisfactory with the ultrasonic sensors, the new lidar, and mechanical improvements in the steering system.
The autonomous robot carried two non-invasive crop sensors, which were located facing to the right side of the vineyard canopy: an infrared radiometer and a multispectral camera. The infrared radiometer measured leaf temperature at a rate of 1.8 Hertz. The reason for installing an infrared radiometer sensor to measure canopy temperature is based on the relationship between the leaf stomatal closure or aperture and its surface temperature: the increase in plant water stress is linked to leaf stomatal closure and implies a rise in leaf temperature. The areas of higher water stress on the studied vineyard plot were near the headlands of the rows, while less stressed plants were located around the middle of the row where there was a depression in the terrain, confirming visual assessment. The multispectral camera was used to measure leaf reflectance at different spectral bands from the visible to the near infrared region of the spectrum, that enable the calculation of the NDVI, and promising estimations of NBI (Nitrogen Balance Index), CHL (Leaf Chlorophyll Index), and ZTM (Zarco-Tejada & Ustin, 2001). The VineScout robot was also equipped with a Global Positioning System that provided global references for the maps. Two different sensors were used as the reference measurements for ground-truth validation contemporarily to vineyard monitoring with the robot, which moved at 1.5 km/h. The satisfactory correlations given for the vigour indices called for the inclusion of the spectral reflectance values at 720 nm, 560 nm as well as the NDVI and ZTM indices in the data output of the robot.

The second VineScout prototype allowed the massive acquisition of crop data for the non-invasive assessment of water status in vineyards. Automatic navigation, as well as power autonomy were satisfactory, and little changes are expected for its final version in terms of mobility and external design. Water status was assessed by the estimation of canopy temperature while plant vigour was evaluated using vegetation indices such as NDVI, CLH, and NBI. Proximal-sensed NDVI yielded values close to the ones manually determined in the field using the reference method. However, despite getting stable readings with the infrared radiometer and the multispectral camera, further research is needed to come up with more sophisticated algorithms that eventually correlate both temperature and vigour with the user-demanded water stress and vigour maps.

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PREDICTION OF PHYTOTOXICITY CAUSED BY GLYPHOSATE ON *BRACHIARIA DECUMBENS* USING RGB IMAGES

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Digital image processing has become very important in several areas, especially in agriculture in order to reduce the cost of field management. With new applications of remote sensing it is possible to deal with abundant digital image processing techniques (Ahamed et al., 2012) to develop sensors.One of the main challenges in this area concerns to discriminating weeds from crop, as well as discriminating healthy from stressed plants based on a threshold of some vegetation index or spectral band (McCarthy et al., 2010).

Given the subjectivity of visual score rules such as ALAM (1974) and EWRC (1964) for quantifying control by herbicides of invasive plants, studies involving image analysis have been developed in order to detect injuries in crops caused by herbicide (Campbell et al., 2008; Ortiz et al., 2011; Huang et al., 2015; Nugent et al., 2018).

The present study aimed to build statistical models for predicting glyphosate phytotoxicity in *Brachiaria decumbens* using digital RGB images.

The experiment was carried out between April and August 2018, at the Instituto Federal Goiano - Campus Urutaí, GO, Brazil, geographic coordinates: 17º 27' 49" S and 48º 12' 06" W. Seeds of *Brachiaria decumbens* L. were sown in pots with 12 L capacity, filled with Red Latosol of 42% clay from an experimental area with known history. About 45 days after sowing, the plants received glyphosate in the following doses: 0%, 15%, 25%, 50%, 75%, 100% of the prescribed dose (1,440 g a.i. ha^{-1}). Each dose (treatment) was applied to four experimental units, which consisted of a pot with two plants. The applications were done with a costal sprayer equipped with XR11002 tips, pressurized with CO_2 providing constant flow rate.

At 7, 14 and 21 days after application (DAA), visual scores of phytotoxicity (%) were assigned by three evaluators using the EWRC (1964) and ALAM (1974) scales. The mean scores of the three evaluators were analyzed.

After the visual evaluations, digital images of the experimental units were obtained with the RGB camera of the iPhone 6, with 8 megapixels resolution. The images were acquired under full sun, between 10:00 a.m. and 2:00 p.m., at the standard height of 0.90 m from the ground and FOV (Field Of View) angle of 90°.

The software R was used to processing images through the following steps: 1) converting RGB pixels to HSV (Hue-Saturation-Brightness) colour space, which is robust to illumination variation, where hue is represented within [0, 360º], with 0º being red, 60º yellow, 120º green, 240º blue and 300º magenta; 2) segmentation based on hue differentiation between soil (background) and plant using the method of Otsu (1979), which consists of determining a threshold for hue; 3) extracting median values of hue for plant pixels. These were used as explanatory variables in regression models of visual phytotoxicity mean score.

As evaluations done at 7 days after application of glyphosate did not promote visual phytotoxicity above 20%, the results presented here concern evaluations done only at 14 DAA. The threshold for hue values that indicates soil pixels were between 330 to the range of 35 to 46, so all the rest were classified as plant pixels. The histograms of hue for plant pixels changed according to the injury level, so that plants with no phytotoxicity presented median of hue around 75 and plants with phytotoxicity above 90% presented median of hue around 40. In general, lesion-free plants present higher pixel frequency around 80 of hue, appearing greener. With doses from 25% of the prescribed dose, the plants showed a significant reduction of green parts.

Figure 1 shows the relationship between phytotoxicity and median of hue. An exponential decrease is observed and the model y = 1571.05*exp(-0.0682*x) was fitted with mean absolute percentage error of 21%.

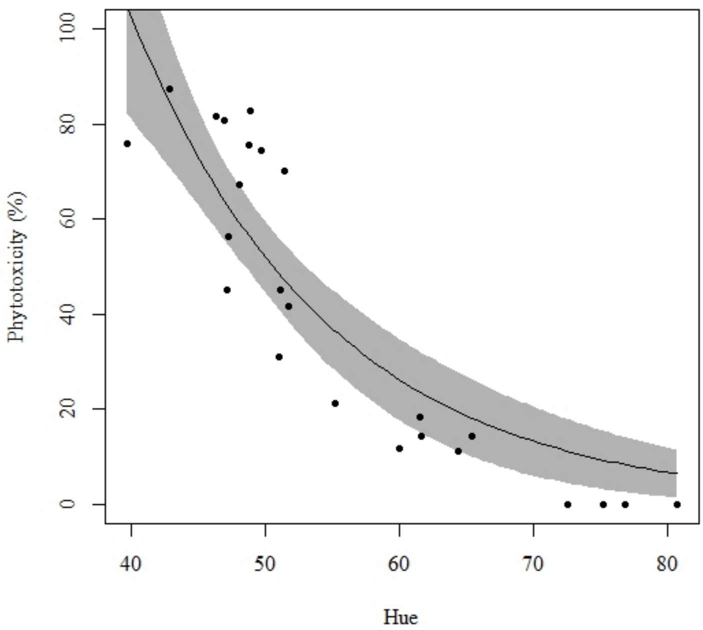

Figure 1: 95% confidence bands for the predicted values of phytotoxicity as a function of median values of hue of *Brachiaria decumbens* subjected to glyphosate at 14 days after application.

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ECONOMIC EFFECTS OF INSUFFICIENT SOIL INFORMATION WITH REGARD TO PHOSPHOROUS

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Introduction

The sustainable use of phosphorous has come to the fore in recent years. European regulations in the agricultural sector call for improved phosphorous (P) efficiency. Furthermore P supply is limited and the debate about environmental influences of nutrient oversupply caused by fertilization requires new approaches that allow the optimal use of resources (Killiches, 2013). The soil sampling grid system of 3 to 5 hectares, which is widely used in practice to determine fertilizer requirements in Germany, can pretend a location homogeneity which is actually not given (Borchardt et al., 2018). A small-scaled soil analysis may identify a heterogeneity of P contents in soil. Results can be used for a variable rate fertilization, which may reduce unnecessary environment effects and maximises yield by an ideal nutrient supply.

Material and Methods

This analysis is based on long-term data within the scope of “On-Farm-Research”. For this purpose, a 65 hectare experimental field in Saxony-Anhalt (Germany) is separated into grids of 36*36 meters (~1/8 ha). This grid size is determined on the technical requirements of the fertilizer spreader at the farm. The field concludes 508 grid cells in total, but especially the peripheral areas (e.g. headlands) are not suited for analysis. Therefore, calculations consider only the 412 reliable grids (~53 ha). The average rainfall is 520 mm per annum and the soil group is 4 – good soil structure. The research aims to demonstrate effects of variable fertilization of phosphorous, lime and potassium in consideration of small-scale soil information. Therefore, three different application strategies are established: variable rate fertilization, constant rate fertilization and a none-fertilization strategy. To calculate nutrient contents in soil of the 1, 3 and 5 ha grids, the corresponding grid size was projected onto the existing grid size. The P-values of the 1,3 and 5 ha structure are determined by the encased 1/8 ha grid cells. Soil analysis have been carried out in 2006, 2011, 2015, 2016, and 2017 (2006 is used in analysis) and a yield mapping system has documented yield of each grid. The measured phosphorous (CAL-method) is categorized into classes, based on the VDLUFA guideline (for dry areas). This guideline is the usual basis to manage German fertilization regulations. For instance, class “A” includes P values < 1,5 and class “B” 1,5 to 3,0 mg CAL-P/100 g soil. The ideal nutrient supply to maximize yield is class “C” (3.0 to 7.5 mg CAL-P/100 g). This class requires only an application of P in the amount of removal by crops. The undersupplied grids (class “A” and “B”) need higher amounts of P-fertilizer to achieve higher P levels in soil. Grids with higher P contents than class “C” are oversupplied, and a reduced P application is necessary (VDLUFA, 2015). For the following calculations, the nutrient content of each grid is assigned to its respective P class. The average yield of the undersupplied grids is compared to the average yield in class “C”. The deviation is reflected in the yield effect. The assumed prices are 17 €/dt winter wheat, 14.50 €/dt winter barley and 37 €/dt winter oilseed rape (price level of local crop dealers).

Results

The small-scale grid cell structure (1/8 ha) shows undersupplied and oversupplied areas with phosphorous, located in the middle of the test field. The small-scale soil analysis -1/8 ha-identified 70 % in class “C”. With an increase of analysis structure to 3 ha the amount of class “C” increases to 93 % and with 5 ha grid size to 99 %. Table 1 demonstrates the changing yield effects of winter wheat, winter barley and winter oilseed rape. The comparison of the

1/8 ha grid size with the grid size of 1, 3 and 5 ha show negative yield effects. The increasing grid size reduces the amount of correctly identified P values in soil and loss of information lowers yield. For instance, suboptimal P contents at the test field generate losses of 44.77 dt (winter wheat) in total. The average yield reduction is 0.84 dt/ha (44,77 dt / ~53 ha). At the assumed price of 17 €/dt the lower yield results in a loss of 14.22 €/ha every year. A larger scale sizes raised yield losses to 46,96 dt (3 ha) and 48,36 dt (5 ha). Depending on the grid size the undersupplied total area changed from 11.56 ha (1 ha grid) to 12.49 ha (5 ha grid). The bottom row illustrates the suboptimal applicated field zones. Nearly 23 % of the total area (~53 ha) is undersupplied with phosphorous and yield potential is not exhausted. Moreover, 2.73 ha of the field is oversupplied with P, when choosing 1 ha soil analysis system. Number of oversupplied grids increase up to 3,61 ha in the highest demonstrated grid system.

Discussion and Conclusion

The experimental field is characterized by a partially heterogeneous phosphorous (This also applies to the pH value and all other macronutrients) availability in soil, which could only be revealed by a small-scale soil analysis. Incorrectly selected sampling grids can lead to largeareas with incorrect phosphorous application. Moreover, the loss of information would xacerbate the disparities because of constant fertilization rates within all over- and undersupplied field areas. As a result, resources are wasted, and unnecessary costs are generated. Furthermore, the yield potential is not exploited, and phosphorous efficiency not maximized. However, depending on other areas in Germany the yield potential may be higher. Especially because the test field is characterized by a high soil class and quality with good compensations capabilities. To sum it up, costs of small-scaled soil analysis can be justified by increasing yields and an environmentally reduction of phosphorous negative effects. New experimental approaches are demonstrating much potential to generate high-resolution soil information less cost intensive. At the moment reduction of grid size for soil-analysis does not seem economically justified. But depending on the nutrient availability at each location, higher yield may confirm the need of small-scaled analysis to achieve the optimal nutrient supply in soil.

Phosphorous	**1 ha**			**3 ha**			**5 ha**		
	Total	*Yield Effect*	*Loss*	*Total*	*Yield Effect*	*Loss*	*Total*	*Yield Effect*	*Loss*
Crop	*dt*	*dt/ha*	*€/ha*	*dt*	*dt/ha*	*€/ha*	*dt*	*dt/ha*	*€/ha*
Winter Wheat	-44,77	-0,84	-14,22	-46,96	-0,88	-14,92	-48,36	-0,90	-15,36
Winter Barley	-48,49	-0,91	-13,14	-50,85	-0,95	-13,78	-52,37	-0,98	-14,19
Winter Oilssed Rape	-22,26	-0,42	-15,39	-23,34	-0,44	-16,14	-24,04	-0,45	-16,62
Undersupplied Area	11,56 ha			12,13 ha			12,49 ha		
Oversupplied Area	2,73 ha			2,74 ha			3,61 ha		

Table 1: Yield Effects

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FORECASTING CROP GROWTH FOR IRRIGATION RECOMMENDATION

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Introduction

Irrigation scheduling is often performed according to growth models, describing the development of the crop and its horticultural management across the season. To determine the water demand of the plant, a crop coefficient (Kc) is defined for each growth stage of the crop. The most known and extensive protocols to determine crop coefficients are described in the FAO56 document (Allen et al, 1998) using chronological time to describe the course of the season. In some studies, the course of the season is described using thermal time (growing degree days (GDD)) (Hsiao et al, 2009). However, calculating thermal time can be somewhat challenging because it requires data of daily temperatures from the beginning of the season as well as selecting threshold temperatures out of multiple options exist in the literature. While threshold temperatures that are reported in the literature obviously vary between species, they might also vary between growth stages (McMaster & Wilhelm, 1997). Many times, counting the days-of-season (DOS) is less complex, although less accurate.

Another approach to estimate Kc is by calculating vegetation indices (VI) from multispectral remote sensing imagery. For instance, the Normalized Difference Vegetation Index (NDVI) was correlated to the vegetation fraction of the crop (Vf) as well as to Kc (Tasumi et al, 2006). These VIs can be used to update the growth model along the season. However, satellite imagery is not always available in desired time intervals, mainly due to cloud cover. Nevertheless, the mentioned methods are only relevant to the present time and cannot be used to predict the behavior of the growth model, which is necessary in order to generate a future irrigation plan.

The objectives of the current research are: 1) to develop an improved growth model to estimate Kc based on multiple parameters in contrast to using chronological or thermal time alone; 2) to describe, by using that model, the growth season of 40 crops at multi-location based on weather history of 10 years; 3) to predict the future growth of the crops by utilizing weather forecasts of 14 days.

Materials and Methods:

The growth model was developed by using state of the art artificial intelligence (AI) methods such as XGBOOT (Chen & Guestrin, 2016) and CNN (Schmidhuber, 2015) based on multi-location, multi-season database. The dataset included field parameters such as crop type, irrigation method, management dates, and soil characteristics as well as daily weather data from a hyper-local virtual weather service (history of 10-years, current weather, and forecasts of 14 days onwards). Kc, which was the dependent variable, was calculated from NDVI. In the current manuscript, the model is demonstrated for the crops listed in Table 1.

Table 1. List of crops used in this study and their locations.

Crop	Countries	No. of fields per country (ordered)
Cotton	Brazil, Israel, Australia, Turkey, USA	8, 4, 2, 1, 1
Almonds	Australia, Israel, USA, Turkey, Spain, Portugal	159, 14, 18, 4, 4, 2
Corn-silage	Italy, Turkey	95, 2
Processing tomato	Italy, USA, Israel	65, 5, 1
Grapevine	Israel, Italy, Australia, New Zealand	19, 14, 8, 4

Results

To evaluate the model accuracy, common metrics such as bias, root-mean-square-error (RMSE) and coefficient of determination (R^2) will be utilized and reported. Firstly, the evaluation will be according to 30% of the data while 70% will be utilized for training. Secondly, the yielded model will be assessed against a thermal time model by using phenological data of actual fields. The third evaluation will report the accuracy of forecasts of 5, 10, and 14 days onwards versus Kc calculated from NDVI.

Results for the above five crops will be published at the ECPA conference, July-2019, and the rest of the crops will be analyzed until the end of 2019.

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GLYPHOSATE DOSES AFFECT NDVI AND SAVI OF *UROCHLOA BRIZANTHA*

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Most vegetation indices use proportions or linear combinations of spectral reflectances at varying wavelengths. They have been adopted to correlate with the specific attributes of leaves. Spectral vegetation indices exploit unique reflectance properties of the vegetation to infer biophysical properties related to the plant canopy (Myneni et al., 1995; Wiegand et al., 1991).

Many forage plant species, such as *Urochloa brizantha* (Hochst. ex A. Rich.) Webster, were introduced in Brazil and some became invasive species in several ecosystems, mainly in the Cerrado (savanna). The knowledge of the response pattern of invasive species is of great economic importance. However, in order to elaborate a rational control plan, using adequate dosages of herbicides is mandatory. In light of this, remote sensing techninques can foster site-specific management.

The main point established in this research was the search for phytotoxicity patterns in *U. brizantha*, which was cultivated in a field experiment in randomized blocks, using plots of 3 x 5 m. Plants were subjected to increasing doses (treatmente) of glyphosate. Evaluations of visual (ALAM, 1974) weed control (%) were performed with digital images captured with an RGN digital camera coupled to a drone up to 28 days after application.

The images processed with the software EBImage (Pau et al., 2010) of software R (www.R-project.org/). We initially performed the image segmentation for vegetation discrimination using reflectance in the Near Infrared Reflectance (NIR) band. Then, the vegetation indices NDVI (Normalized Difference Vegetation Index) and SAVI (Soil Adjusted Vegetation Index) were performed. Regression models were fitted for these indices as functions of glyphosate doses.

Similar exponential behaviours were observed for both indices (Fig. 1). Negative values were obtained from doses as low as 10% glyphosate. About 40% glyphosate was enough to desiccate plants.

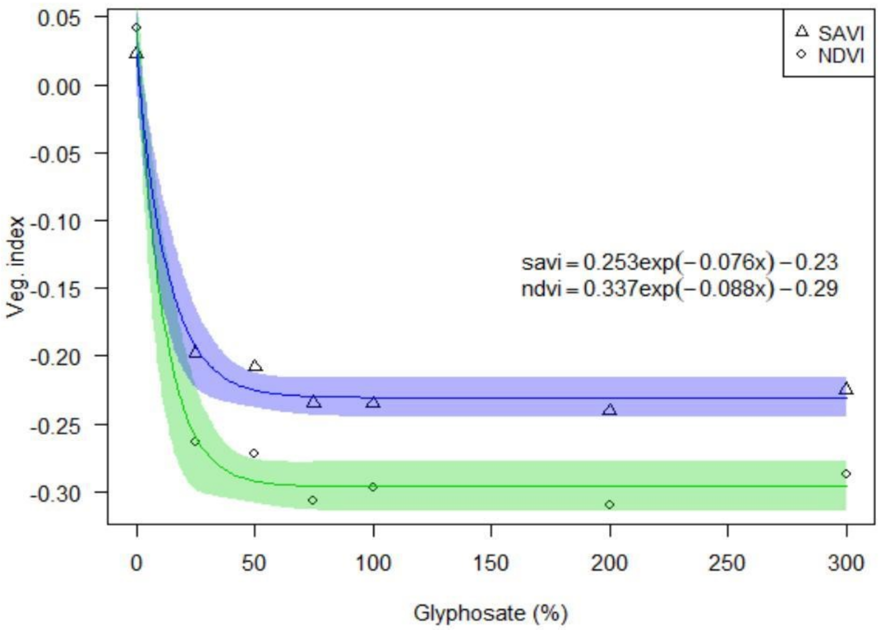

Figure 1. Fitted models for SAVI and NDVI as functions of glyphosate dose (100% = 1,440 g a.i. ha^{-1}).

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AGDATABOX: WEB PLATFORM OF DATA INTEGRATION, SOFTWARE AND METHODOLOGIES FOR DIGITAL AGRICULTURE

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There is a challenge for agriculture to produce more profitably with the world population expected to reach some 10 billion people by 2050. Such challenge can be imputed by the adoption of precision agriculture and digital agriculture, which is known as Agriculture 4.0. Digital agriculture has become a reality with the availability of cheaper and more powerful sensors, actuators and microprocessors, high-bandwidth cellular communication, cloud communication and Big Data. Digital agriculture enables the flow of information from not only used agricultural equipment but also new services that transform data into useful intelligence. In this new paradigm, large amounts of data are available, and the challenge is to add value to them. In this context, the data portals (data visualization) and work platforms (data transformation) are inserted. Availability of specific portals and platforms for precision and digital agriculture is essential to develop and implement a free web platform. Our platform, called AgDataBox (ADB), aims at integrating data, software, procedures and methodologies.
The current research is a joint project coordinated by the Western Paraná State University (Unioeste) and the Federal University of Technology - Paraná (UTFPR) with the cooperation of the Colorado State University (CSU), the United States Agricultural Research Service (USDA) in Columbia, the University of California Davis (UC Davis), the University of São Paulo (ESALQ/USP), and the Brazilian Agricultural Research Corporation (Embrapa). This platform is a continuation of the project for software SDUM (Software for Defining Management Zones, in Portuguese, Software para Definição de Unidades de Manejo) (Bazzi et al. 2013), which was registered with the Brazilian National Institute of Industrial Property (INPI - registration no. BR 51 2014 000720 D) and may be freely downloaded from http//ppat.md.utfpr.edu.br/sdum/sdum-vm.ova.
This Web Platform has an Application Programming Interface (API), which consists of a set of resources accessible through the Hypertext Transfer Protocol (HTTP) for transferring request and response messages expressed in JavaScript Object Notation (JSON) format. The ADB-API, in which the data and processing routines are centered, enables the interoperability of several applications. The following applications (Figure 1) are under development:

1) ADB-Mobile: it operates on devices with Android operating systems and allows recording the variable for producer experience regarding the division of areas in management zones (MZs), other than recording field data, keeping a history of all operations and occurrences of a harvest, storing such data locally on the mobile device and on a data server. ADB-Mobile allows performing operations in offline mode and, posteriorly, synchronizing data with ADB-API in online mode. This app is already available at the Google Play Store.

2) ADB-Map: it works with spatial data aiming to create thematic maps and MZs to subsidize Precision Agriculture and Digital Agriculture;

3) ADB-Admin: its main goal is managing the resources provided by the API (ADB-API) for storing platform data;

4) ADB-IoT: it aims to develop a network of interconnected sensors such as the ones applied to MZs for the climatic and water monitoring of the plant.

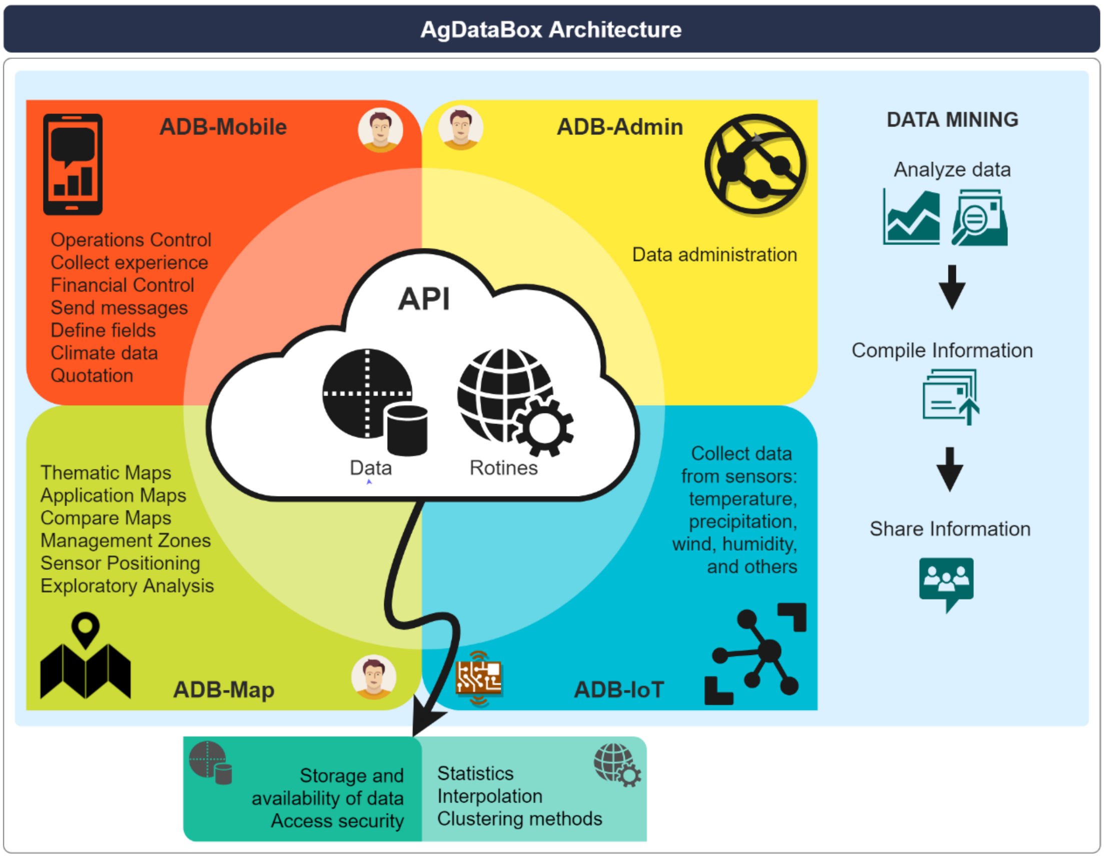

Figure 1. The architecture of the AgDataBox Web Platform with its ADB-API, ADB-Mobile, ADB-Admin, ADB-Map, and ADB-IoT applications.

The leader institutions are responsible to develop and implement the ADB platform and the collaborating institutions will help with the platform validation. The platform will be evaluated over three aspects:

1. Functional requirements: we will take into consideration the scientific studies that make the functionality usual, its acceptance by the scientific community, and the comparison with reference software, when applicable;
2. Non-functional requirements: we will evaluate the part concerning availability of resources and security of the application;
3. Software interfaces: the interface validation will be performed according to the HCI (Human-Computer Interface) literature to evaluate the quality of the graphical interface and assure the software usability.

Status: all applications have their script/study under test phase and with their backend/frontend mostly under development.

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INTRODUCING GEOFIS: AN OPEN-SOURCE DATA PROCESSING AND DECISION PLATFORM FOR PRECISION AGRICULTURE

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Agriculture is an increasingly spatial and temporal data-rich environment, but data needs processing to generate information and make informed management decisions
To benefit from increased data availability, agronomists need tools that allow them to:
(i) visualize the data collected (simple or low-level functions),
(ii) process and enhance visualization of these data (advanced or high-level functions),
(iii) incorporate the knowledge they will convert with these data/information into decision-making.
In Precision Agriculture (PA), there are only a few dedicated software programs and very few of them are open-source. Some freeware tools have been developed, but typically focus on specific processing tasks or on a particular type of data. For example, Yield Editor (USDA; Sudduth et al., 2012) for filtering yield datasets, Vesper (Uni. of Sydney; Minasny et al. 2006)) to spatially interpolate PA data and Management Zone Analysis (USDA; Fridgen et al., 2003) to aggregate these interpolated data. Individually, none of these provide an holistic data-processing approach. Other open and proprietary platforms have been proposed to give farmers access to crop models but are often specific in terms of crop, data and use. An open source platform that takes raw generic PA data through to a decision point is not available to the precision agriculture community yet.

The aim of this abstract is to present the GeoFIS software that has been developed in France to provide users with up-to-date and reliable algorithms to process PA data. GeoFIS has been developed for mainly academic and research purposes, but is also suitable for agronomists/advisors who are comfortable with spatial analysis.

GeoFIS is built on open-source toolboxes and libraries that are able to handle spatial data and to incorporate expert knowledge (Figure 1). PA-specific functions were implemented in R (https://www.r-project.org) while generic spatial data handling is done with Geotools (http://www.geotools.org) and CGAL (https://www.cgal.org). Incorporating expert knowledge is made possible with FisPro (https://www.fispro.org) that uses fuzzy sets for conceptual modeling (Guillaume et al., 2013). GeoFIS is currently available in French, English, Spanish and Portuguese. The interface was designed to enable to explore and model relationships between data, learning algorithms and expert knowledge.

GeoFIS contains a series of low and high-level non-spatial and spatial functionalities to interrogate spatial data. Figure 1 shows the generic flow required in PA, from raw data processing to decision-making, with the functionalities within GeoFIS at each stage indicated. In agricultural systems, data are available in different formats (points, polygons, rasters) and at different scales. Different data need potentially different approaches to (i) data validation and clean-up (quality control); (ii) data display (visualization) and when necessary for (iii) interpolation. These steps transform data into information layers. Within GeoFIS, data can be easily imported (Step 0) and displayed as a map (in its geographical space) and as a histogram (in its attribute space) to 'expertly' identify and remove erroneous data in the geographical and attribute space (Step 1). Interpolation is possible using inverse distance weighting (for small data sets) and via punctual kriging with a global variogram for larger data sets (>100 points) and the outputs can be directly displayed as rasters (Step 2). PA is only effective when effective decisions are made. Three main management functionalities have been incorporated within GeoFIS

(i) to delineate within-field homogeneous zones (Step 3.1) to facilitate data visualization/interpretation and provide practical 'zones' for variable field operations.

(ii) to generate diagnostics based on the data, such as the Technical Opportunity Index, to assess a field's suitability for PA given machinery constraints and the observed production variation (Step 3.2).

(iii) to facilitate multivariate data fusion to simplify layers and knowledge into a single decision layer (Step 3.3), e.g. a prescription fertilizer map based on farmer's experience and canopy sensing information and historical yields.

Case studies and further information are provided in Leroux et al. (2018). Free download and documentation available at www.geofis.org.

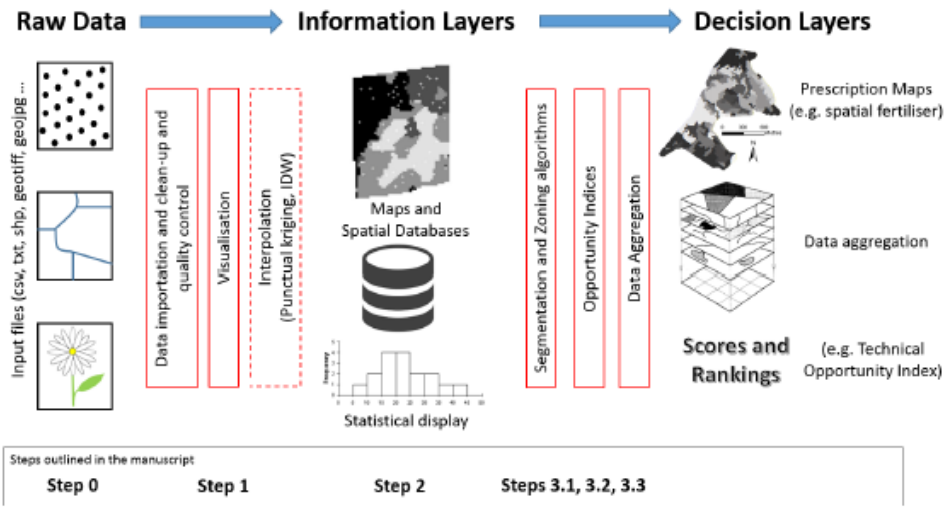

Figure 1 Generic data flow in PA showing GeoFIS capabilities (red boxes), intermediaries and outputs (reproduced with permission from Leroux et al. 2018)

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A DEEP LEARNING-BASED APPROACH FOR CROP CLASSIFICATION USING DUAL-POLARIMETRIC C-BAND RADAR DATA

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Satellite and geographic information system (GIS) data has served as a highly important factor in improving the current systems in collection and development of agricultural maps and data sources. Freely available satellite data is one of the most applied sources for mapping agricultural land and assessing important indices that describe the conditions of fields (Boryan et al., 2011). Sentinel 1 is the first of the Copernicus program satellite constellation conducted by the European Space Agency ESA provides Sentinel 1 satellite data freely for research and industry (Torres et al., 2012). Sentinel 1 data carry a C-band synthetic aperture radar instrument which provides a collection of data in all-weather condition, day or night. These data set have potential to distinguish different crop types at least for single date analysis. A satellite images includes in a significant amount of temporal information (Christiansen et al., 2018). Sentinel 1 data contain combined information on disturbances and noise. On a global scale where broadacre crops are grown, Sentinel-1 mainly records data for the VV and VH polarizations so that we have only two bands to consider and analyze in agricultural domain. In this research, all data set are provided from Fieldbabel service that is built on open-source software to handle preprocessing of the request from the users and export the results to QGIS software. Then using the obtained images, a robust method based on image processing and deep learning is proposed for recognizing five important crop types, namely, winter barley, winter wheat, winter rapeseed, spring barley and maize. To prepare training samples for the proposed network we have applied random crop to increase the number of patch-images in each training step and then U-Net architecture was selected as a network for segmenting sentinel 1 images. Therefore, the network was trained from scratch by radar images between 1th May and 31th July 2017. In the next step, our network was utilized to identify different crops in test set. Finally, the prediction compared with ground-truth images, and the confusion matrix was calculated in pixel level. The pixel-based accuracy were obtained 75, 97, 98, 82, and 75 percent for winter barley, winter wheat, winter rapeseed, spring barley, and maize, respectively. The achieved result indicate that the our method is effective to recognize five different crop types using C-band radar backscatter data that captured from Sentinel 1 satellite (Figure 1).

This architecture consists of a contracting path to capture context and a symmetric expanding path that enables precise localization (Ronneberger et al., 2017). This simpler architecture has grown to be very popular and adapted for a variety of segmentation problems and can be trained successfully with few samples. This network consist of two main part: Down and Up; in the Down part, the key feature extracted using convolutions and pooling layer and in the Up part, All extracted features concatenated from different layers and created final score map. Finally using softmax activation function the output images were obtained. We have chosen Adam optimizer with 0.0001 as a learning rate and cross entropy as the loss function. Based on obtained results we can conclude that the Sentinel 1 dataset are valuable and have potential to recognize different crop types in agricultural domain (Figure 1).

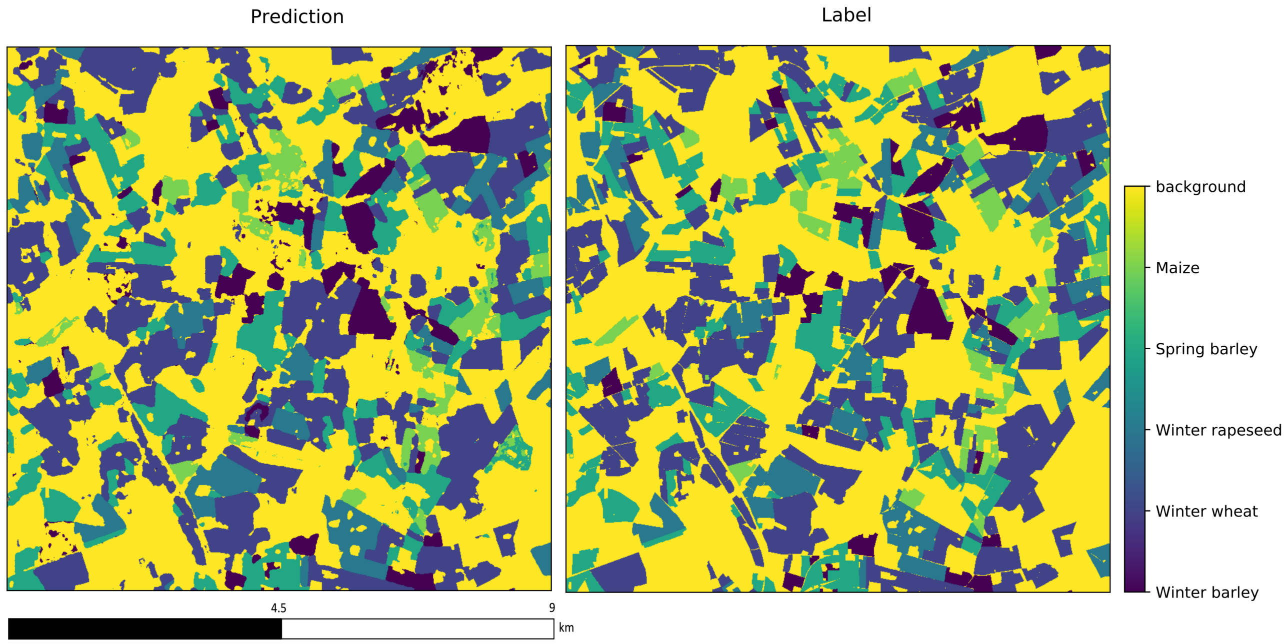

Figure 1: Five different crop types classification using U-Net architecture.

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USE OF SENTINEL 2 IMAGES TO DELINEATE SOIL MANAGEMENT ZONES USING THE CLAY RATIO

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One of the main objectives of precision agriculture is the optimization of resources such as water, fertilizers, herbicides, tillage, etc (Mulla, 2013). This is achieved when designing different plot management zones, based on similar physical-chemical characteristics of the soil (clays, sand, organic matter, etc.) and treating them differentially.
There are no standardized protocols for this type of management zones classification, however, the following parameters are usually used for that type of delimitation: topography, soil Apparent Electrical Conductivity (EC_a), yield, soil (physical-chemical) parameters, etc. (Martínez-Casanovas et al., 2018).

Soil ECa measurements are expanding due to the increasing use of equipment such as the sensors manufactured by Veris Technologies Inc. (Salina, KS, USA), which are a simple and effective tool to obtain information about soil in different soil depths. Terrón et al. (2011) and Fortes et al. (2014) showed that soil cation exchange capacity, calcium content, clay percentage and pH have a strong spatial correlation with the soil EC_a. However, this type of EC_a surveys supposes an additional cost for the farmer and, in many times, it implies a difficult logistic problem.

With the program Copernicus (European Commission, ESA), and their satellites, new opportunities for earth observation and agriculture have appeared. Sentinel 2 offers, without cost, satellite images with a spatial resolution of 10, 20 or 60 meters, every 5 days or less. With 13 different bands, from visible to short wave infrared (SWIR) provides an attractive opportunity to collect, analyse and use data for different purposes.
Previous studies have already established relationships between soil types and soil characteristics with spectral bands (Gholizadeh et al. 2018) and this particular study intends to analyse the relationship between EC_a and the spectral Clay Ratio index, which is calculated dividing band 11 (SWIR1) with band 12 (SWIR2) (B11/B12).

The study was carried out in Extremadura in the Southwest of Spain, on a 32 ha plot. Veris 3150 platform was used to sample soil superficial EC_a (0 - 0.3 m deep) (≈ 7.000 points ~ 4 m in the transect and 12 m between transects) on three different surveys in time (02/19/2009; 01/27/2011; 11/11/2012). All samples were normalized generating a new variable ECsN and a Principal Components Analysis was performed using ArcGIS software (Version 10.6.1, ESRI Inc. Redlands, CA, USA) obtaining the first principal component (PC1ECsN) that explains 97,10 % of variance.

The soil characteristics expressed by the soil EC_a map were correlated with the Clay ratio on 70 parcel points extracted with the Zonal Statistic tool of ArcGIS with a 15 m buffer. The mean values were extracted for these 70 areas over the PC1-ECsN and the Clay Ratio Index raster images (the last calculated from 29SQD tile image, 11/13/2016, Sentinel 2A 037 satellite relative orbit). With both variables a simple linear regression was carried out and it was obtained a determination coefficient (R^2) of 0.70.

In conclusion, Sentinel 2 spectral bands can be used as an alternative to the EC_a maps with the consequent cost savings in the delineation of management zones in precision agriculture activities.

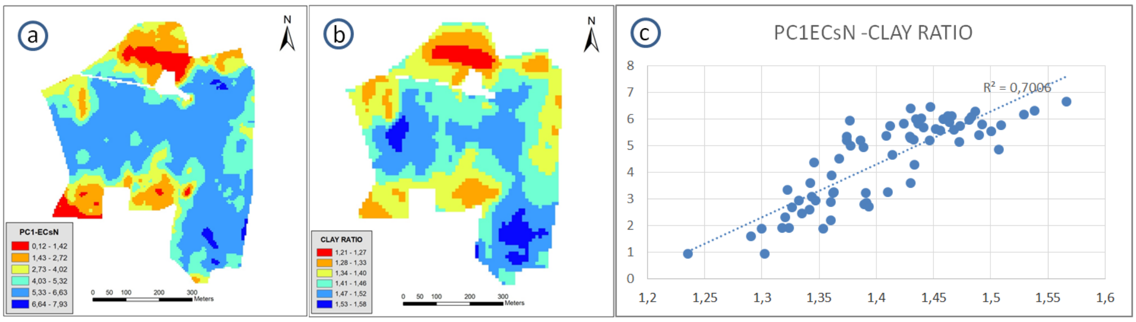

Figure 1: a) PC1-ECsN; b) Clay Ratio; c) Linear regression between PC1- ECsN and Clay Ratio.

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ASSIMILATION OF LEAF AREA INDEX MEASUREMENTS INTO A CROP MODEL FRAMEWORK: PERFORMANCE COMPARISON OF TWO ASSIMILATION APPROACHES

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A number of approaches have been developed (see Jin et al. 2018 for a review) to assimilate field-measured or remote sensing-derived crop canopy state variables into crop models, with the Ensemble Kalman Filter (EnKF) being widely used (Hu et al., 2019; Silvestro et al., 2017). EnKF uses a Monte Carlo setup based on perturbing a set of parameter values to create a model ensemble. The Leaf Area Index (LAI) is the most commonly used crop variable assimilated into crop models (Jin et al., 2018). We compared the performance of two different LAI assimilation approaches into a crop modelling framework for winter wheat in various locations.

Winter wheat was grown on commercial fields in seven different locations (one cultivar per site) across the countries Germany, France and Netherlands during the growing period of 2016/2017. LAI measurements using the LI-COR LAI-2200C Plant Canopy Analyser (LI-COR Inc., Nebraska, U.S.A.) were repeatedly conducted in 60 randomly distributed points across each field. We collected soil texture accordingly, weather data and biomass as well as grain yield.

We employed the generic <LINTUL5> model (Wolf, 2012) in the modelling framework SIMPLACE. Water stress was the only growth-inhibiting factor considered. We only included LAI measurements for assimilation that were conducted before flowering.

Two approaches to assimilate LAI values into SIMPLACE <LINTUL5> were implemented: The Ensemble Kalman Filter Biomass approach (EnKF-Biomass) and the Ensemble Kalman Filter Soil+SLA approach (EnKF-Soil+SLA).

The EnKF-Biomass approach perturbed the three parameters ScaleFactorSLA, ScaleFactorRUE and the maximal relative increase in LAI (RGRLAI). ScaleFactorSLA scaled all predefined development stage-dependent SLA values uniformly, ScaleFactorRUE all predefined development stage-dependent RUE values accordingly. RGRLAI described the maximal relative increase in LAI during the juvenile stage of the plant, when the leaf growth was not limited by the available assimilates.

The EnKF Soil+SLA approach was implemented based on the idea that the within-field heterogeneity of crop growth and yield are caused by variable site characteristics. We therefore used EnKF in combination with three parameters that scaled 1) the soil water content at simulation start (SoilWaterInit), 2) the maximal rooting depth that could be reached by the plants (MaximalRootDepth), and 3) a scaling factor for the development stage-dependent specific leaf area (ScaleFactorSLA). By perturbing the first two parameters at initialization, the model induced water stress (by reducing the transpiration factor TRANRF) at varying points in time during the growing season.

The model was run for each point in each field, in combination with the assimilation approaches, and subsequently compared to measured biomass and grain yield. We also included the ensemble mean (EM) in the analysis, where no data assimilation occurred. The model ensemble was created by perturbing the same three parameters as in the EnKF Soil+SLA approach (SoilWaterInit, MaximalRootDepth, ScaleFactorSLA).

The mean absolute percentage error (MAPE) between measured and simulated values ranged from 8% to 36% for biomass, and from 7 % to 85 % for grain yield (see Table 1). EnKF Soil+SLA and EM outperformed the EnKF Biomass approach. Estimations for biomass were better than estimations for grain yield.

Table 1 : Mean Absolute Percentage Error between simulated and measured biomass and grain yield. EM: Ensemble Mean, BM: Biomass, GY: Grain Yield

Site	EM		EnKF Biomass		EnKF Soil+SLA	
	BM	GY	BM	GY	BM	GY
GROS (DE)	0.09	0.07	0.34	0.29	0.13	0.07
HITD (DE)	0.12	0.18	0.36	0.85	0.08	0.16
MUEH (DE)	0.12	0.23	0.18	0.27	0.12	0.21
WUER (DE)	0.22	0.22	0.31	0.35	0.17	0.20
SAVE (FR)	0.33	0.42	0.29	0.32	0.30	0.39
TREM (FR)	0.12	0.16	0.35	0.51	0.13	0.13
VALT (NL)	0.15	0.20	0.24	0.21	0.15	0.22

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MODEL WITH SATELLITE IMAGES AS DECISION SUPPORT FOR PGR USE IN WINTER WHEAT

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Introduction

A lodging risk model was developed, that combined crop biomass in the normalized difference vegetation index (NDVI) from satellite images, and field level information of various factors with impact on lodging. The model ranks the lodging risk on field level into three categories: low, medium or high risk of lodging in winter wheat. It was integrated in spring 2018 in the Danish field management support app, CropManager.dk. The model supports the aim of Integrated Pest Management (IPM), that Decision Support Systems (DSS) should be used to assess an eventually need for PGR use.

Model

The model indicates risk of lodging in winter wheat in a particular field, around the time where decision on use of PGR should be taken. In Table 1, the parameters in the lodging risk model are shown. It is: winter wheat variety, soil type, sowing date, different factors handling nitrogen application and effect, and NDVI index. Except from NDVI, all information could be found in the database for every field. Detailed registrations from most farmers' fields in Denmark are collected in a central database that is used for day-to-day field management and for reporting to authorities. The database is used to develop digital tools that can be used at the farm and field level, to help the farmer improving crop management, with the current project and model as an example. The advice from the model is proposed as a field ranking with respect to lodging risk.
The risk for lodging in the model is divided into three groups (low, medium and high). If the sum of scores is less than -2 the lodging risk is expected to be low. If the total scores are between 3 and -2 then the lodging risk is expected to be medium. If scores sum to more than 3, the lodging risk is expected to be high. The parameters and scores in the model are based on experience and experiments, both national and international. The output of the model is shown in three colour categories in CropManager.dk. Green fill in a field polygon indicate low risk for lodging. Yellow indicate medium lodging risk, and red indicate high lodging risk in winter wheat.

Remote sensing integration

Satellite images from the beginning of April until mid-end of May are used. The NDVI index is added to the model every time a new 10 days period with images is present. For every period, the biomass is divided into three groups. Low biomass is defined as the 20th percentile of NDVI, medium biomass is between the 20th and 70th percentile of NDVI. The high biomass is defined as observations above the 70th percentile of NDVI.
For every 10 days period, approximately 48.000-116.00 satellite images from winter wheat fields are included in the model. Sometimes NDVI images are lacking due to sky's or other reasons. If NDVI data are missing in a field, then biomass is excluded from the model, and the score for the field can still be calculated. To get the correct output of the model it is important that the registrations in the database are correct. So far, the farmer hasn't had a reason to use some of the data e.g. sowing date and variety, and insufficient registration was found in many cases. In the future, it is important that the farmer is aware of the need for correct registration.
Ground truth validation of the model has not been made so far, this will be the next step in 2019. The validation can be done with information from farmers and advisors whether there

will be lodging or not, and followed by information on the use of PGR. Flight photos from July when lodging is visual will be planned, and comparisons to model output will be made.

Table 1: Factors included in calculation of score for lodging risk in winter wheat

Lodging risk and cropping factors	Low risk	Medium risk	High risk	Variation in score for each factor
Winter wheat variety	High straw strength	Medium straw strength	Low straw strength	-1, 0 or 2
Soiltype	Sandy, not irrigated	Sandy, irrigated	Clay and humus rich soil	-1, 0 or 1
Sowing date	Late September to October	Around medio September	Beginning of September	-1, 0 or 2
Biomass (NDVI)	Low NDVI-index	Medium NDVI-index	High NDVI-index	-1, 0 or 1
Biomass correction 2019 (NDVI)	General high level	General high level	General high level	1
Nitrogen (applied + planned - need)	< -30 kg N per ha.	-30 - 30 kg N per ha.	> 30 kg N per ha.	-1, 0 or 1
Nitrogen before 1. th of April	< 60 kg N per ha.	60 -100 kg N per ha.	> 100 kg N per ha.	-1, 0 or 1
N effect previous years (crop + fertiliser)	< 4 kg N per ha.	4 - 25 kg N per ha.	> 25 kg N per ha.	-1, 0 or 1
Maximum total score in each category	-6	1	10	

NDVI satellite images of the crop in spring is the overall result of the different cropping conditions that have affected the winter wheat crop, and they are a good indicator for crop density, canopy size and lodging risk. The full expression of factors that determine lodging risk may not be visual in the crop and on satellite images at the time when the decision on PGR use should be made.

Discussion

The feedback from the users of the lodging risk model are positive, and they find the output easy applicable and made in an intuitive way. When data are present for more years, the model will be further developed with more weight on NDVI, and with the aim to develop a lodging risk index that can be used as step one, in combination with VRA maps for PGR use, as step two, and perhaps advice on what PGR dose to apply as step three. Similar lodging models can be made for other crop species.

PREDICTING PRECISION NITROGEN SIDE-DRESS APPLICATIONS FOR MAIZE WITH A SIMULATION MODEL

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Consistent maize yields of near 16000 kg ha^{-1} is a goal of many maize growers in the state of Georgia, USA. To achieve this goal, some growers are increasing the application rates of fertilizers and irrigation water. Experiments conducted by the authors over the past 3 years have shown that nutrients and water are not always the limiting factors in achieving higher yields in this area (Orfanou et al., 2019). In a study conducted during 2018 in southern Georgia, maize management practices that *can be applied at large scales* and that increase nutrient and water use efficiencies while increasing yields were evaluated. Three fertilization strategies × three irrigation management strategies were compared in replicated plots at the University of Georgia's (UGA) Stripling Irrigation Research Park (SIRP).

In southern Georgia, all maize production is irrigated with center pivot irrigation systems. Because of this, fertigation, or the application of fertilizers through the irrigation system was one of the strategies selected because it can be used to apply nutrients in small doses throughout the growing season. Multiple doses theoretically increase nutrient use efficiency (NUE) because they reduce losses to the environment and increase the potential for keeping nutrients readily available in the root zone. In 2018 there were four fertigation events. The timing and application rates of fertigation side-dress events were preplanned and not based on actual availability of nitrogen (N) in the soil. The nitrogen application rates, yield results, and NUE of the three fertilization strategies used in 2018 at SIRP were:

Traditional – applied N = 337 kg ha^{-1}, yield = 14616 kg ha^{-1}, NUE = 43 kg yield kgN^{-1}
Fertigation 1 – applied N = 337 kg ha^{-1}, yield = 14112 kg ha^{-1}, NUE = 42 kg yield kgN^{-1}
Fertigation 2 – applied N = 281 kg ha^{-1}, yield = 14490 kg ha^{-1}, NUE = 52 kg yield kgN^{-1}

Mathematical simulation of the results
NUE can be increased and loss of N to the environment can be reduced by using mathematical models to estimate plant uptake and leaching and to estimate how much fertilizer is needed and when it is needed in side-dress applications. Several such models have been developed by researchers. The STICS (Simulateur mulTIdiscipli-naire pour les Cultures Standard) model (INRA, France) was selected for predicting the timing of nitrogen side-dress applications because it requires fewer inputs than most similar models. Model inputs include general parameters, plant parameters, soil parameters, initial conditions, and crop management information. Model outputs include soil water content (mm^3 mm^{-3}) and soil NH_4^+ and NO_3^- (kg ha^{-1}). Data from the 2018 study were used to calibrate and validate the model. Figure 1 presents calibration results for soil water content.

Predicting precision nitrogen applications
The 2018 experiment was repeated during the 2019 growing season. One fertigation treatment was to use the STICS model to schedule both the amount and timing of up to five side-dress applications. A second fertigation treatment was a preplanned schedule of four fertigation events. Both fertigation treatments were compared to the traditional method of a single side-dress application. Maize was planted on 27 March 2019. The traditional side-dress and first preplanned fertigation event took place on 30 April 2019. As of the writing of this summary, the STICS model was predicting adequate soil nitrogen. The poster describes the outcome of the 2019 experiment.

Following the 2019 experiment, the model will be incorporated into the SmartIrrigation Corn App -- a smartphone application for scheduling irrigation in corn that is available for iOS and Android platforms (www.smartirrigationapps.org). The methodology used by the application for scheduling irrigation was described by Vellidis et al. (2016). The modified application will allow growers to schedule both irrigation and side-dress applications of nitrogen.

This project was funded by a grant from the United Stated Department of Agriculture – National Institute of Food and Agriculture.

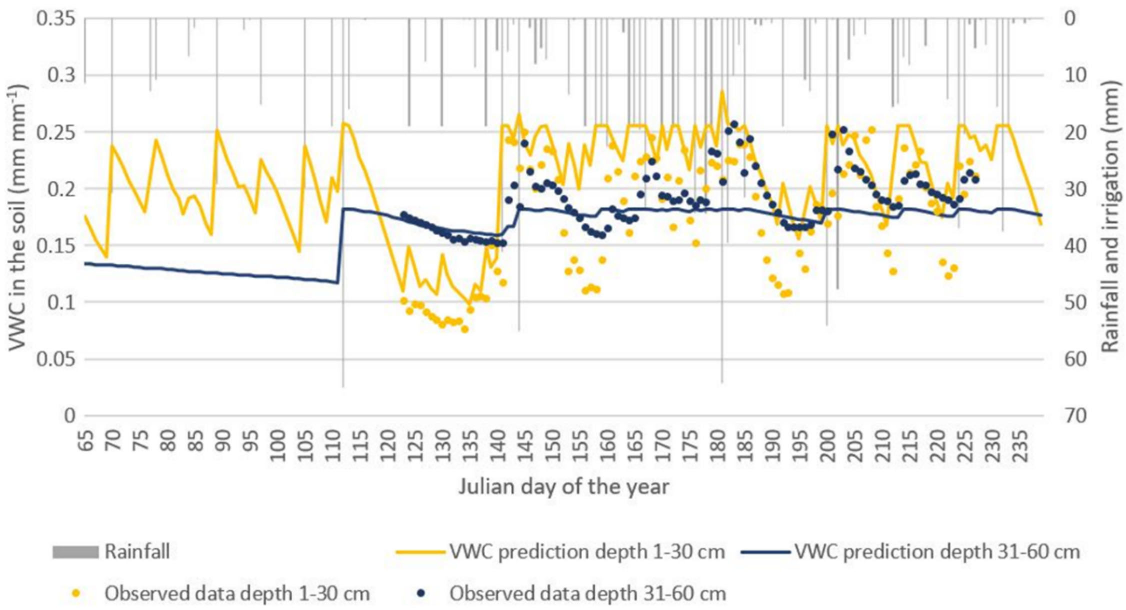

Figure 1: STICS calibration results for soil water content using data from the 2018 experiment.

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A WEB-TOOL TO ASSESS THE COST AND BENEFITS OF PRECISION FARMING SYSTEMS

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Keywords: Web-tool, software, cost and benefits

Precision agriculture uses a wide range of technologies that spans from sensing systems that map crop variability to auto-guidance and farm management systems. The objective of this study was to develop a web-tool (http://app.pamcoba.eu/) to assess costs, benefits and environmental performance of precision farming tools on different farms (Figure 1). One advantage of this web-tool is its capability to be modified according to the current and future user needs. For achieving this, a fully customizable database was developed, allowing the modification of the tool and its parameters through its administration panel.

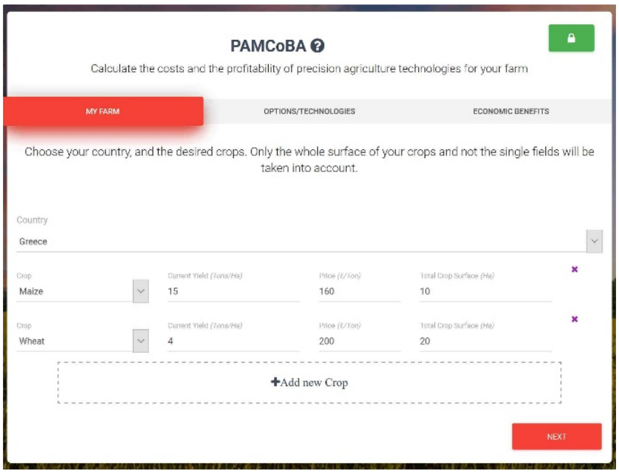

Figure 1. PAMCOBA Interface

The development of PAMCoBA web-tool was built upon the PHP (Hypertext Preprocessor) language and specifically the Laravel framework which, at the moment, the most popular tool on the web for developing fast and stable web applications. The database is based on a MySQL server instance and was designed following the global guidelines for maintaining data integrity and security where custom scripts and functions were defined for automated backup mechanisms. For the development of the form from which the visitors (users) are able to interact with the system and perform their analysis, the VueJS framework was used which is one of the most common JavaScript frameworks that enable developers to create fast and reliable applications.
The selection of technologies as well as the default values of the used parameters was based on a review conducted in the ICT-Agri ERA-net (2019) project PAMCOBA (http://ict-agri.eu/node/36322). All values given from the tool are differentiate for each country, operation and crop in order to increase accuracy of the assessment. Moreover, the web-tool database is fully modular, allowing the modification of its parameters, the addition of new ones (technologies, crops, operations etc.), as well as the creation/modification of the relationships between the various current parameters.

The web-tool conveys a specific process of assessment in which the farmer is guided through a step-by-step approach. During the first step ("Farm Details"), the user can enter information regarding the farm structure and size. More specifically, crop type, country and crop cover area (ha), average yield (kg/ha) and product price (€/kg) can be inserted by the user. In this way, the tool allows the user to change the input data regarding a real and practical situation in her/his own farm, which may vary during the time.
The methodology for achieving the economic and environmental assessment (for the selected operations and technologies), is based on the comparison of the conventional agriculture results, compared to the results created from the benefits provided by the selected PA technologies. For this reason, all the inputs provided from the users are used for calculating the current production costs and yield, as well as for the calculation of the production costs and yield using the selected technologies. Moreover, the NPV (Net Present Value) of the selected technologies is calculated and the final results are projecting the total benefits achieved after 12 years of using the selected technologies at the specified farm.
The web-tool was validated by means of different case studies involving small and medium farms from different rural areas in Europe (Switzerland, Denmark, Italy and Greece). For retrieving validation data, the tool was linked with a wide range of sources for extracting and updating data for farms (i.e. farm sizes, input costs).
Although the PAMCoBA web-tool is already fully modifiable and extendable, future enhancements will take place in the form of follow-up versions. In these versions, the tool will be enriched with additional parameters that will allow the tool to make the additional calculations by including more inputs, operational costs and profit factors. Furthermore, additional features are scheduled to be developed to allow the users to simulate their current conditions more accurately (owned equipment, soil homogeneity, etc) and additional countries will be incorporated into the system with their equivalent metadata (prices and costs for fertilizers etc). All of these enhancements will make the platform fully open to new smart farming technologies with premium analysis and reporting methods for the end-user.

Conclusion

PAMCoBA is a unique tool, capable of helping stakeholders to understand the economic and environmental benefits of PA technologies in an easy and friendly way. Its increased modifiability and expendability, as well as the capability of allowing users to enter their specific data and to re-run the analysis by altering system values, can help users to understand how each PA technologies can affect their farms and thus support them to the adoption of PA practices.

Acknowledgements

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USING A CROP GROWTH MODEL TO IMPROVE THE WAGENINGEN POTATO LATE BLIGHT DECISION SUPPORT SYSTEM

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Potato late blight (*Phytophthora infestans* L.) is the most serious disease of potato (*Solanum tuberosum* L.), globally responsible for an annual loss of around €4800M (Haverkort et al., 2008). Potato late blight is controlled using frequent fungicide applications (Cooke et al., 2011). Optimizing the timing of these applications improves the quality of late blight control and typically reduces the total amount of fungicides used. The Akkerweb late blight app is a web-based decision support system implementing a preventive late blight control strategy aiming to only apply fungicides just before predicted late blight infection events.

The app's late blight model uses local hourly weather data (current and forecast) to identify infection events in the near future and near past. Another important input for the model is the amount of new leaf area that has grown since the last fungicide application. This newly grown leaf area has not yet been sprayed with fungicide and is therefore not or only partially protected. Currently the late blight app uses an empirical, S-shaped curve which describes the total amount of leaf area as a function of thermal time; the derivative of this curve gives the rate of growth of leaf area. Unfortunately, the empirical curve tends to over-estimate the rate

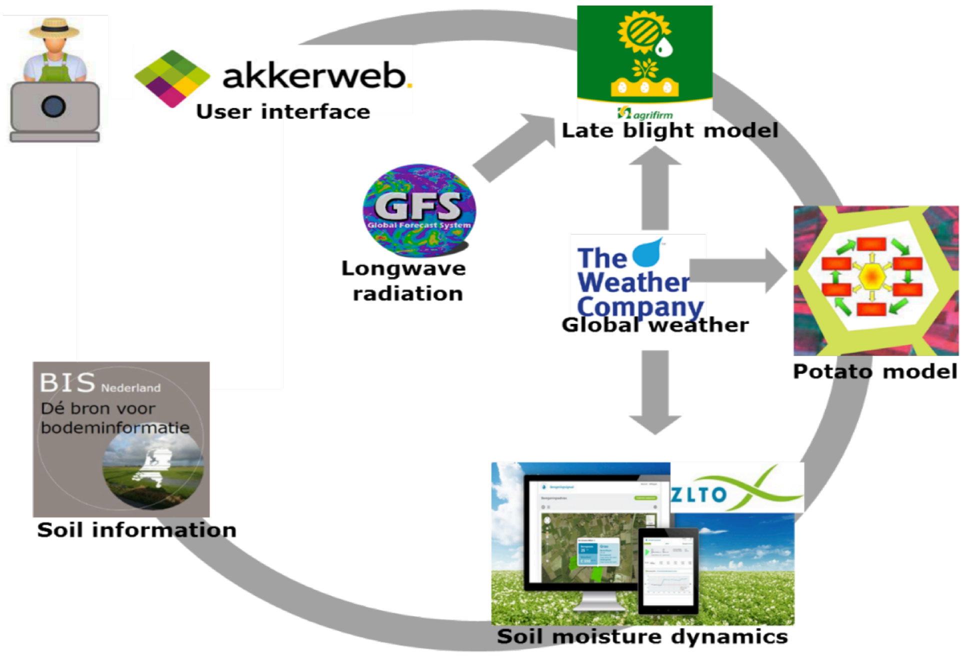

Figure 18: Diagram of the potato late blight decision support system.

of leaf growth when the crop is experiencing drought and it tends to under-estimates leaf growth rate when drought stress is relieved and the crop resumes growing. Therefore, we substituted the empirical leaf growth model with a mechanistic crop growth model which simulates leaf growth in response to the availability of water and nitrogen.

The introduction of a mechanistic potato growth model into the decision-support system necessitated a number of changes. It was judged advantageous to use an existing operational irrigation scheduling system to supply the potato growth model with soil moisture dynamics. Therefore, the potato model was modified so that it is able to use externally simulated soil water content. Similarly, it was judged advantageous to use the national soils database (Wösten, 2012) to supply the irrigation scheduling system with site-specific soil hydrological characteristics. Therefore, a web service was created to query the national soils database and retrieve the hydrological characteristics of any given field. A globally operating supplier of weather data was used to supply all models with current and forecast weather. Finally, the late blight model was improved by calculating the duration of leaf wetness (rain, "dew" or mist) with a model that includes short and long-wave radiation to calculate dew formation and evaporation (Heusinkveld et al., 2018, Jacobs et al., 2005, Jacobs et al., 2009). For this it was necessary to implement a near real-time connection to Global Forecast System (NCEP, 2019).

This work describes the processing chain that is being set up to operationalize the chain of models described above. The individual links in the chain are implemented as web services that exchange xml- or json-formatted information. The updated system is currently being evaluated and will be offered on a commercial basis once the evaluation has been satisfactorily completed.

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COMBINING NEW HIGH RESOLUTION SATELLITE IMAGERY WITH CROP GROWTH MODELING OF POTATO IN THE NETHERLANDS

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Introduction

Both satellite imagery and crop growth modelling can be used for crop growth monitoring. Operational applications combining satellite imagery and crop growth modelling exist since the 1990s. These applications are mostly at the national or continental scale and have been used for in import-export planning and early warning for upcoming famines. Operational applications at the field level were limited by lack of high-resolution images. As of 2017, Sentinel images are available at a sufficiently high spatial and temporal resolution to allow for applications at the field level. Applications at this scale can serve precision agriculture applications, such as preventive fungicide spraying, split fertiliser application, irrigation planning, haulm killing, etc... (Kempenaar et al., 2018; van Evert et al., 2017a,b). Here we present results of a study simulating potato at the field level for 72 fields in the Netherlands during the years 2015-2018.

Material and methods

DMC (2015, 2016) and Sentinel (2017,2018) imagery were retrieved from www.groenmonitor.nl. The WDVI vegetation index from these images was converted to aboveground biomass and leaf area index based on relations established by Bouman et al. (1992). Two crop growth models (Wofost, Tipstar) were used.
Late planting or late emergence can cause severe yield penalties (van Oort et al., 2012), while potato emergence is difficult to predict based on temperature only (van Delden et al., 2000). Emergence date and the relative growth rate of the leaves (RGRL) parameter, which together determine early exponential growth of the leaves, were estimated from imagery. A limited number of additional parameters, notably parameters governing leaf senescence, could not be directly calculated, these were calibrated by minimising the difference between measured and simulated Leaf Area Index. Soil physical parameters were acquired from the BOFEK2012 soil map which provides van-Genuchten parameters for 2-6 soil layers to a depth of 120 cm. Weather data from the nearest weather station were acquired through a webservice of the Dutch national weather service (KNMI). Model accuracy was tested for fields with and without water stress, while all fields received ample fertiliser.

Results

Cloud free 25 m resolution DMC images were available at an interval of on average 17 days (21 images /year). Cloud free 10 m Sentinel images were available at an interval of on average 40 and 11 days in 2017 and 2018 (9 and 33 images/year). WDVI correlated strongly with aboveground biomass measured by one farmer who conducted field samples in his plots (R^2 = 0.91, n=96), both in fields with and without water stress. Parameter RGRL was estimated with an accuracy of R^2 = 0.86 (n=124). Table 1 shows the accuracy with which four crop variables were simulated by the two models. Figure 1 shows an example of observed and simulated leaf area index. Accuracies were slightly lower for plots with water stress. Tipstar underestimated yields under water-stress, which resulted in a low accuracy (R^2 = 0.38).

Conclusions

Results presented here are part of an ongoing effort to develop tools for operational decision support for farmers in the Netherlands. Our results show that high-resolution imagery and crop growth modelling can be combined, for parameter estimation and for model testing. In general high accuracies can be obtained. Tipstar's yield response to drought stress requires further attention.

Table 2: Model accuracies as R^2 values for key crop variables

Model	Water stress	Ground-cover	Leaf Area Index (LAI)	Aboveground biomass	Yield (tuber biomass)
Tipstar	No	0.71	0.64	0.34	0.81
	Yes	0.61	0.59	0.43	0.38
Wofost	No	0.67	0.62	0.58	0.81
	Yes	0.68	0.65	0.59	0.77

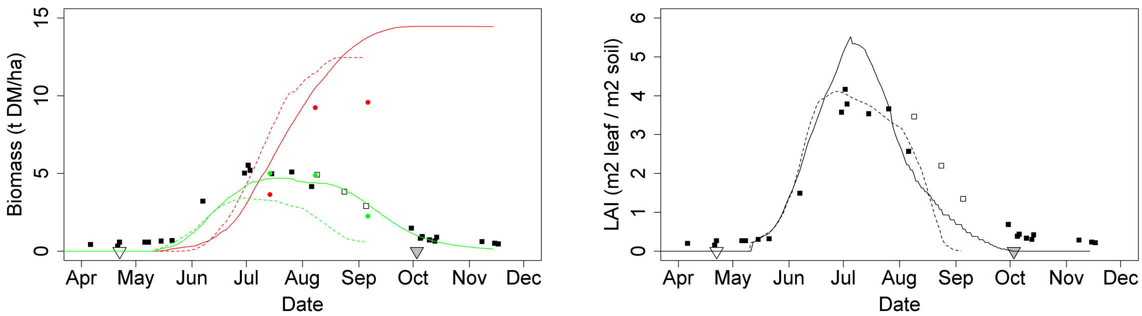

Figure 19: Simulation output for one of the plots

Acknowledgements

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LOCALIZED SPRAYING IN OILSEED RAPE CROP WITH A CONVENTIONAL BOOM SPRAYER

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Introduction

As a part of ECOPHYTO plan established by the French government to reduce the use of chemical plant protection products (PPP), specific spraying equipment are needed, for example to spray only the row of the crop. Often these devices have small spray boom widths and they are very expensive. The objectives of the project “PLEVOP” (development of in-row sprayer in oleaginous crops and protein crops), proposed by the technical Institute Terres-Inovia, are to define the conditions for successful localized post-emergence spraying for the herbicide application on the row using large width devices. This work is carried out in connection with a manufacturer of agricultural equipment (the Marechal company), an agricultural cooperative (CAL) and a French public Institution of Higher Education (AgroSup Dijon). The first year, experiences were conducted on oilseed rape crops using GPS-RTK as guidance system embedded on the tractor; the second year, trials were realized on oilseed rape and sunflower using a camera interface placed on the boom as guidance system. Three weeding strategies practices are compared: "full herbicide treatment" *vs*. "herbicide treatment on the row + inter-row hoeing" and a "no treatment". After weed counting and identification, we evaluated the biological efficiency on weeds and the effectiveness of such operations. Moreover, working with a conventional sprayer for a localized spraying, we have developed an automatic calculator tool to help farmer to determine the required amount of herbicide and water depending on its use conditions (nozzle type, nozzle height, speed of passage, boom height, field size, etc...).

Oilseed rape: First trial of localized herbicide treatment with a conventional boom sprayer

Experiences were conducted in the Lorraine region in France in 2017-2018 on oilseed rape crop. Plants were treated post-emergence with an herbicide at the stage four leaves. The sprayer was equipped with GPS-RTK as guidance system and the boom width was 16m (Figure 1). The sprayer characteristics were: nozzle=110°, boom height=16cm, spray band=45cm for the full herbicide treatment and nozzle=40°, boom height=27,5cm and spray band=20cm for the localized treatment.

The results of this first year of experimentation show that localized treatment and full treatment have much lower infestations than the untreated reference. On the crop row, the infestations of the "localized treatment" and "full treatment" modalities are similar, which shows that on the crop row the localized treatment is as effective as a full treatment. On the inter-row, the modality " herbicide treatment on the row then hoeing" is slightly more infested in weeds than the inter-row of the modality "full treatment", which shows that the hoeing is slightly less satisfying than the full treatment. Nevertheless, when we compare the inter-row of the modality " localized treatment on the crop row and then hoeing in the inter-row" with the inter-row of the untreated reference, we notice a hoeing efficiency that is not negligible.

In the modality "full treatment", we observe that the crop row is slightly dirtier than the inter-row one can possibly interpret that by an umbrella effect of the rapeseed crop during the

treatment. In the untreated reference, we observe that the crop row is less dirty than the inter-row; this is probably due to a competitive effect of rapeseed on weeds on the row.
Thus, the results of modality "localized treatment on the row then hoeing" on oilseed rape crop are encouraging. The localized treatment area with no hoeing also shows that the treatment on the crop row is not enough to have a good efficiency overall surface and that hoeing is important. That is the complementarity of chemical weeding and mechanical weeding which makes it possible to obtain the 80% efficiency observed.

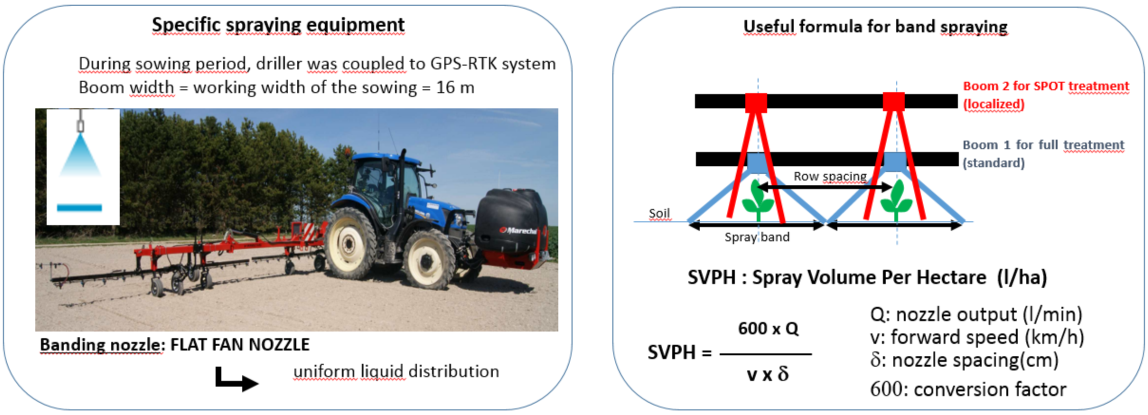

Figure 1: Specific spraying equipment and spraying formula used for the PLEVOP project

A Decision Support Tool for localized spraying

A single conventional sprayer with a large spray boom (16 m) was used for both "full treatment" and "spot treatment" strategies. In both cases, complex calculations were made to determine exactly the amounts of herbicide and water. So we had to create a decision support tool (DST) to help farmers depending on their own spraying parameters but also to provide information about the environmental benefits of a localized spraying (Treatment Frequency Index (TFI) reduction for example). As an example, considering the spray parameters described previously for both treatment (full and localized) and according a tractor speed of 10km/h, a nozzle output of 0.65l/min and using an herbicide product (2litre/ha) the results of calculation are deduced from the decision support tool. They indicate that: for the "full treatment", 86.7litre of water and 2litre of herbicide are required for a field of one hectare whereas as for the treatment on the row strategy, with a spray band of 20cm, only 0.89litre of herbicide and 86.7litre of water are required for a field of one hectare.

Conclusions and Future Outlook

We have tested in rapeseed crop, the use of a single conventional sprayer with a spray boom of 16m for a full and localized herbicide treatment thanks to a GPS-RKT type guidance system. The "full treatment" and "localized treatment" modalities were compared to the reference "no treatment". Results were encouraging, demonstrating that "localized treatment on the crop row then hoeing" is as efficient as "full treatment" modality. During experiences, the spraying settings had to be changed for the automatic calculations of herbicide and water quantities. The guidance system with a camera interface has to be evaluated as well. Overall, we developed a decision support tool (DST) in order to assist farmers in the volume calculations of whatever their spraying settings. Thus, environmental benefits have been added to sensitize the farmer to the positive effects of herbicide reduction. We would also like to finalize the decision support tool with an economic cost estimation. Finally, we would like to test our system on other crops (protein crops for example) and using other phyto-pharmaceutical products.

AUTOMATIC WEED RECOGNITION FOR SITE-SPECIFIC HERBICIDE APPLICATION

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Introduction

Weed occurrence is not uniformly within fields and often spatially aggregated. Thus the site-specific management of herbicide applications is mandatory and a prerequisite for precision agriculture. This practice will make a reduced use of plant protection products (PPP) possible and lead to a more sustainable agricultural production. In order to maintain the effectiveness, the treatments should be adapted to the distribution of weed species on field. For this purpose three components are required: a direct injection sprayer that facilitates an application of individual PPP, accurate weed maps localising the identified weed species and an assistance system, which manages the wealth of information (e.g. weed distribution, regulatory requirements, and weather data) (Pohl et al., 2018a). We have developed and tested the prototype of such a system in first practical field trials.

Field trials

To develop and validate the assistance system in terms of weed mapping, trials were carried out on three wheat fields (~ 6 ha each) in 2018 and 2019. Weed abundance and distribution was assessed both manually and with an unmanned aircraft system (UAS) within a grid size between 12x12 m and 24x24 m. The collected dataset was used to generate maps of weed distribution. The creation of application maps was then based on the principle of damage threshold for key weed species. Application on the test field was carried out with the direct injection system both site-specific and herbicide-specific. Herbicide efficacy was assessed 4-6 weeks after application.

Automatic weed recognition

In a previous study an image classifier based on a Bag of Visual Words (BoVW) framework was tested for the recognition and mapping of weed species, using an UAS with a commercial camera at flight altitudes of 1 to 6 m (Pflanz et al., 2018). A similar flight campaign was carried out in the present trial. Images were collected using a commercial camera both during the manual weed assessment at 50-70 cm above ground and with an UAS at a flight altitude of 5 m. Additional images of mono- and dicotyledonous weed species were collected under controlled conditions in small concrete plots.

Results

From the collected UAS images, more than 5.000 weed plants were annotated on species level, along with wheat and soil as background classes for training and validation of the models. For the image classification support vector machines were trained after building a visual dictionary of local features from the collected UAS images. A window-based processing of the models was used for mapping the weed occurrences in the UAS imagery (Figure 1). The results showed that the BoVW model allowed the discrimination of single plants with high accuracy for *Matricaria recutita* L. (MATCH), *Galium aparine* L. (GALAP), *Viola arvensis* M. (VIOAR), *Veronica hederifolia* L. (VERHE), and winter wheat (TRZAW) and soil, within the generated maps.

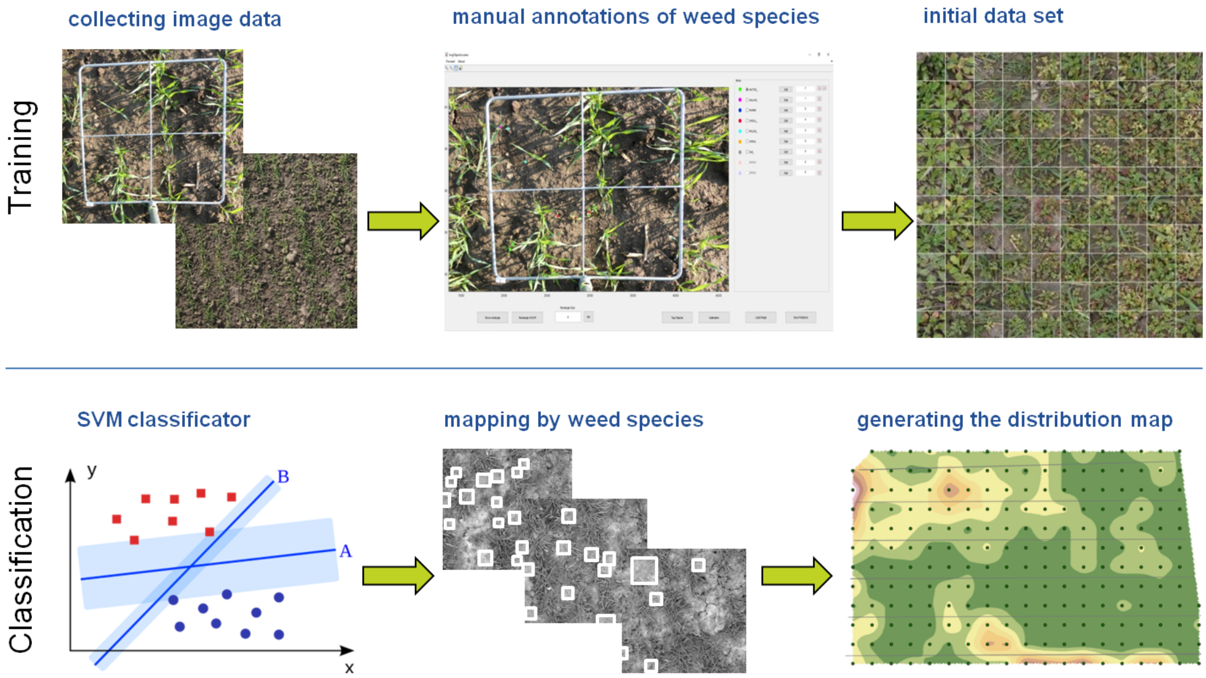

Figure 20: Procedure of object-based weed detection. Upper line: Different spatial weed distributions were captured above ground and annotated by species on PC. This image data set consisting of field recordings is the initial basis for the BovW training. Bottom line: Image segmentation allows weed plants to be located in individual images, from which an application map is then generated (shown for the distribution of MATCH).

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ETHICAL AND LEGAL ASPECTS OF OPEN DATA IN AGRICUTURE AND NUTRITION

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Introduction

Open Data offers a great potential for innovations from which the agricultural sector can benefit decisively due to a wide range of possibilities for further use. However, the use of open data is associated with some technical, ethical and legal challenges.
The technical challenges are associated with the need to create and develop new standards, platforms and infrastructures to allow access and better use of the data according to FAIR principles. In the last couple of years, the use of open data has also raised some ethical and legal issues as more and more stakeholders have entered into the agricultural sector developing new technologies that focus mainly on the collection, analysis and management of agricultural data.
The aim is to identify gaps and develop solutions through policy and legal frameworks to help ensure fair distribution of the benefits of open data, increasing motivation among actors involved in agriculture and nutrition, to use open data and make it more readily available. The main objective is to develop a clearer position on data ownership and responsibilities, and to highlight the often-complex legal issues related to open data in the areas of law, data protection, intellectual property rights (copyrights, patents, database rights, breeder's rights...), licensing contracts, traditional knowledge and personal privacy. This can be achieved by analysing legal regulations and socio-political actors at play.

Methods

The first step will be to look at systems of governance that support a fairer, equal distribution of benefits, and where transactions are based on mutual interest and trust. Such systems can be implemented through laws and policies as well as codes of conduct, regulation and social agreements, depending on the individual situations and needs of the communities in question. The agricultural sector can be strengthened through greater collaboration, awareness of open data rights, ownership issues and possible solutions. External stakeholders would need to act taking into consideration the needs and rights of other parties involved. The aim is also to initiate further independent activities. We will explore how best practices implemented in some countries could be replicated, and used to benefit, other countries. Taking good governance examples from local, national and regional model frameworks, we will examine at how they can be used as an example for larger-scale legal systems.
The review of existing codes of conduct, voluntary guidelines and principles relevant for farm data sharing, takes place in the context of a global collective action that several partners in the agricultural sector are conducting on Empowering Farmers through Equitable Data Sharing. Therefore, the review includes codes that revolve around farm data and only tangentially codes that broadly cover agricultural data: general agricultural data codes potentially include flows that do not concern the farmer (government statistics, research data) and are only partially relevant to our focus. An interesting point from the perspective of our collective action is that, as the review shows, the existing farm data codes do not have farmers or Farmers' Organizations as primary target audience - not to mention smallholder farmers - but rather the agribusinesses and ag tech companies that work with farmers and use their data. They are an instrument for these companies to ensure the data sharing by gaining the trust of farmers through transparent documentation of good practices**.** So, while being prepared by bodies that represent also farmers (big farmers' associations of developed countries) and

indirectly raising farmers' awareness of their data rights, they are not written primarily for farmers and, so far, surely not for smallholder farmers.

Conclusions

As explained above, this review aims to extract and recommend the essential aspects and points for a general, scalable and further customizable code of conduct "template" that best addresses the needs of the farmer**.** Based on the vision of our collective action, such a code has to enable "inclusive data ecosystems that nurture equitable sharing, exchange and use of data and information by all and for all participants in agri-food value chains, with special consideration of smallholder farmers, the most vulnerable to inequitable data flows". In terms of rationale for a code of conduct on the treatment of data and guidelines on how they should be drafted, it may be useful to also consult the European Data Protection Board's Guidelines 1/2019 on Codes of Conduct and Monitoring Bodies under Regulation 2016/679 (EDPB Guidelines), which refer to codes of conduct mainly as a mechanism to demonstrate compliance with the GDPR, but provide some useful reflections that can be applied to such codes in general. Building on the examples of the existing ag data codes reviewed, the focus seems to be on consent, disclosure and transparency and typical aspects expected to be covered by such codes.

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US Farm Bureau "Privacy and Security Principles for Farm Data" https://www.fb.org/issues/technology/data-privacy/privacy-and-security-principles-for-farm-data (last assessed 30.04.2019)

ESTIMATING GROWTH INDICES AND PREDICTING GRAIN YIELD OF WINTER WHEAT BASED ON FIXED-WING UAV PLATFORM AND MULTISPECTRAL IMAGERY

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Unmanned aerial vehicles (UAV) have gone through a notable development in recent years and now are powerful sensor-carrying platforms applied in many aspects. Fixed-wing UAV is a relatively new platform with higher flying speed and longer endurance compared with widely used multi-rotor UAV. In this study, a Sequoia 4.0 multispectral camera (Figure 1b) with built-in global positioning system (GPS) device (Parrot Inc, Seattle, WA, USA) was mounted on eBee SQ (Figure 1a) fixed-wing UAV platform (senseFly Inc, Cheseaux-Losanne, Switzerland) for acquiring high resolution images of winter wheat, aiming at developing reliable estimation models for rapid and non-destructive diagnosis of wheat growth status.

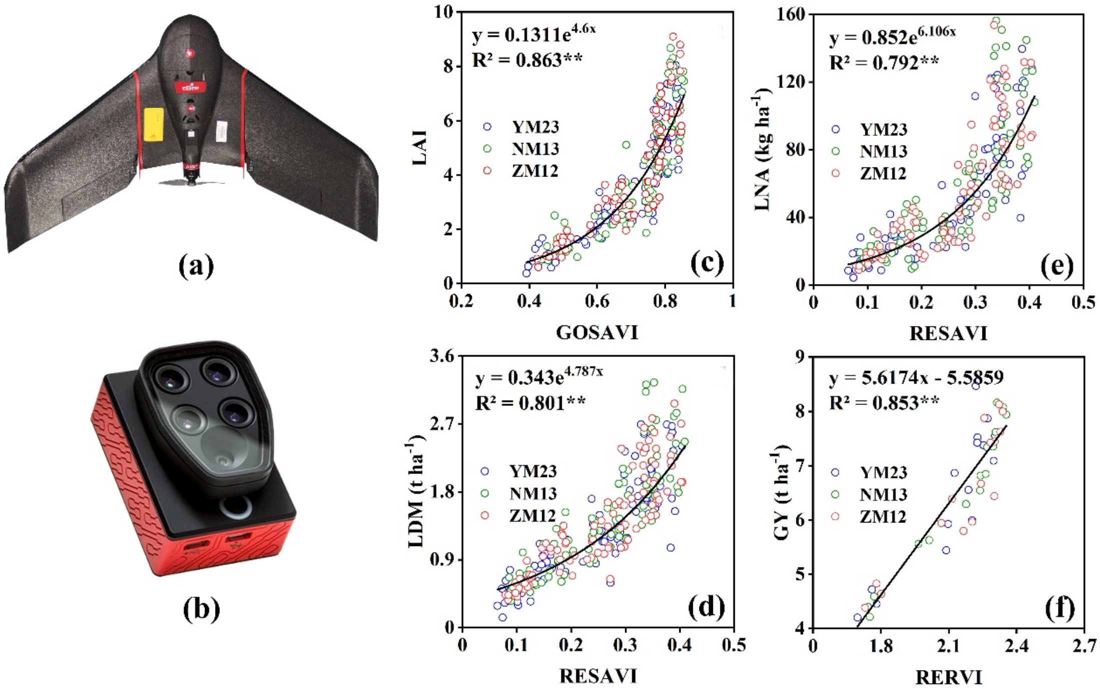

Figure 1: (a) eBee SQ fixed-wing UAV platform; (b) Sequoia 4.0 multispectral camera (Green, Red, RE, NIR); The quantitative relationships between vegetation indices and LAI (c), LDM (d), LNA (e) and GY (f).

Two field experiments with different wheat varieties (YM23, NM13, ZM12) and N rates (0, 90, 180, 270, 360 kg N ha^{-1}) were conducted during 2017-2018 at Xinghua (119°53′ E, 33°04′ N) and Lianyungang (119°25′ E, 34°30′ N) Experimental Stations in Jiangsu Province of China, the former experiment provided the calibration dataset and the latter served as the validation dataset. Multispectral images of winter wheat were acquired at an altitude of 80 meters from tillering stage to flowering stage, and all flights were taken on sunny days and no wind or breeze. Wheat agronomic indices, including leaf area index (LAI), leaf dry mass (LDM), leaf N accumulation (LNA) and grain yield (GY), were measured synchronously. UAV images were used to extract multispectral data (Green, Red, RE, NIR) after image mosaicking, a set of vegetation indices (e.g. GOSAVI, RESAVI) were calculated to analyze the relationships with agronomic indices (LAI, LDM, LNA, GY), the most sensitive spectral bands and vegetation indices were selected to establish non-destructive estimation model of wheat growth indices and grain yield based on fixed-wing UAV platform.

According to the results, green optimized soil adjusted vegetation index (GOSAVI, Rondeaux et al, 1996), which contains green band, had strong relationship with LAI for entire growth stages, with R^2 value reached 0.86 (Figure 1c). Two red-edge based indices (normalized difference red-edge index, NDRE, red-edge soil adjusted vegetation index, RESAVI) (Barnes et al, 2000; Sripada et al, 2006) showed robust correlation with both LDM and LNA. Moreover, RESAVI (R^2 = 0.80 and 0.79) (Figure 1d and 1e), showed stronger relationship than NDRE (R^2=0.76 and 0.75), implying soil adjusted parameters from RESAVI can eliminate the impact of soil background on UAV images in some degree. The best growth period for yield prediction was flowering stage, and the best performed spectral index was red-edge ratio vegetation index (RERVI, Jasper et al, 2009), with R^2 value reached 0.85 (Figure 1f). Multiple linear regression (MLR) using combination of two growth stages data indicated that the combination of heading and flowering stages could improve the model accuracy for yield prediction (R^2 = 0.89). Model validation (R^2 = 0.69-0.81, RRMSE = 0.18-0.31) using independent dataset also confirmed that fixed-wing UAV platform carrying a multispectral camera is capable of acquiring stable and effective data for monitoring growth indices and predicting grain yield of winter wheat.

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MEASURING IN-SITU TIME SERIES ON THE DEGRADATION OF FRUIT CHLOROPHYLL IN APPLE

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For fruit analyses in practice, it has been shown that the respiration rate, starch index, fruit flesh firmness, and the fruit chlorophyll content are feasible parameters to analyse the fruit developmental stage. Furthermore, the buying decision and consumer acceptance is influenced by fruit colour. Particularly, the chlorophyll content of the fruit skin and first cell layers of parenchyma (Zude and Herold, 2002) provides the green ground colour of fruit, which brightens when the chlorophyll content decreases and conversion of chlorophyll_b to chlorophyll_a, and from chlorophyll_a to pheophytins take place during fruit development (Seifert et al., 2015).

In the present study, a new sensor was tested for in-situ fruit measurements by means of multi-spectral analysis. The optical geometry of the sensor provided remission readings (Figure 1, left).

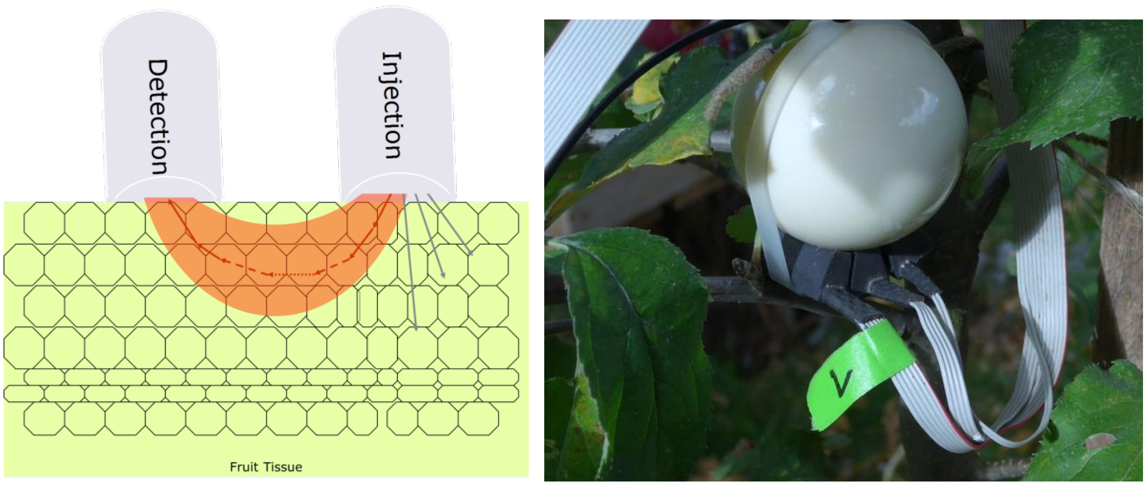

Fig. 1: Schematic of the pathway of light measured in the remission geometry realised in the sensor head (left) and one of the multispectral sensor heads located on the Teflon sphere used for calibration (right).

Trees of *Malus* x *domestica* Borkh. 'JonaPrince' on M9 rootstock grown in an experimental station were equipped with the multispectral sensor system for in-situ analysis of the time series of fruit development. The sensor provided diurnal courses of chlorophyll and anthocyanin indices. Temperature data were achieved from the weather station of the orchard and the growing degree-days were calculated applying 6 °C as base temperature (Edey, 1989). The water status of trees was monitored with three dendrometers, providing continuous data on the maximum daily shrinkage of the trunk.
The multi-spectral fruit data were analysed as means over 3 fruits considering 6 readings during the night, when the signal to noise ratio was <0.5 %. No influence of the water status of the tree on the sensor signal was found. The effect of temperature on the signal was already reduced during the night with low temperature amplitude, and corrected in the software. Temperature correction was carried out with a data set obtained on a Teflon sphere (Figure 1, right).

The chlorophyll-related NDVI [-1, 1] showed low values compared to calibrated NDVI data [0; 1] published earlier (Zude, 2003) using handheld spectrophotometers. However, the shape of curve considering the NDVI, and corresponding content of chlorophyll appeared similar to earlier publications. The inflection point of the curve relating to the harvest date of the fruit, was found 121 dafb (29th August 2018), when 172 growing degree-days were reached (integral of 2035°C). The automated non-destructive sensor can support the acquisition of fruit data into the field to gain insight into the actual fruit development.

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