Revista Ciência Agronômica, v. 51, Special Agriculture 4.0, e20207720, 2020
Centro de Ciências Agrárias - Universidade Federal do Ceará, Fortaleza, CE
www.ccarevista.ufc.br

Scientific Article
ISSN 1806-6690

Precision agriculture and the digital contributions for site-specific management of the fields

Agricultura de precisão e as contribuições digitais para a gestão localizada das lavouras

Jose Paulo Molin[1], Helizani Couto Bazame[1], Leonardo Maldaner[1], Lucas de Paula Corredo[1], Mauricio Martello[1] and Tatiana Fernanda Canata[1]

ABSTRACT - Site-specific management practices have been possible due to the wide range of solutions for data acquisition and interventions at the field level. Different approaches have to be considered for data collection, like dedicated soil and plant sensors, or even associated with the capacity of the agricultural machinery to generate valuable data that allows the farmer or the manager to infer the spatial variability of the fields. However, high computational resources are needed to convert extensive databases into useful information for site-specific management. Thus, technologies from industry, such as the Internet of Things and Artificial Intelligence, applied to agricultural production, have supported the decision-making process of precision agriculture practices. The interpretation and the integration of information from different sources of data allow enhancement of agricultural management due to its capacity to predict attributes of the crop and soil using advanced data-driven tools. Some examples are crop monitoring, local applications of inputs, and disease detection using cloud-based systems in digital platforms, previously elaborated for decision-support systems. In this review, we discuss the different approaches and technological resources, popularly named as Agriculture 4.0 or digital farming, inserted in the context of the management of spatial variability of the fields considering different sources of crop and soil data.

Key words: Artificial Intelligence. Cloud Computing. Decision-support System. Internet of Things.

RESUMO - As práticas de gestão localizada têm sido possibilitadas devido à ampla variedade de soluções para a aquisição de dados e as intervenções em nível de talhão. Diferentes abordagens devem ser consideradas para a coleta de dados, como os sensores de solo e de planta dedicados ou mesmo associados à capacidade das máquinas agrícolas gerarem dados relevantes que permitam ao agricultor ou ao gerente agrícola inferir a variabilidade espacial dos talhões. No entanto, elevados recursos computacionais são necessários para converter os extensos bancos de dados em informações úteis ao gerenciamento localizado da lavoura. Assim, as tecnologias oriundas da indústria, como a Internet das Coisas e a Inteligência Artificial, aplicadas à produção agrícola, têm direcionado o processo de tomada de decisão das práticas de agricultura de precisão. A interpretação e a integração de informações de diferentes fontes de dados permitem o aprimoramento do manejo agrícola devido à sua capacidade de predizer atributos de planta e de solo por meio de ferramentas avançadas baseadas em dados. Alguns exemplos são o monitoramento de cultivos, aplicações localizadas de insumos, e detecção de doenças por meio de sistemas baseados em nuvem nas plataformas digitais, previamente elaborados para os sistemas de apoio à decisão. Nesta revisão, discutimos as diferentes abordagens e recursos tecnológicos, popularmente denominados como Agricultura 4.0 ou Agricultura Digital, que se inserem no contexto do gerenciamento da variabilidade espacial das lavouras considerando diferentes fontes de dados de planta e de solo.

Palavras-chave: Inteligência Artificial. Computação em Nuvem. Sistema de Apoio à Decisão. Internet das Coisas.

DOI: 10.5935/1806-6690.20200088
Editores do artigo: Professor Daniel Albiero - daniel.albiero@gmail.com e Professor Alek Sandro Dutra - alekdutra@ufc.br
*Author for correspondence
[1]Departamento de Engenharia de Biossistemas, Laboratório de Agricultura de Precisão, Escola Superior de Agricultura Luiz de Queiroz/ESALQ, Universidade de São Paulo/USP, Piracicaba-SP, Brasil, jpmolin@usp.br (ORCID ID 0000-0001-7250-3780), helizanicouto@usp.br (ORCID ID 0000-0001-5685-1099), leonardofm@usp.br (ORCID ID 0000-0003-2675-767X), lucaspcorredo@usp.br (ORCID ID 0000-0001-8175-5461), mauriciomartello@usp.br (ORCID ID 0000-0003-3251-915X), tatiana.canata@usp.br (ORCID ID 0000-0003-3255-5361)

THE DIGITAL CONTEXT AND AGRICULTURE 4.0: CONCEPT AND APPLICATIONS

Agricultural innovations have supported the development of solutions to optimize crop production, mainly focused on intensification and sustainability. Over the years, agricultural systems have been exposed to different levels of technology, from mechanization to smart devices, to improve the efficiency of the farm operations considering the whole management cycle - from crop monitoring to recommendations. The application of technologies (Internet of Things - IoT, wireless sensors, Artificial Intelligence - AI, etc.) in agriculture has been providing advancements to the remote control of objects using integrated communication networks (BASSOI *et al.,* 2019) and to the adoption of decision support systems for farm management (FOUNTAS *et al.,* 2015; ZHAI *et al.,* 2020).

The progress on agricultural management based on precision agriculture (PA) principles is part of what is called Agriculture 4.0, which was proposed after the creation of the Industry 4.0 from the German government (ANDERL, 2015; ZHAI *et al.*, 2020). At this point it is worth mentioning the definition of PA as stated by the International Society of Precision Agriculture (ISPA), recently updated, according to which "PA is a management strategy that gathers, processes and analyzes temporal, spatial and individual data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production" (ISPA, 2019).

Agriculture 4.0, also called Digital Farming or Smart Farming, was mainly designed to deal with increasing productivity, allocating resources (land, water, energy), adapting the supply chain to climate changes, and avoiding food waste (YUAN *et al.*, 2018; ZHAI *et al.*, 2020). Other features should be discussed to extend the current technologies considering its economic viability and its potential applicability for site-specific management.

The main challenge of using digital information in agriculture is to add value to the different sources of data (crop, field, machines, economic aspects, etc.), and to transfer these data into knowledge. Some initiatives are the elaboration of decision support systems to the operational strategies of the farmers (BONFANTE *et al.*, 2019; YAZDANI *et al.,* 2017). Other initiatives involving digital tools are the data analysis for crop selection using data compilation (soil fertility) and decision tree algorithm (RAJESWARI; SUTHENDRAN, 2019), the crop management based on supervised learning models for yield prediction and disease detection (PANTAZI *et al.*, 2016; RAMOS *et al*., 2017), and a cloud-based system for spray planning for pests control in vineyards and orchards (RUPNIK *et al*., 2019).

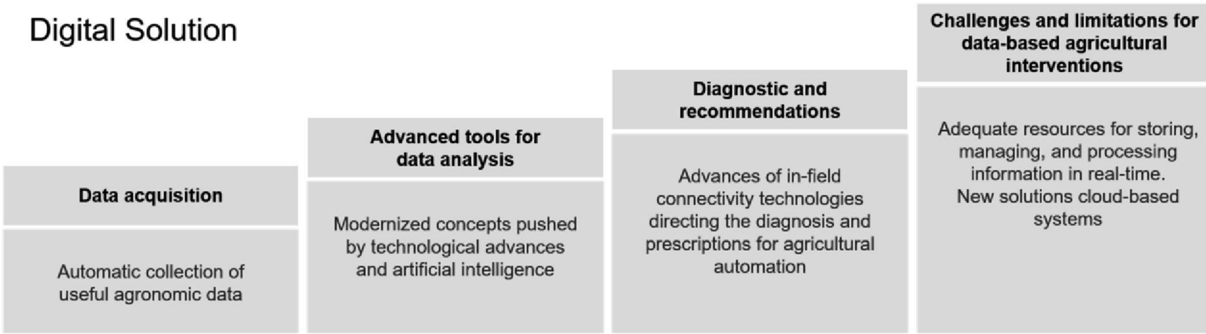
The digital platforms enable us to obtain more representative data of the agronomic inputs, soil condition, machinery efficiency, and weather aspects for supporting decision-making by the farmers (SAIZ-RUBIO; ROVIRA-MÁS, 2020). Also, agricultural robots associated with remote sensing tools demonstrate the capability to diagnose and access specific areas for local applications (SHAMSHIRI *et al.*, 2018). The identification of potential areas for intervention is an example that allows robotic applications for agricultural practices, such as the identification of plant disease (AMPATZIDIS; BELLIS; LUVISI, 2017), crop harvesting (VASCONEZ; KANTOR; AUAT CHEEIN, 2019; WILLIAMS *et al.*, 2019), weed detection (WU *et al.*, 2020), traffic control (BALL *et al.*, 2015; REINA *et al.*, 2016), among others.

Pedersen *et al.* (2017), assessed the economic benefits of agricultural robots under sugar beet field conditions. They found financial viability using robots for early seeding and re-seeding of the crop. Also, the robotic systems in agriculture collaborate with the design of autonomous machinery. McPhee *et al.* (2020), proposed small autonomous machinery (50 kW) as an alternative to reduce soil compaction promoted by combine harvesters (>300 kW) and to optimizing the operational logistics of the harvest.

Another approach is implementing robotic systems for emerging practices, such as urban agriculture and greenhouses (AMPATZIDIS; BELLIS; LUVISI, 2017; SHAMSHIRI *et al.*, 2018), which requires understanding the influence of external factors on the controlled environment (smaller scale in agriculture). IoT-based solutions have been developed to provide a non-destructive quantification of physiological characteristics of the plants, involving applications from data collection to controlling the action. In this case, the performance of automated systems is satisfactory due to the limited elements to be monitored. However, some challenges have been faced to implement it for commercial applications. Some examples are the competitiveness with traditional agriculture (larger scale) for horticulture, costs production, adaptive algorithms for local control, among others.

The purpose of this paper is to discuss the main approaches and technological resources involved in the digital context, considering it to manage the spatial variability of the fields based on different sources of crop and soil data, as syntheticaly represented on Figure 1.

Figure 1 - Synthesis of the analysis related to the contributions of digital solutions to the spatial variability present in the agricultural fields and its management



DIGITAL SOLUTIONS

Data acquisition

Accelerating the dynamics of acquisition, accuracy, and accessibility of soil, plant, and climate data is essential to the success of crop management. Increased demands for real-time data analysis and their accessibility speed have caused the development of modern technologies, especially in the data collection process (KAMILARIS; KARTAKOULLIS; PRENAFETA-BOLDÚ, 2017; SIVARAJAH *et al.*, 2017). According to Lee *et al.* (2010), PA demands intensive field data acquisition. Remote and local sensors or sensor networks can be applied to monitor plant and soil attributes, soil conditions, and plant health (especially pest and disease detection). Wireless Sensor Networks (WSNs) technology is one of the required Information and Communication Technologies (ICTs) to achieve an automatic collection of useful agronomy data, and support subsequent analysis for intelligent decision-making (OUYANG *et al.*, 2019). This technology can provide processed real-time field data from sensors physically distributed in the field (CAMILLI *et al.*, 2007). The WSN consists of a collection of spatially distributed and independent devices that collect information and digitally transmit it over a wireless channel (LANDALUCE *et al.*, 2020).

Specifically, image sensors can be used for remote sensing techniques to monitor vegetative growth, real-time surveillance against the deceptive labeling of production centers. Machine vision is a powerful tool for field management. A camera installed on-board of equipment performing some field operation or autonomous vehicles carrying sensors can provide automatic method for crop/weed discrimination in real-time (GARCÍA-SANTILLÁN; PAJARES, 2018; RAJA *et al.*, 2020; WANG; ZHANG; WEI, 2019). Proximal optic systems can be used for disease-symptom detection (CHEN *et al.*, 2020; OBERTI *et al.*, 2014), and identification of invertebrate pests on green leaves (LIU; CHAHL, 2018).

Cameras on-board Remotely Piloted Aircraft (RPA) systems is another powerful tool to collect high-resolution data at the field level in real-time. A typical application of RPA technology is to acquire high-resolution visible, spectral, infrared or thermal imagery at a low altitude to achieve large cope farmland monitoring and hazard prediction (GAŠPAROVIĆ *et al.*, 2020; PANDAY *et al.*, 2020). RPA imaging has been used to detect weeds (DE CASTRO *et al.*, 2020; TANUT; RIYAMONGKOL, 2020), plant diseases (MATESE; DI GENNARO, 2018), perform plant count estimations (KOH *et al.*, 2019), and characterize plant dimensions (DE CASTRO *et al.*, 2020; WEISS; BARET, 2017). Another use of RPA imagery is the automation of locations for soil sampling based on a soil map created from RPA imaging after plowing, and wearable augmented reality smart glass to assist the user in collecting soil samples (HUUSKONEN; OKSANEN, 2018).

Smartphone technology is promising for the future development of agriculture, as it can facilitate and improve many operational procedures and can be combined with PA technologies (MICHELS *et al.*, 2020). Smartphones have a large number of sensors, e.g. motion sensor (Accelerometer, Gyroscope, Magnetometer), image sensors (cameras), environmental sensors (temperature, relative humidity, pressure, light), positioning sensors (GNSS) and, connectivity modems (cellular network, Wi-Fi, Bluetooth) (MENDES *et al.*, 2020). According to these authors, mobile applications allows to allocate different information in one place that farmers can access. From there, the farmers can get crop maps, monitor their crops in real-time, receive alerts, and perform tasks.

Digital images captured by smartphones were studied to predict soil texture (SWETHA *et al.*, 2020), and soil organic matter (FU *et al.*, 2020). Li *et al.* (2020), used a smartphone-based image analysis technique for measuring plant growth characteristics in controlled environment. Prasad *et al.* (2014), depicted a mobile vision system that aids in the plant disease identification process. The system worked by capturing images of plant leaves investigated for diseases, then preprocessing those images, and transmitting it to remote laboratories. Golicz *et al*. (2020), studied the viability of utilizing smartphones in soil analysis. Pallagani *et al.* (2019), made available a smartphone app developed using the disease prediction model. The farmer can capture the crop images using the app and analyze the presence or absence of diseases, thereby demonstrating the feasibility of the solution.

The smartphones are powerful platforms, but limitations have to be considered, as they were developed, and are continuously improved for individuals and predominantly in urban areas. It brings expectations and challenges to the agricultural sector, especially on connectivity demand and availability, and the fact that these devices are personally carried, which places limitations of covering extensive cropping areas, commonly condition forBrazilian agriculture. Also, their image sensors are still based on RGB cameras and for the specific demands of agriculture, more detailed imagery are necessary.

Wireless Underground Sensor Networks (WUSN) are one of the types of WSN with embedded sensor nodes (BAYRAKDAR, 2019; JAO; SUN; WU, 2013). WUSNs can be used to monitor soil conditions so that parameters such as water content, mineral content, salinity, and temperature can be maintained at optimal levels (MAHDAVIPOUR *et al.,* 2017; STUNTEBECK; POMPILI; MELODIA, 2006). Hu *et al.* (2010), developed a specific wireless sensor and actor-network application for PA with the ability of intelligent irrigation and emphasized that the functions of the platform can be extended to other PA applications. Bayrakdar (2019) studied a smart insect pest detection technique with qualified underground wireless sensor nodes for PA.

Although there are already many studies with sensors for data collection in real-time using WSN, according to Landaluce *et al.* (2020), all of them, regardless of their application, present several common challenges. The latency is affected by the communication mechanisms, such as coding techniques or the routing and rerouting of the messages, as well as the scalability of the system; and at the same time, it degrades the energy consumption of the network. Also, the data rate balances the energy consumed by the system and the scalability to interrogate a higher number of nodes at the same time. The computing techniques relevance for analysis and processing large database becomes highlighted.

Advanced tools for data analysis

AI is a subject of engineering where machines become intelligent through programmed algorithms. It is a continuous exploration approach that studies how to make a computer or any other machine to think and solve problems the same way human beings do (PATHAN *et al.,* 2020). It enables machines to perform certain functions based on past learning experiences. Among the different AI techniques, two have been widely used for agriculture: supervised and unsupervised learning. Both techniques require a training dataset to learn on, however, the supervised learning requires that the correct answers be provided during learning, while the unsupervised will generalize the dataset behavior to similar group observations. Machine learning models based on decision trees, support vector machines, artificial neural networks, convolutional neural networks, and recurrent neural networks are examples of supervised learning algorithms used for regression and classification. Examples of unsupervised learning algorithms used for data clustering are k-means, fuzzy c-means, Gaussian mixture, and partial component analysis. These algorithms help to solve complex challenges for human beings by transferring the decision making to the machine through data, and a deep and robust learning.

In agriculture, technological advances pushed by AI is helping farmers to move from traditional to modernized concepts. Brogan and Edison (1974) performed one of the pioneer studies using machine vision for the classification of agricultural products. The authors developed a pattern recognition algorithm using morphological attributes for the automatic classification of grains. Other researchers working with that have created theories and practices that incorporate smart devices to contribute to the crop management (KHANNA; KAUR, 2019). Recent research has shown that popular AI applications in agriculture are related to the detection and harvesting of fruits using agricultural robots (XIONG *et al.,* 2020), identification and classification of plants (BAO *et al.,* 2019; GRINBLAT *et al.,* 2016; LIU *et al.*, 2020; MAZZIA *et al.,* 2020; TU *et al.*, 2020), detection and classification of pests and diseases (CRUZ *et al.,* 2019; KAUR; PANDEY; GOEL, 2018; SHARIF *et al.,* 2018), crop and soil monitoring (AMPATZIDIS; BELLIS; LUVISI, 2017; AMPATZIDIS; PARTEL; COSTA, 2020; VALENTE *et al.*, 2020), recognition of nutritional deficiencies (CHOI; CHA, 2019), development of maps for crop management (TALAVIYA *et al.,* 2020), among others. AI provides a simple and objective analysis with high accuracy, making it feasible to automate and optimize laborious tasks.

AI has provided farmers and technicians solutions to many crop-related issues. Due to the decrease in equipment costs and growth in computational performance, this approach has become ever more popular in recent years in agriculture. These new technologies are slowly being introduced and evolving into a scenario where crop management will be carried out based on individual plants (PATRÍCIO; RIEDER, 2018). The use of these techniques has many advantages when compared to manual labor and traditional methods, however, there are still many challenges to be overcome (BARBEDO, 2016).

Diagnostics and recommendations

The continuous evolution of remote and proximal sensing techniques, whether of edaphic or crop attributes, allied to the advances of in-field connectivity technologies, has directed the development of agricultural automation for real-time diagnosis and prescriptions (SHAFI *et al.*, 2019). This method of agricultural intervention for site-specific management is based on geo-positioned values, which is unitary information (e.g., pixel) associated with geographical coordinates. Thus, each crop area, as a production unit with spatially intrinsic specificities, is translated into a set of pixels by specific sensing technology. The set of pixels estimate the level transitions of any attribute that one wants to represent, composing a layer of information. The acquisition of layers providing different crop and soil information, through sensors and coming from the network (e.g. data from yield monitors, weather stations, hydrography, soil fertility, disease incidence, orbital images) requires virtual platforms to integrate and manage the database. Thus, Agricultural Decision Support Systems (ADSS) platforms have aided in the management of the database and user information availability (LINDBLOM *et al.*, 2017; SAIZ-RUBIO; ROVIRA-MÁS, 2020).

The most current and comprehensive definition of ADSS was made by Zhai *et al.* (2020): “an ADSS can be defined as a human-computer system, which utilizes data from various sources, aiming at providing farmers with a list of advice for supporting their decision-making under different circumstances”. ADSS development is closely related to the IoT and cloud computing concepts, which offer advances to PA utilizing enhancing connectivity applications at the field (RUPNIK *et al.*, 2019; ZAMORA-IZQUIERDO *et al.*, 2019).

In agricultural context, the IoT provides objects of interest (e.g. harvesters, tractors, implements, weather stations, sensors, satellite imagery, etc.), which collect specific crop data, to be detected and controlled remotely in the existing and future network infrastructure. This network makes it possible to integrate physical objects responsible for collecting crop information with computer-based systems (FERRÁNDEZ-PASTOR *et al.*, 2018; JHA *et al.*, 2019; OJHA; MISRA; RAGHUWANSHI, 2015; POPOVIĆ *et al.*, 2017). However, ADSS depends on high-level computer resources in terms of storage, memory, processors, connectivity, and communication between parts of the system. Cloud computing service models are based on these requisites, which offer flexibility by software platform that can be located and managed remotely (ZAMORA-IZQUIERDO *et al.*, 2019). It includes Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS), and Software-as-a-Service (SaaS) (POPOVIĆ *et al.*, 2017). These platforms facilitate processing, as they can work on-demand and avoid the installation of complex systems at the local level (ZAMORA-IZQUIERDO *et al.*, 2019).

The main purpose of ADSS is to provide useful and reliable information based on a database, leaving it to the user to make a decision based on this information (ZHAI *et al.*, 2020). Therefore, the integration between different data collection systems, via IoT tools, and the storage and processing of this robust database, through cloud computing, represents essential step towards converting information from farming into information for supporting decision making. However, the database quality must consist of a thorough reading of the intrinsic crop characteristics. Extensive crop attributes database coming from different sensors and technologies require, in addition to the storage and processing technologies, these ADSS platforms for information management and assisting to necessary interventions based on multiple variables. Also, more complex analyzes and in-depth as are the complexities of cause and effect in biophysics systems.

Yield data, for example, are a reflection of all interventions, human or not, carried out during the crop development cycle, constituting the noblest data layer for handling spatial variability (VEGA *et al.*, 2019). Through this information, it is possible to make nutrient recommendation maps based on exported nutrients. Thus, information related to the crop obtained with digital agriculture tools allows for more in-depth and detailed analysis, taking into account the different variables that will reflect on crop yield. Through these tools, the concept of PA intensifies, as the idea of handling crop attributes spatial variability gains input from technological resources for data analysis, and prescription of recommendations, also improving the resolution of interventions.

Challenges and limitations for data-based agricultural interventions

As previously highlighted, as information systems and Internet technologies advance, large sets of agricultural data are inevitably obtained, analyzed, and processed to assist farmers in making decisions aimed at increasing the sustainability of activities, both environmentally and economically. However, the use of adequate resources for storing, managing, and processing this information is essential when applications based on PA are developed. Researchers are looking for new solutions based on designing software architectures in the cloud-based systems. This demand is due to the large amount of data that can be stored and processed, and the need to generate information to make decisions in the field (LÓPEZ-RIQUELME *et al.,* 2017).

Considering that the construction of this type of agricultural information storage must be extremely beneficial, new techniques based on cloud computing must be considered to achieve this objective, mainly because many of the existing PA systems are currently implemented using hosting servers on traditional websites (VYAS; BOROLE; SINGH, 2016). On the other hand, those that include cloud computing techniques often use generic cloud providers that do not offer specific agriculture-oriented services. Also, most PA-based systems are generally designed ad-hoc to solve a specific problem in a specific crop; therefore, most solutions are not easily applicable in another context (SALES; REMEDIOS; ARSENIO, 2015). In this sense, some authors have developed and evaluated the cloud-based software architecture using different resources, López-Riquelme *et al*. (2017), for example, evaluated the development of a cloud-based software architecture using FIWARE and observed that, in this way, agronomic data can be stored reliably and safely.

In addition to the aspects related to hosting and availability of data in the cloud, other limitations related to field interventions should be noted. Due to the complexity of agricultural systems, modeling and intervention become more difficult in the field, since they are affected by several factors, such as environmental conditions, soil characteristics, diseases, weed management, and water availability for the crop.

The data collected from the field has been concentrated on the machines, with companies and service providers offering cloud-based solutions for data captured from the machine. Those data normally come from the Controller Area Network (CAN), already available on some equipment, but limited to machine performance parameters. There are good opportunities to implement additional data, related to the crop, like yield, losses, and quality, as proposed by Corrêdo *et al.* (2020), on sugarcane harvesters, to improve not only the machine operation and its automation, but to create data layers of the crop.

Although the amount of data has increased dramatically in recent years, its availability and quality still restrict the capabilities of existing models to include factors of importance and to be accurate enough to gain user's trust. Even when large data sets are available, machine learning techniques focusing on learning data still face challenges. Tantalaki *et al.* (2019), mention the main weaknesses, computational demand and processing time; specialized knowledge, adjustments; data transformation, and aggregation techniques. Also, data types have changed; in addition to simple numerical values, the data can include qualitative measures, images, or videos.

Another limiting point for the intervention is the selection of variables. Establishing a consistent set of variables that guarantee robust and satisfactory results for all techniques is a challenge. The complexity to model the behavior of some crops makes it difficult to select the variables (ZHAI *et al.,* 2020). Models with large datasets are not always synonymous of high performance, as a large number of irrelevant features would simply increase the likelihood of overturning. The challenge for future models includes not only modeling the known factors that affect crop yield but also incorporating all other external factors that can improve the model. For this, it is necessary to collect large and adequate datasets that describe the production process. In this context, a real-time intervention based on large datasets is still a challenge to be overcome in the context of PA.

CONCLUSIONS

1. World agriculture is facing several challenges with the data acquisition and processing , and delivery of information useful for decision making. However, technological advances for data collection from different sources, and the development of decision support systems are focused on managing the temporal and spatial variability of the crops at the field.
2. The acquisition of diversified data in different harvests over the years, combined with advances in analytical techniques and computational processing, will make it possible to aggregate different layers of information to characterize the complexity of the factors that interfere with yield and quality aspects of the crop. Based on concise and robust databases, the machines could support decisions, such as which crop is best suited for planting, the management practices, and harvest time for a given part of the field. This information would enable more assertive management, increasing the yield and quality of agricultural products, in addition to saving on inputs and greater sustainability of the agricultural production system.
3. The association of these technologies and concepts around the site-specific management of the fields is the

key to develop autonomous interventions in the future. Therefore, the application of technologies classified as digital agriculture is based on and incorporated into the basic concepts of PA.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the Coordination for the Improvement of Higher Education Personnel (Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - CAPES) for the graduate scholarship provided to the authors H.C.B., M.M., and T.F.C. (Finance Code 001). Also, to the National Council for Scientific and Technological Development (Conselho Nacional de Desenvolvimento Científico e Tecnológico - CNPq) for granting a graduate scholarship to L.F.M. (Grant No. 168643/2017-0), and to the financial support of São Paulo State Research Support Foundation (Fundação de Amparo à Pesquisa do Estado de São Paulo, FAPESP) for granting a graduate scholarship to L.P.C. (Grant No. 2018/25008-8).

REFERENCES

AMPATZIDIS, Y.; BELLIS, L. DE; LUVISI, A. iPathology: Robotic applications and management of plants and plant diseases. **Sustainability (Switzerland)**, v. 9, n. 6, p. 1-14, 2017.

AMPATZIDIS, Y.; PARTEL, V.; COSTA, L. Agroview: Cloud-based application to process, analyze and visualize UAV-collected data for precision agriculture applications utilizing artificial intelligence. **Computers and Electronics in Agriculture**, v. 174, n. May, p. 105457, 2020.

ANDERL, R. Industrie 4.0 -Technological approaches, use cases, and implementation. **Automatisierungstechnik**, v. 63, n. 10, p. 753-765, 2015.

BALL, D. *et al*. Robotics for sustainable broad-acre agriculture. **Field and Service Robotics** Springer, 2015, p. 439-453.

BAO, Y. *et al*. Field-based robotic phenotyping of sorghum plant architecture using stereo vision. **Journal of Field Robotics**, v. 36, n. 2, p. 397-415, 2019.

BARBEDO, J. G. A. A review on the main challenges in automatic plant disease identification based on visible range images. **Biosystems Engineering**, v. 144, p. 52-60, 1 abr. 2016.

BASSOI, L. H. *et al*. Agricultura de precisão e agricultura digital. **TECCOGS: Revista Digital de Tecnologias Cognitivas**, n. 20, p. 17-36, 2019.

BAYRAKDAR, M. E. A Smart Insect Pest Detection Technique with Qualified Underground Wireless Sensor Nodes for Precision Agriculture. **IEEE Sensors Journal**, v. 19, n. 22, p. 10892-10897, 15 nov. 2019.

BONFANTE, A. *et al*. LCIS DSS-An irrigation supporting system for water use efficiency improvement in precision agriculture: A maize case study. **Agricultural Systems**, v. 176, n. april, p. 102646, 2019.

BROGAN, W. L.; EDISON, A. R. Automatic classification of grains via pattern recognition techniques. **Pattern Recognition**, v. 6, n. 2, p. 97-103, 1 out. 1974.

CAMILLI, A. *et al*. From wireless sensors to field mapping: Anatomy of an application for precision agriculture. **Computers and Electronics in Agriculture**, v. 58, n. 1, p. 25-36, 1 ago. 2007.

CHEN, X. *et al*. Identification of tomato leaf diseases based on combination of ABCK-BWTR and B-ARNet. **Computers and Electronics in Agriculture**, v. 178, p. 105730, 1 nov. 2020.

CHOI, S. Y.; CHA, D. Unmanned aerial vehicles using machine learning for autonomous flight; state-of-the-art. **Advanced Robotics**, v. 33, n. 6, p. 265-277, 19 mar. 2019.

CORRÊDO, L. P. *et al*. Sugarcane Harvester for In-field Data Collection: State of the Art, Its Applicability and Future Perspectives. **Sugar Tech**, 2020.

CRUZ, A. *et al*. Detection of grapevine yellows symptoms in Vitis vinifera L. with artificial intelligence. **Computers and Electronics in Agriculture**, v. 157, p. 63-76, 1 fev. 2019.

DE CASTRO, A. I. *et al*. Mapping cynodon dactylon infesting cover crops with an automatic decision tree-OBIA procedure and UAV imagery for precision viticulture. **Remote Sensing**, v. 12, n. 1, 1 jan. 2020.

FERRÁNDEZ-PASTOR, F. J. *et al*. Precision agriculture design method using a distributed computing architecture on internet of things context. **Sensors (Switzerland)**, v. 18, n. 6, p. 1731, 28 maio 2018.

FOUNTAS, S. *et al*. Farm management information systems: Current situation and future perspectives. **Computers and Electronics in Agriculture**, v. 115, p. 40-50, 2015.

FU, Y. *et al*. Predicting soil organic matter from cellular phone images under varying soil moisture. **Geoderma**, v. 361, p. 114020, 1 mar. 2020.

GARCÍA-SANTILLÁN, I. D.; PAJARES, G. On-line crop/weed discrimination through the Mahalanobis distance from images in maize fields. **Biosystems Engineering**, v. 166, p. 28-43, 1 fev. 2018.

GAŠPAROVIĆ, M. *et al*. An automatic method for weed mapping in oat fields based on UAV imagery. **Computers and Electronics in Agriculture**, v. 173, p. 105385, 1 jun. 2020.

GOLICZ, K. *et al*. Adapting smartphone app used in water testing, for soil nutrient analysis. **Computers and Electronics in Agriculture**, v. 175, p. 105-532, 1 ago. 2020.

GRINBLAT, G. L. *et al*. Deep learning for plant identification using vein morphological patterns. **Computers and Electronics in Agriculture**, v. 127, p. 418-424, 1 set. 2016.

HU, J. *et al*. **Design and implementation of wireless sensor and actor network for precision agriculture**. Proceedings - 2010 IEEE International Conference on Wireless Communications, Networking and Information Security, WCNIS 2010. **Anais**...2010.

HUUSKONEN, J.; OKSANEN, T. Soil sampling with drones and augmented reality in precision agriculture. **Computers and Electronics in Agriculture**, v. 154, p. 25-35, 1 nov. 2018.

ISPA. International Society of Precision Agriculture. Available in: <https://www.ispag.org>. Access date: September 04th , 2020.

JAO, J.; SUN, B.; WU, K. **A prototype wireless sensor network for precision agriculture**. Proceedings - International Conference on Distributed Computing Systems. **Anais**...2013.

JHA, K. *et al*. A comprehensive review on automation in agriculture using artificial intelligence. **Artificial Intelligence in Agriculture**, v. 2, p. 1-12, 1 jun. 2019.

KAMILARIS, A.; KARTAKOULLIS, A.; PRENAFETA-BOLDÚ, F. X. A review on the practice of big data analysis in agriculture. **Computers and Electronics in Agriculture**, v. 143, p. 23-37, 1 dez. 2017.

KAUR, S.; PANDEY, S.; GOEL, S. Semi-automatic leaf disease detection and classification system for soybean culture. **IET Image Processing**, v. 12, n. 6, p. 1038-1048, 1 jun. 2018.

KHANNA, A.; KAUR, S. Evolution of Internet of Things (IoT) and its significant impact in the field of Precision Agriculture. **Computers and Electronics in Agriculture**, v. 157, p. 218-231, 2019.

KOH, J. C. O. *et al.* Estimation of crop plant density at early mixed growth stages using UAV imagery. **Plant Methods**, v. 15, n. 1, p. 1-9, 19 jun. 2019.

LANDALUCE, H. *et al.* A Review of IoT Sensing Applications and Challenges Using RFID and Wireless Sensor Networks. **Sensors**, v. 20, n. 9, p. 2495, 28 abr. 2020.

LEE, W. S. *et al.* Sensing technologies for precision specialty crop production. **Computers and Electronics in Agriculture**, v. 74, p. 2-33, 1 out. 2010.

LI, C. *et al.* Measuring plant growth char-acteristics using smartphone based image analysis technique in controlled environment agriculture. **Computers and Electronics in Agriculture**, v. 168, p. 105123, 1 jan. 2020.

LINDBLOM, J. *et al.* Promoting sustainable intensification in precision agriculture: review of decision support systems development and strategies. **Precision Agriculture**, v. 18, n. 3, p. 309-331, 2017.

LIU, G. *et al*. YOLO-tomato: A robust algorithm for tomato detection based on YOLOv3. **Sensors (Switzerland)**, v. 20, n. 7, 1 abr. 2020.

LIU, H.; CHAHL, J. S. A multispectral machine vision system for invertebrate detection on green leaves. **Computers and Electronics in Agriculture**, v. 150, p. 279-288, 1 jul. 2018.

LÓPEZ-RIQUELME, J. A. *et al.* A software architecture based on FIWARE cloud for Precision Agriculture. **Agricultural Water Management**, v. 183, p. 123-135, 31 mar. 2017.

MAHDAVIPOUR, O. *et al.* Opto-Dielectrometric Sensor for Measuring Total Incombustible Content in Underground Coal Mines. **IEEE Sensors Journal**, v. 17, n. 19, p. 6443-6450, 1 out. 2017.

MATESE, A.; DI GENNARO, S. F. Practical applications of a multisensor UAV platform based on multispectral, thermal and RGB high resolution images in precision viticulture. **Agriculture (Switzerland)**, v. 8, n. 7, 23 jul. 2018.

MAZZIA, V. *et al.* Real-time apple detection system using embedded systems with hardware accelerators: An edge AI application. **IEEE Access**, v. 8, p. 9102–9114, 2020.

MCPHEE, J. E. *et al.* Managing soil compaction - A choice of low-mass autonomous vehicles or controlled traffic? **Biosystems Engineering**, v. 195, p. 227-241, 2020.

MENDES, J. *et al*. Smartphone Applications Targeting Precision Agriculture Practices—A Systematic Review. **Agronomy**, v. 10, n. 6, p. 855, 16 jun. 2020.

MICHELS, M. *et al.* Smartphone adoption and use in agriculture: empirical evidence from Germany. **Precision Agriculture**, v. 21, n. 2, p. 403-425, 1 abr. 2020.

OBERTI, R. *et al*. Automatic detection of powdery mildew on grapevine leaves by image analysis: Optimal view-angle range to increase the sensitivity. **Computers and Electronics in Agriculture**, v. 104, p. 1-8, 1 jun. 2014.

OJHA, T.; MISRA, S.; RAGHUWANSHI, N. S. Wireless sensor networks for agriculture: The state-of-the-art in practice and future challenges. **Computers and Electronics in Agriculture**, v. 118, p. 66-84, 1 out. 2015.

OUYANG, F. *et al.* Automatic delivery and recovery system of Wireless Sensor Networks (WSN) nodes based on UAV for agricultural applications. **Computers and Electronics in Agriculture**, v. 162, p. 31-43, 1 jul. 2019.

PALLAGANI, V. *et al*. **DCrop: A deep-learning based framework for accurate prediction of diseases of crops in smart agriculture**. Proceedings - 2019 IEEE International Symposium on Smart Electronic Systems, iSES 2019. **Anais**...Institute of Electrical and Electronics Engineers Inc., 1 dez. 2019.

PANDAY, U. S. *et al*. A Review on Drone-Based Data Solutions for Cereal Crops. **Drones**, v. 4, n. 3, p. 41, 12 ago. 2020.

PANTAZI, X. E. *et al.* Wheat yield prediction using machine learning and advanced sensing techniques. **Computers and Electronics in Agriculture**, v. 121, p. 57-65, 2016.

PATHAN, M. *et al*. Artificial cognition for applications in smart agriculture: A comprehensive review. **Artificial Intelligence in Agriculture**, v. 4, p. 81-95, 2020.

PATRÍCIO, D. I.; RIEDER, R. Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review. **Computers and Electronics in Agriculture**, 153, p. 69-81, 1 out. 2018.

PEDERSEN, S. M. *et al.* Robotic Seeding: Economic Perspectives. **Precision Agriculture: Technology and Economic Perspectives**. Springer, 2017, p. 167-179.

POPOVIĆ, T. *et al*. Architecting an IoT-enabled platform for precision agriculture and ecological monitoring: A case study. **Computers and Electronics in Agriculture**, v. 140, p. 255-265, 1 ago. 2017.

PRASAD, S.; PEDDOJU, S. K.; GHOSH, D. **Energy efficient mobile vision system for plant leaf disease identification**. IEEE Wireless Communications and Networking Conference, WCNC. **Anais**...Institute of Electrical and Electronics Engineers Inc., 10 nov. 2014.

RAJA, R. *et al.* Real-time weed-crop classification and localisation technique for robotic weed control in lettuce. **Biosystems Engineering**, v. 192, p. 257-274, 1 abr. 2020.

RAJESWARI, S.; SUTHENDRAN, K. C5.0: Advanced Decision Tree (ADT) classification model for agricultural data analysis on cloud. **Computers and Electronics in Agriculture**, v. 156, n. october 2018, p. 530-539, 2019.

RAMOS, P. J. *et al*. Automatic fruit count on coffee branches using computer vision. **Computers and Electronics in Agriculture**, v. 137, p. 9-22, 2017.

REINA, G. *et al*. Ambient awareness for agricultural robotic vehicles. **Biosystems Engineering**, v. 146, p. 114-132, 2016.

RUPNIK, R. *et al.* AgroDSS: A decision support system for agriculture and farming. **Computers and Electronics in Agriculture**, v. 161, p. 260-271, 2019.

SAIZ-RUBIO, V.; ROVIRA-MÁS, F. From smart farming towards agriculture 5.0: A review on crop data management. **Agronomy**, v. 10, n. 2, 3 fev. 2020.

SALES, N.; REMEDIOS, O.; ARSENIO, A. **Wireless sensor and actuator system for smart irrigation on the cloud**. IEEE World Forum on Internet of Things, WF-IoT 2015 - Proceedings. **Anais**...Institute of Electrical and Electronics Engineers Inc., 2015.

SHAFI, U. *et al*. Precision agriculture techniques and practices: From considerations to applications. **Sensors (Switzerland)**, v. 19, n. 17, 2 set. 2019.

SHAMSHIRI, R. R. *et al.* Research and development in agricultural robotics: A perspective of digital farming. **International Journal of Agricultural and Biological Engineering**, v. 11, n. 4, p. 1-14, 8 ago. 2018.

SHARIF, M. *et al*. Detection and classification of citrus diseases in agriculture based on optimized weighted segmentation and feature selection. **Computers and Electronics in Agriculture**, v. 150, p. 220-234, 1 jul. 2018.

SIVARAJAH, U. *et al*. Critical analysis of Big Data challenges and analytical methods. **Journal of Business Research**, v. 70, p. 263-286, 1 jan. 2017.

STUNTEBECK, E. P.; POMPILI, D.; MELODIA, T. **Wireless underground sensor networks using commodity terrestrial motes**. 2006 2nd IEEE Workshop on Wireless Mesh Networks, WiMESH 2006. **Anais**...Institute of Electrical and Electronics Engineers Inc., 2006.

SWETHA, R. K. *et al*. Predicting soil texture from smartphone-captured digital images and an application. **Geoderma**, v. 376, p. 114-562, 15 out. 2020.

TALAVIYA, T. *et al*. Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. **Artificial Intelligence in Agriculture**, v. 4, p. 58-73, 1 jan. 2020.

TANTALAKI, N.; SOURAVLAS, S.; ROUMELIOTIS, M. Data-Driven Decision Making in Precision Agriculture: The Rise of Big Data in Agricultural Systems. **Journal of Agricultural & Food Information**, v. 20, n. 4, p. 344-380, 2 out. 2019.

TANUT, B.; RIYAMONGKOL, P. The development of a defect detection model from the high-resolution images of a sugarcane plantation using an unmanned aerial vehicle. **Information (Switzerland)**, v. 11, n. 3, 1 mar. 2020.

TU, S. *et al.* Passion fruit detection and counting based on multiple scale faster R-CNN using RGB-D images. **Precision Agriculture**, v. 21, n. 5, p. 1072-1091, 1 out. 2020.

VALENTE, J. *et al*. Automated crop plant counting from very high-resolution aerial imagery. **Precision Agriculture**, v. 21, n. 6, p. 1366-1384, 2020.

VASCONEZ, J. P.; KANTOR, G. A.; AUAT CHEEIN, F. A. Human–robot interaction in agriculture: A survey and current challenges. **Biosystems Engineering**, v. 179, p. 35-48, 2019.

VEGA, A. *et al*. Protocol for automating error removal from yield maps. **Precision Agriculture**, v. 20, n. 5, p. 1030-1044, 2019.

VYAS, D.; BOROLE, A.; SINGH, S. Smart Agriculture Monitoring and Data Acqusition System. **International Research Journal of Engineering and Technology**, v. 3, n. 3, p. 1823-1826, 2016.

WANG, A.; ZHANG, W.; WEI, X. A review on weed detection using ground-based machine vision and image processing techniques. **Computers and Electronics in Agriculture**, v. 158, p. 226-240, 1 mar. 2019.

WEISS, M.; BARET, F. Using 3D Point Clouds Derived from UAV RGB Imagery to Describe Vineyard 3D Macro-Structure. **Remote Sensing**, v. 9, n. 2, p. 111, 28 jan. 2017.

WILLIAMS, H. A. M. *et al.* Robotic kiwifruit harvesting using machine vision, convolutional neural networks, and robotic arms. **Biosystems Engineering**, v. 181, p. 140–156, 2019.

WU, X. et al. Robotic weed control using automated weed and crop classification. **Journal of Field Robotics**, v. 37, n. 2, p. 322-340, 2020.

XIONG, Y. *et al*. An autonomous strawberry harvesting robot: Design, development, integration, and field evaluation. **Journal of Field Robotics**, v. 37, n. 2, p. 202-224, 7 mar. 2020.

YAZDANI, M. *et al*. A group decision making support system in logistics and supply chain management. **Expert Systems with Applications**, v. 88, p. 376-392, 2017.

YUAN, J. *et al*. Urbanization, rural development and environmental health in China. **Environmental Development**, v. 28, n. october, p. 101-110, 2018.

ZAMORA-IZQUIERDO, M. A. *et al*. Smart farming IoT platform based on edge and cloud computing. **Biosystems Engineering**, v. 177, p. 4-17, 1 jan. 2019.

ZHAI, Z. *et al*. Decision support systems for agriculture 4.0: Survey and challenges. **Computers and Electronics in Agriculture**, v. 170, 1 mar. 2020.