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Sensors applied to Digital Agriculture: A review

Sensores aplicados à Agricultura Digital: Uma revisão

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ABSTRACT - Sensors are the basis of digital agriculture; they provide data that allows the development of agricultural control and supervisory systems, and it helps analyze the performance of management practices. Further, sensors can be used to provide data for algorithms developed to automate the prescription of inputs. Among the sensors used in agriculture, those used to monitor soil, plants, and crop yield are reviewed in this work. In soil monitoring, the aim is to measure variables associated with the physical and chemical characteristics of soil to evaluate soil fertility and compaction. In plant monitoring, sensors are used to detect diseases and pests, weed infestation, and nutritional stress. Sensors present in the yield monitors of the harvesters allow the generation of yield maps. Finally, remote sensing techniques for predicting crop yields are analyzed owing to their potential applications in crop management.

Key words: Yield monitor. Soil sensors. Remote sensing. Proximal sensors. Sensors for crop monitoring.

RESUMO - Os sensores são a base da agricultura digital. Eles fornecem os dados para permitir o desenvolvimento de sistemas de supervisão agrícola e para analisar o desempenho das práticas de gestão. Sensores podem ser usados para fornecer dados aos algoritmos desenvolvidos para automatizar a prescrição de insumos na agricultura. Dentre os sensores utilizados na agricultura com finalidades diversas, são revisados neste trabalho aqueles utilizados para monitorar o solo, as plantas e a produtividade das lavouras. No monitoramento do solo, busca-se medir as suas características físicas e químicas, que possibilitam avaliar, por exemplo, a sua fertilidade e compactação. No monitoramento de plantas, os sensores são utilizados para detectar doenças e pragas, infestação de plantas daninhas e avaliar o estado nutricional. Os sensores presentes nos monitores de produtividade das colhedoras permitem gerar os mapas de produtividade. O avanço das técnicas de sensoriamento remoto, nos sensores utilizados e ferramentas computacionais, permite predizer as produtividades das lavouras.

Palavras-chave: Monitor de produtividade. Sensores de solo. Sensoriamento Remoto. Sensores proximais. Sensores para monitoramento das culturas.

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INTRODUCTION

Humanity faces a great challenge in guaranteeing food security for a world population that grows at a rate of 1.05% per year in 2020 (WORLDOMETER, 2020). The global population is expected to rise from 7.8 billion people in 2020 to approximately 10 billion in 2050 (PISON, 2019). This population growth will demand an increase in food production, and this production will have need to be achieved under the scenario of the scarcity of new areas to be integrated into agricultural production and the scarcity of some inputs used in agriculture. Under this new scenario, humanity must increase efficiency in food production.

One approach to increase food production is by reducing the yield gap (VAN ITTERSUM *et al.*, 2013; WU *et al.*, 2018). The actual yield achieved by farmers is less than the potential yield of the crops. The reduction of this gap can be achieved by using technologies that allow the farmer to better monitor the soil–plant–atmosphere system such that factors that lead to reduced crop yields can be detected and managed to decrease yield losses. One approach to reduce yield gaps is to apply precision agriculture techniques in digital agriculture. Precision agriculture uses site-specific management to increase the efficiency of agricultural production systems.

Digital agriculture uses sensors to measure variables associated with crop growth and production. Thus, these devices can be present in machines that apply inputs, in systems used to monitor plant growth, and in harvesters. Although there is considerable diversity in the available sensors for these systems (WELTZIEN, 2016), there are still areas that require improvements in existing sensors and the development of new analysis methods to combine the data of the many different sensors used for crop management.

Professionals working in agriculture need to know the characteristics of each type of sensor so that they can choose and apply the ideal device to measure specific variables. In this review, the main sensors used to map soil attributes, plant attributes, and crop yield will be presented.

SENSORS FOR MAPPING SOIL ATTRIBUTES

Data regarding soil attributes is important for decision making in the management of soil fertility. Further, it helps identify possible factors that affect the crop yield or quality of agricultural products directly or indirectly. In digital agriculture, the characterization of soil attributes becomes even more important because spatial and temporal variability in the production area can be considered in the decision-making process. Based on this information, it is possible to define the ideal cultivar and plant population and the lime and fertilizer dosages for each specific point in the production area. However, for the spatial and temporal characterization of soil attributes, it is often necessary to use a dense grid of soil sampling. Another strategy is to use soil sensors to characterize the spatial variability of soil attributes.

The crop can be considered a good “soil sensor” as plant development characteristics and crop yield generally depend on soil conditions. An analysis of the yield maps obtained in different seasons can be used as the starting point for soil characterization. Thus, it is possible to define zones with high, medium, and low crop yield potential. From soil samples collected in each of these zones, it is possible to identify the soil attributes that may limit crop yield. This type of management reduces the number of samples required to characterize the spatial variability of the soil and allows for a more accurate fertilizer and lime recommendation. In Brazil, soil grid sampling has been widely used in recent years to define the application of lime and fertilizers because of the difficulty faced by producers in terms of collecting data and generating yield maps.

Grid sampling with a high density of points requires excessive time for sample collection, and it results in high costs for laboratory analysis. In addition, the reduction in the grid sampling density can lead to errors in the estimation of the spatial variability of soil attributes, which can cause recommendation errors. An optimal sampling system should provide an estimate with a lower sampling cost without failing to represent the existing variability in the production field. Even if working with the optimal number of samples, the number of samples required depending on the field conditions may incur a high investment for the farmer. The reduction in the number of soil samples by delimiting management zones based on yield maps is not widely adopted because of the difficulties farmers face in generating these maps. Financial and operational difficulties justify the development of soil sensors.

Many attempts have been made to develop sensors to determine the physical and chemical attributes of the soil (ADAMCHUK *et al.*, 2004; ANDRADE *et al.*, 2020; CORWIN; SCUDIERO, 2019; FU *et al.*, 2020; QUEIROZ *et al.*, 2020; VISCARRA ROSSEL; BOUMA, 2016; WAN *et al.*, 2020; ZHAO *et al.*, 2021). However, because of the heterogeneous nature of soils, sensor responses are affected by the combination and interaction of chemical and physical attributes (ADAMCHUK *et al.*, 2004; CHO *et al.*, 2016). Further, not all nutrients present in the soil are available to plants; this heterogeneous soil characteristic affects the behavior of the sensors, thereby causing prediction errors. Given that more than one soil attribute affects the value read by the sensor, it is necessary to eliminate or minimize the influence of the physical attributes of the soil (MAYRINK *et al*., 2019). One solution is to use sensors and simultaneously collect some soil samples at specific points for sensor calibration (KWEON; MAXTON, 2013). Another approach involves the use of sensors to characterize the spatial variability of the soil followed by a segmentation process to create management zones (VALENTE *et al*., 2012).

Soil sensors can be divided-based on the principle of operation-into categories of electrical and electromagnetic sensors, optical and radiometric sensors, mechanical sensors, acoustic sensors, electrochemical sensors, and pneumatic sensors (ADAMCHUK *et al*., 2004). Among these, electrical and electromagnetic sensors and optical and radiometric sensors are currently the most popular for use in agriculture, mainly in the on-the-go systems.

Sensors that measure the apparent electrical conductivity (ECa) of the soil are the most used electrical and electromagnetic sensors. Because of their ease of use and reliability, ECa sensors have been applied to characterize soil spatial variability. The electrical resistivity method is the most common method used to measure soil ECa; this method is based on the application of four electrodes on the soil surface. An electric current was applied between two electrodes and the potential difference was measured at the other two electrodes (CORWIN; LESCH, 2005). More than one arrangement of the four electrodes can be used to build this type of sensor. The Wenner matrix-where the electrodes are arranged in line, are equally spaced, and with the current being applied to the external electrodes and the electrical potential being measured in the inner electrodes-is the most common arrangement used to measure soil ECa.

When measuring the soil ECa, electrical charges can flow in the soil in three ways: (a) in the liquid phase, through the solids dissolved in the water contained in the large pores of the soil; (b) in the solid–liquid phase, through exchangeable cations associated with clay minerals; and (c) in the solid phase, through solid particles that are in contact with each other (CORWIN; LESCH, 2005; CORWIN; SCUDIERO, 2019). Because of these three phases, electrical conductivity can be influenced by multiple physical and chemical attributes of the soil such as salinity, clay content, moisture, density, and organic matter. Therefore, the objective of measuring the ECa is to characterize the spatial variability of the soil and to not determine a specific soil attribute. If the soil is not affected by salinity, ECa is more sensitive to the content and type of soil clay (CHO *et al*., 2016; COCKX *et al*., 2007; DENG *et al*., 2020; NOCCO *et al*., 2019; QUEIROZ *et al*., 2020). However, this variability is identified only if the clay has a certain level of spatial variability over the field. Therefore, the use of the ECa sensor does not eliminate the need for soil sampling. The best approach is to use soil ECa maps to define management zones, and then, to collect a soil sample in each zone for its characterization. Owing to the low cost and speed of measurement, ECa soil sensors allow the generation of soil maps with better spatial resolution than when generating maps by grid sampling.

Optical and radiometric sensors used for soil characterization are devices that measure the electromagnetic energy reflected by the soil at certain wavelengths. Their operating principle consists of using light emitters and receivers in the visible and infrared wavelengths. These sensors can capture light at specific wavelengths or at hundreds of wavelengths within a range of the electromagnetic spectrum (ZHAO *et al*., 2021). As with electrical and electromagnetic sensors, optical and radiometric sensors are often affected by a combination of soil attributes.

There is great contemporary interest in the use of optical and radiometric sensors to characterize the physical and chemical attributes of the soil. Sensors are used to acquire hundreds of variables, which after modeling such as with machine learning algorithms, can estimate attributes of soil texture, cation exchange capacity, organic matter, pH, Ca, Mg, K, P, etc. (KWEON; MAXTON, 2013; MAYRINK *et al*., 2019; TANG *et al*., 2020; ZHAO *et al*., 2021). A criticism to estimating the chemical attributes directly in the soil sample or in the field is that not all attributes present in the soil can be absorbed by plant roots. Some strategies are being studied to estimate the soil attributes available to plants (MAYRINK *et al*., 2019). One idea being tested is to use extractors in the soil samples before proceeding with measurements using radiometric sensors. The great advantage of using sensors with measurements taken directly in the field, especially in the on-the-go systems, is the greater operational capacity that these sensors can have. Therefore, it is possible to collect a large amount of data over a short period of time. A small number of soil samples at specific points in the field can be collected for sensor calibration to improve model prediction in these systems (CHRISTY *et al.*, 2003; KWEON; MAXTON, 2013).

Another radiometric sensor that shows promising results is the X-ray fluorescence (XRF) sensor for determining soil textural attributes, base saturation, and cation exchange capacity (RAWAL *et al*., 2019). More recently, the XRF sensor has been combined with a magnetic susceptibility sensor (ANDRADE *et al*., 2020) and an infrared and visible reflectance sensor to predict the cation exchange capacity and soil texture attributes (ANDRADE *et al*., 2020; BENEDET *et al*., 2020; WAN *et al.*, 2020). The combination of a higher number of soil sensors provides many layers of data that allow the generation of more accurate and robust prediction models (VISCARRA ROSSEL; BOUMA, 2016). The combination of data from different sensors can be combined into smart sensors.

Smart sensors can use, for example, artificial intelligence algorithms to produce models that employ data of different variables to improve the prediction of soil attributes and reduce noise. Smart sensors can often transmit data wirelessly. For example, thermal conductivity sensors were combined with time-domain reflectometer (TDR) moisture sensors to predict soil density (TIAN *et al.*, 2020). Naderi-Boldaji *et al.* (2019) used a combination of mechanical, electrical, and acoustic sensors to determine soil compaction. Thus, there is a trend in increasing the types of sensors and their combination with machine learning algorithms to generate more robust models to predict soil attributes. For conventional laboratory analysis, rapid tests will probably be available in a short time to predict soil attributes using cell phone images or low-cost sensors.

SENSORS FOR PLANT GROWTH MONITORING

One area of digital agriculture that has received special attention is the development of sensors to monitor the development of crops. This is one of the most challenging fields of research due to the difficulties that the environment imposes on crop sensing. Sensors are used to detect the presence of weeds, detect water stress and stresses caused by nitrogen deficiency, and to detect diseases and infestation by pests and insects (PATRÍCIO; RIEDER, 2018). The differing characteristics of different crops and cropping systems have increased the challenges.

There are two crop monitoring methods: one that uses proximal sensors and another that uses remote sensing. Proximal sensors are close or in direct contact with the sensed object, whereas in remote sensing, the sensor is far from the target. Aerial or orbital platforms are used to transport sensors (ANASTASIOU *et al.*, 2018) in remote sensing.

Sensors for detecting weeds

Weeds compete with crops for nutrients, light, and water. If a weed is not detected and removed early, it will have a negative effect on the development of the crop, thereby causing yield reduction (MAVRIDOU *et al.*, 2019). In precision and digital agriculture, sensors have been used for site-specific weed control. This control consists of applying herbicides only where a weed is detected or applied at a variable rate depending on the species, distribution, and density of the infestation (LOPEZ-GRANADO, 2011). Weed detection sensors are used in variable rate application systems based on sensors or for generating weed infestation maps (FRASCONIA *et al.*, 2017; LOPEZ-GRANADO *et al.*, 2016). The sensors can be installed on ground or aerial vehicles. However, in cases where the weed is in the initial stage of development, high spatial resolution images are required to perform the detection. Therefore, there are limitations to the use of images obtained by sensors coupled to aerial vehicles or satellites to detect weed infestation (CASTALDI *et al.*, 2017).

Sensors for detecting weeds can be divided into two groups: sensors that do not generate images, and sensors that generate images (PETEINATOS *et al.*, 2013). In the first group, sensors that measure one or more characteristics at a single point of the crop were presented. Among the characteristics are light reflected or emitted by the plant at specific wavelengths and the height of the plant above the ground. Both types of information can be used to detect weeds, and to differentiate them from the soil and the crop (GAO *et al.*, 2018). The second group of sensors includes the use of RGB and NIR sensors with machine vision techniques for image processing. According to Peteinatos *et al.* (2013), this second group of sensors is the most investigated technique.

One example of the type of sensors that uses spectral characteristics for weed detection is the WeedSeeker® sensor (Trimble Agriculture, USA). This sensor consists of a light emitting source and an optical receiver. The light source emits light with red and near-infrared wavelengths. The soil and weed reflect the light emitted at different intensities, thereby allowing differentiation between them. This sensor is normally attached to ground vehicles and used in automated herbicide application systems. The sensor is connected to a controller, and whenever a weed is detected, the controller triggers a solenoid valve by applying herbicide over the detected weed (KODALI *et al.*, 2014).

Another technique based on spectral characteristics is exposing leaves to radiation for a specific time interval and intensity, which causes the leaves to emit fluorescent radiation. The intensity of the emitted fluorescence is highly dependent on the properties of the leaf and its physiological state. Therefore, fluorescence is highly related to plant species, which allows the differentiation of weeds from crop plants (SU *et al.*, 2019).

Ultrasonic sensors and light detection and ranging (LIDAR) sensors are used to differentiate plants based on their height (PETEINATOS *et al.*, 2013). Andujar *et al.* (2011) proposed the use of an ultrasonic sensor to differentiate broadleaf weeds from grasses based on their heights. The results were promising and indicated the potential for using this technology in autonomous weed control systems. According to the authors, this technology can be used alone or coupled with other weed detection technologies.

For sensors that generate images, computer vision tools are the most commonly used techniques for detecting weeds (LIU; BRUCH, 2020). For processing images acquired by cameras, spectral characteristics, biological morphology, textures, and spatial patterns are used to detect weeds and to differentiate them from crop plants and soil. Because of their efficiency in detecting and classifying weeds, the use of machine learning algorithms to extract characteristics from images is increasing (YU *et al.*, 2019). The variation in light conditions, leaf overlap, and nonsignificant differences between weeds and crop plants are the limitations to the use of machine vision techniques for weed detection (MAVRIDOU *et al.*, 2019).

Sensors for detecting pests and diseases

Sensors have been used to replace molecular tests used for detecting pests and diseases in plants. Molecular tests are destructive and invasive, and they have disadvantages such as the time required and the complexity of the procedures (GOLHANI *et al.*, 2018). Techniques based on spectral characteristics and images have the potential for the rapid and accurate detection of plant diseases, including those in the early stages of infestation (THOMAS *et al.*, 2017).

Sensors can be coupled to ground or aerial vehicles, and the generated data can be used for generating infestation maps or in variable application systems based on sensors. In the latter case, sensors send information to the controllers. Such a controller is responsible for triggering the spraying system to apply crop protection products only to infected plants (SANKARAN *et al.*, 2010). Sensors for detecting weeds, pests, and diseases can be classified into active and passive sensors. Active sensors have an artificial light source and a receiver that measures the intensity of the light reflected by the plant. Passive sensors measure reflected solar radiation or thermal radiation emitted by the plant (MARTINELLI *et al.*, 2015).

The spectral characteristics of the plant are influenced by variables that describe the structure of the canopy, such as the area and leaf orientation, spatial arrangement and roughness, and the optical, dielectric, or thermal characteristics of plant components (MAHLEIN, 2016). A plant that is under stress induced by disease, pest, or nutritional deficiency reacts with its protection mechanisms, thereby causing changes in variables such as leaf area index, chlorophyll concentrations, or leaf temperature. Therefore, a sick plant has a spectral characteristic that is different from a healthy plant that is not under stress, and it is possible to differentiate them (SANKARAN *et al.*, 2010). Among the techniques based on spectral characteristics and images for the detection of diseases and pests in plants, the main ones are fluorescence imaging and spectroscopy, multispectral or hyperspectral imaging, and spectroscopy in the visible and infrared bands (ZHANG *et al.*, 2019a).

Fluorescence spectroscopy involves measuring the fluorescence of a target object after emitting radiation (usually ultraviolet radiation). Fluorescence imaging is an advanced form of fluorescence spectroscopy, wherein images are obtained using a charge-coupled device (CCD) camera (LENK *et al.*, 2007). Visible and infrared spectroscopy involves the use of sensors to measure light intensity emitted or reflected by the plant in the visible and infrared spectrum (SANKARAN *et al.*, 2010). This technique provides considerable information on the physiological stress levels of plants. Therefore, they can sometimes be used to detect diseases even before symptoms are visible to the human eye (LOWE *et al.*, 2017).

Hyperspectral sensors are used to measure light intensity reflected by the plants using hundreds of narrow contiguous wavelength intervals (JIN *et al.*, 2017). Therefore, more detailed information of an object can be obtained using hyperspectral sensors. Other techniques based on spectral characteristics include infrared thermography, terahertz spectroscopy, nuclear magnetic resonance spectroscopy, and X-ray images. According to Sankaran *et al.* (2010), these techniques are expensive, and therefore, no commercial applications have been observed. However, developments are underway to reduce costs and improve performance; thus, commercial adoption is expected.

A major challenge in utilizing techniques based on spectral characteristics, such as techniques that use hyperspectral sensors, to detect pests and diseases in crops is the selection of the wavelength and the development of a classification algorithm that can detect a specific disease (BARBEDO, 2016). Often, parametric methods such as simple or multiple regression cannot detect whether a plant is affected by its spectral characteristics. Therefore, nonparametric approaches such as principal component analysis, fuzzy logic, support vector machine, cluster analysis, partial least square, artificial neural networks, and convolutional neural networks are employed (GOLHANI *et al.*, 2018).

Sensors for detecting plant nutritional stress

Nutrient deficiency and infestation by weeds, pests, and diseases are factors that reduce yield and prevent the crop from reaching its productive potential (VAN ITTERSUM *et al.*, 2013). Prior to the use of sensors, a visual technique that employs color guides was used to determine the nutritional status of the plant. This technique has the limitation of not allowing quantitative and accurate assessments (GRAEFF *et al.*, 2008). Another technique is laboratory leaf analysis, which is time consuming and requires the application of specific methods for the correct acquisition and interpretation of data (CUNHA *et al.*, 2016). The two main sensor-based techniques to determine the nutritional status of plants are chlorophyll meters and sensors based on spectral characteristics.

Chlorophyll meters estimate the amount of chlorophyll per unit area of the leaf surface. Chlorophyll meters produce a dimensionless value that is strongly related to the actual amount of chlorophyll in the leaf (KALAJI *et al.*, 2017). Chlorophyll meters are manual devices that must be attached to the leaf surface or placed close to it. Commercial equipment for measuring chlorophyll includes SPAD-502 (Konica Minolta Sensing America, USA), N-tester (Step Systems, Germany), and MC-100 Chlorophyll Concentration Meter (Apogee Instruments, USA) (PADILLA *et al.*, 2018). Because they are operated manually and provide only estimates, the results obtained with chlorophyll meters are time consuming and not always accurate (NAUŠ *et al.*, 2010).

Sensors based on spectral characteristics measure the intensity of the light emitted or reflected by the plant at specific wavelengths. For example, the spectral characteristics of the plant canopy in the visible spectrum are highly dependent on chlorophyll. As nitrogen is an important component of chlorophyll, spectral characteristics are sensitive indicators of nutrient deficiency levels (ABULAITI *et al.*, 2020). Data obtained by sensors are used to determine vegetation indices such as the vegetation index of normalized difference (NDVI) (HEEGE *et al.*, 2008). Based on calibrations, these vegetation indices can be used to assess the nutritional status of the plant and to estimate future crop yield. Typical applications of this type of sensor refer to the assessment of the nutritional status of the plant related to nitrogen (COLAÇO; BRAMLEY, 2018).

Nutritional stress sensors can be coupled to ground and air vehicles in the same way as sensors used for detecting pests, diseases, and weeds. The sensors can be onboard aerial vehicles such as satellites, airplanes, and unmanned aerial vehicles (BARBEDO, 2019; QUEMADA *et al.*, 2014; SEVERTSON *et al.*, 2016). Although some sensors coupled to satellites are capable of generating images with submetric resolutions, these images do not allow the individual analysis of most types of plants. Therefore, nutritional deficiency is only detected by satellite systems when it is spread in several plants. Sensors attached to unmanned aerial vehicles can provide images with a spatial resolution of less than 1 cm (BARBEDO, 2019). Thus, sensors attached to unmanned aerial vehicles are suitable for assessing nutritional stress in plants (CABRERA-BOSQUET *et al.*, 2012). An example of a sensor used on a ground vehicle is GreenSeeker® (N-Tech Industries, California, USA), and it is used to analyze the nutritional status of plants with respect to nitrogen. This sensor can be connected to a controller responsible for applying nitrogen fertilizer at a variable rate (MOHAMED, 2018).

SENSORS FOR YIELD MAPPING

The yield map is one of the main components of precision and digital agriculture, and it is widely used in decision making related to crop management (SANCHES *et al.*, 2019; VORIES *et al.*, 2019). Yield maps allow farmers to determine changes in crop yield in the field and can guide investigations into the causes of spatial yield variations (PRICE *et al.*, 2017). For example, Pagani and Mallarino (2015) analyzed yield maps of corn and soybean fields to determine the soil pH that resulted in the maximum yield. Two approaches for obtaining a yield map have been used in digital agriculture. The first is to determine the actual yield simultaneously with the harvest (SEARCY, *et al.*, 1989); the second is to predict yield while the crop is still in development (GAN *et al.*, 2018). Both methods use a wide range of sensors.

The system used to determine the actual yield during harvest is a yield monitor (PRICE *et al.*, 2017). In national and world markets, the yield monitor is a standard accessory for grain combine harvesters (CHANGHUA *et al.*, 2018). Yield monitors were first developed for combine harvesters. For other crops, commercial yield monitors or prototypes are being developed.

A yield monitor can be divided into four subsystems: a set of sensors for yield determination, a receiver of the global navigation satellite system (GNSS) for georeferencing the yield data, an electronic processing unit for data manipulation and storage, and a console for allowing interaction with the user (CHUNG *et al.*, 2016; CHANGHUA *et al.*, 2018). Among the set of sensors, the most critical one measures the mass or volumetric flow of the product being harvested (MAJA; EHSANI, 2010). The principle adopted to measure mass or volumetric flow will depend on the crop in which the sensor will be used and the choice of the manufacturer.

In addition to product flow, other sensors are often used to measure harvester speed, angular speed of the pulley of the clean grain elevator or screw conveyor, inclination of the harvester, and moisture of the product being harvested. Depending on the sensor, the generated signal is influenced by the inclination of the harvester and the operating speed of the grain elevator. Thus, a harvester tilt sensor and an angular elevator speed sensor were used for necessary grain flow corrections. Harvester speed is necessary for yield calculation, and it can be measured by sensors installed on the machine wheel or radar sensors based on the Doppler effect or by the GNSS receiver (CHUNG *et al.*, 2016). The crop yield must be adjusted to a standard water content; therefore, yield monitors are equipped with a grain moisture sensor. The principles used in grain moisture sensors can be capacitive, microwave, acoustic, and infrared reflectometry (CHUNG *et al.*, 2016). A GNSS receiver is used for georeferencing the yield data, and therefore, a yield map can be generated. To ensure accuracy in position determination, a GNSS receiver with real-time correction features is used.

The console-installed in the harvester cab-informs the operator of data to increase the efficiency of the harvesting operation. Further, this console is used to insert information necessary for the operation of the yield monitor such as the operating width of the platform and the data for sensor calibration. Finally, the electronic processing unit of the console functions to process the data of the different sensors, obtain the position of the GNSS receiver, communicate with the terminal, and record the yield data in a file (WHELAN; TAYLOR, 2013).

Grain flow sensors used in yield monitors

When reviewing sensor technologies for grain yield monitors, Chung *et al.* (2016) presented the main sensors used to measure mass or volumetric flow. To measure the grain mass flow, fingers and impact plates with force sensors (load cell) and impact plates with angular displacement sensors (potentiometer) are used.

To measure volumetric flow, Chung *et al.* (2016) discussed paddle wheels and optical transmitter and receiver sets. A paddle wheel comprises cells with a known volume, and the count of the number of filled cells used to determine volumetric flow. The optical principle is to correlate the amount of light attenuated by grains with volumetric flow.

Another principle is to correlate the torque required to drive the elevator with the mass flow of grains (ZANDONADI *et al.*, 2008). Besides the principle that uses the paddle wheel, many (SCHUELLER *et al.*, 1985) presented principles are indirect methods of measurement. Therefore, calibration is required to correlate the signal generated by the sensor with the mass (or volumetric) grain flow.

The calibration of the grain yield monitors is recommended whenever there is a change in harvest and tillage conditions such as travel speed, variety (or cultivar), and grain moisture (AHMAD; MAHDI, 2018). Although it is an important procedure to guarantee the accuracy of the data obtained (SCHUSTER *et al.*, 2018), the time required and the tasks involved create a barrier to its realization. To solve these problems, manufacturers are looking for yield monitors with automatic calibration and those that do not require calibration have been developed.

Schuster *et al.* (2018) developed an alternative method to measure the volumetric flow of grains to reduce or eliminate the need for calibrations. The method involves measuring the grain velocity through a cross section with a known area. This section is formed by two plates installed on the grain screw conveyor. The speed was obtained by processing the images obtained by a camera installed in this section.

Sensors for sugarcane yield monitor

Although it not yet common in the Brazilian sugar and alcohol industry (SANCHES *et al.*, 2019), yield maps have great potential for adoption to increase financial returns of sugarcane crops (MANHÃES *et al.*, 2014). Equipment costs, the lack of qualified professionals, and the lack of information on digital agriculture in sugarcane are factors that prevent its adoption (SILVA *et al.*, 2011).

To generate the yield map, sensors are used to determine the mass or volume of stalks harvested directly or indirectly, and a GNSS receiver is used for georeferencing the data point where each quantity was harvested (JENSEN *et al.*, 2012). When reviewing the state-of-the-art of sugarcane harvesters, Corrêdo *et al.* (2020) reported the following sensors: load cell and deflection plate installed in the stalk elevator (MAILANDER *et al.*, 2010, QUADERER; CASH, 2015), a pressure sensor to measure the torque demand in the hydraulic drive motor of the stalk elevator (WENDTE *et al.*, 2001), optical/laser sensor (PRICE *et al.*, 2011, 2017), and three-dimensional sensors (DARR *et al.*, 2015). The stereoscopic optical system (three-dimensional sensor) is used in a John Deere harvester yield monitor (John Deere Company, USA); this sensor is used to determine the fraction of foreign matter. The load cell principle installed in the stalk elevator was adopted in Case IH harvesters (CNH Industrial America LLC, USA).

Monin *et al.* (2019) proposed a method to obtain a sugarcane yield map that does not require equipment calibration. The method used the position data of the harvester and the wagons used to store the stalk. An algorithm was developed in QGIS to obtain the necessary distance so that the wagon with a 10 Mg capacity was filled. From this distance and the width of the line, a yield map was generated. The authors reported that the method can be improved with the use of accurate position data and a better estimation of the stalk mass in the wagons obtained by a camera installed in this section. The initial results indicated the potential use of the method in yield monitors.

Sensors for coffee yield monitor

The Jacto Company (Máquinas Agrícolas Jacto S.A, Brazil) has developed a coffee yield monitor for their K3 coffee harvester (SARTORI *et al.*, 2002). The K3 harvester is a one-row harvesting machine. The machine has a conveyor belt composed of cells of known volume. The angular speed of this belt is controlled electronically based on the level of coffee in the tank to completely fill each cell of the belt. Based on the number of filled cells, the harvester speed, and the distance between coffee rows (defined by the user), the coffee yield is determined in L ha^{-1}. A GNSS receiver is used for georeferencing the data points.

Sensors for forage yield monitor

Maughan *et al.* (2012) presented some of the sensors used to determine the flow for yield monitors of forage harvesters for producing hay and silage. The first principle consists of measuring the displacement of the harvester feed rollers and correlating it with the flow. Vertical displacement sensors, linear potentiometers, and load cells are used to measure displacement. The second principle is to use an impact plate, similar to the one used in grain harvester yield monitors. A third principle was to measure the torque demanded in harvester mechanisms considering that greater flow requires greater torque in these mechanisms. For balers, load cells are used to monitor the mass of the bale, and these data are used to generate the yield map (KAYAD *et al*., 2015). In addition to flow sensors, near-infrared sensors are used to determine the water content of the forage (KHAREL *et al.*, 2019; LONG *et al.*, 2016).

Ramsey *et al.* (2015) proposed and evaluated the use of an infrared or ultrasonic sensor to measure the height of plants immediately before being cut. These sensors were installed in the harvester, and measurements were performed during the cutting operation. Linear regression models were developed to calculate the mass flow of forage based on plant height. Field tests indicated errors of less than 10%. However, it was observed that the sensors stopped responding in some of the tests performed. The authors associated this occurrence with the use of sensors that are not resistant to dust and moisture.

Sensors for cotton yield monitor

For cotton crops, the principle adopted is the measurement of the flow of the harvested cotton in the ducts that transport it to the storage reservoir on the harvester. The flow is measured from the attenuation of light or the reflectance of microwaves, both of which are influenced by the flow of cotton being transported (VORIES *et al.*, 2019). Thus, a calibration curve is used to obtain the cotton flow as a function of the signal emitted by the sensors. Cotton properties such as capsule size, seed size, presence of foreign matter, fiber quality, and water content influence this calibration (VORIES *et al.*, 2019). As with yield monitors for other crops, calibration is required whenever there is a change in operating conditions or crop conditions. This procedure is extremely important for generating reliable yield maps (PELLETIER *et al.*, 2019a, b, c).

Sensors for yield monitors of olives, citrus, peanuts, and vegetables

A yield monitor prototype for olives was designed by Castillo-Ruiz *et al.* (2015) and installed in a combine harvester with a lateral canopy agitator. The monitor was composed of a control box and a force sensor installed in the support of the fruit reservoir. The force sensor was used to measure the accumulated fruit mass, and the data were georeferenced by a GNSS receiver. Based on the registration position, the data were processed to obtain the olive mass produced in each tree. The monitor was efficient in detecting a mass between 8.4 and 85.8 kg $plant^{-1}$ in a field with high yield spatial variability. The authors reported that the yield map can be used to optimize the control of fungal diseases.

Maja and Ehsani (2010) developed a yield monitor for a citrus harvester. The yield monitor consisted of a GNSS receiver, a mass flow sensor, and data processing and storage units. The mass flow sensor consisted of four load cells connected to a plate that detected the impact force generated by the fall of the fruits. A mathematical model based on a mass-spring-damper system was developed to relate the impact force with the mass flow of oranges. Field tests showed a correlation (R^2) of 0.97 between the measured mass and the actual mass. In regions with high and low yields, the error was 9.16% and 3.56%, respectively. The authors concluded that calibration based on a linear relationship was not suitable for all yield ranges.

Jacques *et al.* (2017) proposed a prototype yield monitor for crops such as onions, carrots, turnips, and lettuce. The system consisted of using image processing to count the fruits transported on the harvester belt. The number of fruits was associated with the position of the harvester, which was obtained by a GNSS receiver. The authors reported that the limiting factors found were light conditions and the process of hiding objects.

Thomasson *et al.* (2006) developed a yield monitor for peanuts based on an optical sensor to measure the mass flow of pods transported in ducts using air currents. The adopted principle is related to the mass flow to the reflectance measured by the sensor. This same sensor was previously used by authors in the development of a yield monitor for cotton. Authors concluded that the measured mass flow was strongly correlated with the harvested pod mass.

The development presented by Krik *et al.* (2012) consisted of a yield monitor for experimental peanut plots wherein the harvested mass is small compared to commercial crops. The system comprised a basket supported by load cells to store and evaluate the mass of pods harvested in an experimental plot. After the measurement, a gate was opened, and the pods were transported to the reservoir of the harvester. The system was developed to reduce the number of people required to collect the experimental plots and eliminate the necessity of calibrations. The system was precise in collecting and determining peanut mass. However, the authors reported that additional studies were included for georeferencing the acquired data.

Yield maps for manually harvested crops

Crops that are manually harvested (e.g., oranges and apples) present difficulties in generating yield maps because there are no machines to instrument. Several authors have used a methodology to generate a yield map that consists of determining the position of each box or bag that was harvested with the aid of a GNSS receiver (COLAÇO *et al.*, 2020; SCHUELLER *et al.*, 1999). The mass (or volume) of fruits in each box or bag can be determined with the aid of instruments or the nominal capacity of the box or bag can be adopted. Using this methodology, Colaço *et al.* (2020) evaluated two methods for generating the yield map: one based on the area covered by each box or bag and the other based on their distribution in the area. Further, the authors evaluated the influence of positioning errors and the box or bag mass estimation error on the yield map. They concluded that, the box or bag distribution method produces more realistic maps compared to the coverage area method as the positioning error increases, especially in cases of higher density of boxes or bags. In both methods, the mass estimation errors showed a low effect on the yield map. This methodology was successfully used to generate yield maps for carrot (WEI *et al.*, 2020) and olive (FOUNTAS *et al.*, 2011) crops.

Cleaning yield data

Since data produced by yield monitors may show systematic errors, a data cleaning procedure may be necessary before data use (DRIEMEIER *et al.*, 2016; LEROUX *et al.*, 2018). Some factors that cause errors in yield maps are the delay of harvested crops in the harvester mechanisms, error in the establishment of the harvester width, errors in the GNSS receiver, and the precision and calibration of the sensors (CHUNG *et al.*, 2016; SUDDUTH *et al.*, 2007). Research has pointed out that 10% to 30% of the data generated in the yield monitors may have incorrect values and the need to be removed (COELHO *et al.*, 2018; SUN *et al.*, 2013). Methods that use filters or perform classification, identification, and removal of these points have been developed (KHAREL *et al.*, 2019; MALDANER; MOLIN, 2020; SUN *et al.*, 2013; VEGA *et al.*, 2019).

Sudduth *et al.* (2007) developed the Yield Editor software for cleaning yield data. The authors reported the existence of different filtering techniques for specific errors; however, a standardized method has not yet been proposed. The software was developed to simplify the process of applying the filters. A map viewer allowed the user to interact with data, evaluate the effects, and change the parameters of the filters. Twelve specific filters were implemented for delay in grain flow, entry and exit from the harvest area, operating speed above and below specified value, sudden variations in travel speed, width of the harvest platform less than the specified value, minimum and maximum yield, standard deviation of yield, position of the GNSS receiver, and manual removal. The software was tested on corn, soybeans, wheat, sorghum, oats, and barley crops. Based on user comments, Sudduth *et al.* (2012) proposed a second version of the yield monitor software with a module to automate the process of selecting parameters and filters.

When developing procedures for generating management zones based on yield data, Taylor *et al.* (2007) stated that the removal of erroneous data is important to ensure correct agronomic decisions. They proposed a ten-step procedure; the first step describes the removal of inconsistent data. That is, data outside the range considered acceptable for a given crop. The second step was the removal of inliers and outliers, that is, data within the acceptable range and which differ from the closest neighbors. The other steps were related to the generation of management zones.

Zanella *et al.* (2019) correlated yield data from a soybean field with management zone maps generated from vegetation indices calculated from LandSat and Sentinel satellites. Before use, the authors filtered the yield data using steps proposed by Taylor *et al.* (2007). Coelho *et al.*

(2018) adopted the steps proposed by Taylor *et al.* (2007) to implement an embedded system for geostatistical analysis with a function that allowed the removal of erroneous data while the user was still in the field of data acquisition.

Autocalibration of yield monitor

The sensors used in yield monitors need to be calibrated to characterize the relationship between the signal generated by a sensor and the measured variable. However, calibrations are highly dependent on the conditions under which the calibration is performed (REIKE *et al.*, 2011). Significant measurement errors may occur outside the calibration conditions. Thus, calibration is recommended whenever there are changes in variety (or cultivar) or field and operating conditions (PELLETIER *et al.*, 2019a, b, c). If calibrations are not adopted, data generated by the yield monitor cannot be used in precision agriculture (VORIES *et al.*, 2019). To solve this problem, manufacturers and researchers have been working on the development of self-calibrating yield monitors.

Reike *et al.* (2011) proposed a mathematical model to relate impact force with flow rate considering friction interactions between grains, collisions between grains and the impact plate, and the nonlinearities associated with the movement of grains when being launched by the blades of the grain elevator and the orientation of the impact plate. The developed model could be adapted to different operating conditions, while maintaining the accuracy of the calibration. Simulations were performed using the discrete element method. In the simulations, the masses were predicted with an average square root of the normalized residue of less than 4.02% for grains with different moisture contents.

The yield monitor proposed by Changhua *et al.* (2018) used the principle of light emitter and optical receiver to measure the volumetric flow of grains in the elevator. A discharge screw speed sensor and a grain height sensor in the reservoir were added to the yield monitor. The signal from the additional sensors was used by the processing unit to correct the grain flow calculated from the optical receiver. The error obtained in the yield monitor was less than 5.8% in the experimental field tests.

Pelletier *et al.* (2019a, b, c) developed an automatic calibration system for the John Deere 7460 cotton harvester (John Deere Company, USA), which is a harvester with a reservoir for storing the harvested cotton. A pressure sensor was installed in the hydraulic cylinder responsible for moving the reservoir during discharge. From a linear regression model, the pressure in the hydraulic cylinder was associated with the cotton mass accumulated in the reservoir during the harvesting operation. The determination of this mass was used to self-calibrate the sensor responsible for measuring the cotton flow. The authors reported an error in measuring the cotton mass below 2.5%, thereby indicating its applicability to self-calibrating the flow sensor.

Beck and Pickett (2010) proposed an automatic system to calibrate the grain flow sensors in grain harvesters. The system consisted of two transceivers: one installed in the grain harvester and the other installed in the agricultural truck or trailer used to receive the grains, thereby establishing wireless communication between the equipment. This truck or trailer equipped with a scale system transmitted the mass data to the harvester. Using this data, the yield monitor of the harvester performed the self-calibration of the mass flow sensor.

The active yield system (THOMASSON *et al.*, 2019) used in the John Deere grain harvesters (John Deere Company, USA) employs three load cells to estimate the grain mass in the harvester reservoir continuously. The mass variation detected by these load cells was used to correct the calibration curve of the impact plate.

Predicting grain yield

Crop yield prediction is one of at least five sub-processes that are part of crop management in digital agriculture (CHERGUI *et al.*, 2020). Other sub-processes are soil monitoring, climate monitoring, disease and weed monitoring, and irrigation monitoring. Crop yield prediction has become possible because of the amount of data generated with proximal and remote sensors and the existence of processing techniques that can handle this large amount of data (CHERGUI *et al.*, 2020; LOBELL *et al.*, 2015).

Tagarakis *et al.* (2017) used the GreenSeeker proximal sensor to predict the sorghum crop yield from the measurement of NDVI throughout the development of the crop. The comparison with true yield data indicated that the technique was accurate for estimating sorghum yield. Using the same sensor, Zhang *et al.* (2019b) estimated the yield in wheat fields.

A useful tool for predicting crop yield using remote sensing is the Google Earth Engine platform (LOBELL *et al.*, 2015). Georeferenced and atmospheric-corrected images from the LandSat satellite can be quickly processed using this tool. The authors estimated the crop yield of 17,000 corn fields and 11,000 soybeans fields in the United States in different years with this tool. The predictions using satellite images and climatic data were compared with the yield monitor data. The authors concluded that there are approaches to improve the performance of the developed method; these include adding other crop models, using other types of images such as thermal and radar images, using different models of multiple linear regression, and using other algorithms for correcting cloud shadows. However, the basic version of the method generated estimates that captured an average of one third, and sometimes more than half of the crop yield variation.

Zanella *et al.* (2019) correlated data on soybean yield in the 2015/2016 and 2016/2017 seasons with vegetation indices calculated from images from the satellites LanSat7-8 and Sentinel2 in two seasons of crop development. The authors concluded that the vegetation indices modified simple ratio, green chlorophyll vegetation index, and shortwave infrared water stress index were significantly correlated with yield data. Therefore, the images can be used to detect crop spatial variability related to crop yield.

Recent advances in sensors installed on satellites that enable spatial resolution of less than 10 m have enabled the prediction of crop yield in small fields in developed countries (JIN *et al.*, 2019). Crop yield prediction is an alternative to adopting precision agriculture techniques because the use of harvesters with a yield monitor may not be feasible in some scenarios (BURKE; LOBELL, 2017; ZHANG *et al.*, 2019b). Jin *et al.* (2019) used the Google Earth Engine platform and images from Sentinel 1 and 2 satellites to predict yields from small corn fields in Kenya and Tanzania. Other examples of using satellite images were the prediction of yield maps for carrot crops (WEI *et al.*, 2020) and wheat (TOSCANO *et al.*, 2019).

An alternative to satellite images is images obtained by sensors coupled to unmanned aerial vehicles (UAVs). The use of UAVs allows greater temporal and spatial resolution and is less affected by the occurrence of clouds (SAGAN *et al.*, 2019). Sarron *et al.* (2018) used images obtained from a UAV equipped with an RGB camera to predict mango crop yield. The authors obtained a correlation (R^2) greater than 0.77 and an average square root of the error between 20 and 29%, using the true yield measured in 60 plants.

Maimaitijiang *et al.* (2020) used a UAV equipped with several sensors to estimate soybean crop yield. The sensors used were a multispectral camera, two RGB cameras (installed perpendicular and at 45º in relation to the ground), a camera for determining NDVI, and an infrared thermal camera. The images were processed using the following data fusion techniques: deep neural networks, partial least squares regression, random forest regression, and support vector regression. The authors concluded that data fusion improves the accuracy of crop yield prediction. It was also observed that the models based on deep neural networks produced predictions with greater precision.

CONCLUSION

The main sensors used in digital and precision agriculture were presented in this review. Owing to the wide variety of sensors used in contemporary agriculture, this review was restricted to sensors for soil, crop growth, and crop yield monitoring. As indicated in the review, soil apparent electrical conductivity sensors are widely used; further, there is a trend in the development of multisensory systems for the characterization of the spatial variability of soils. Sensors for weed, pests, and disease detection and for crop nutritional stress determination were presented. Most of these sensors are based on the reflectance characteristics of the crop or pest. Remote sensing and proximal sensing techniques have been developed globally for monitoring different crop systems. The sensors used for yield mapping were presented. As the calibration of these sensors is a barrier to yield adoption, approaches to overcome this problem were discussed. As the prediction of crop yield can be used for making decisions about crop management, techniques being used for this purpose were also discussed.

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