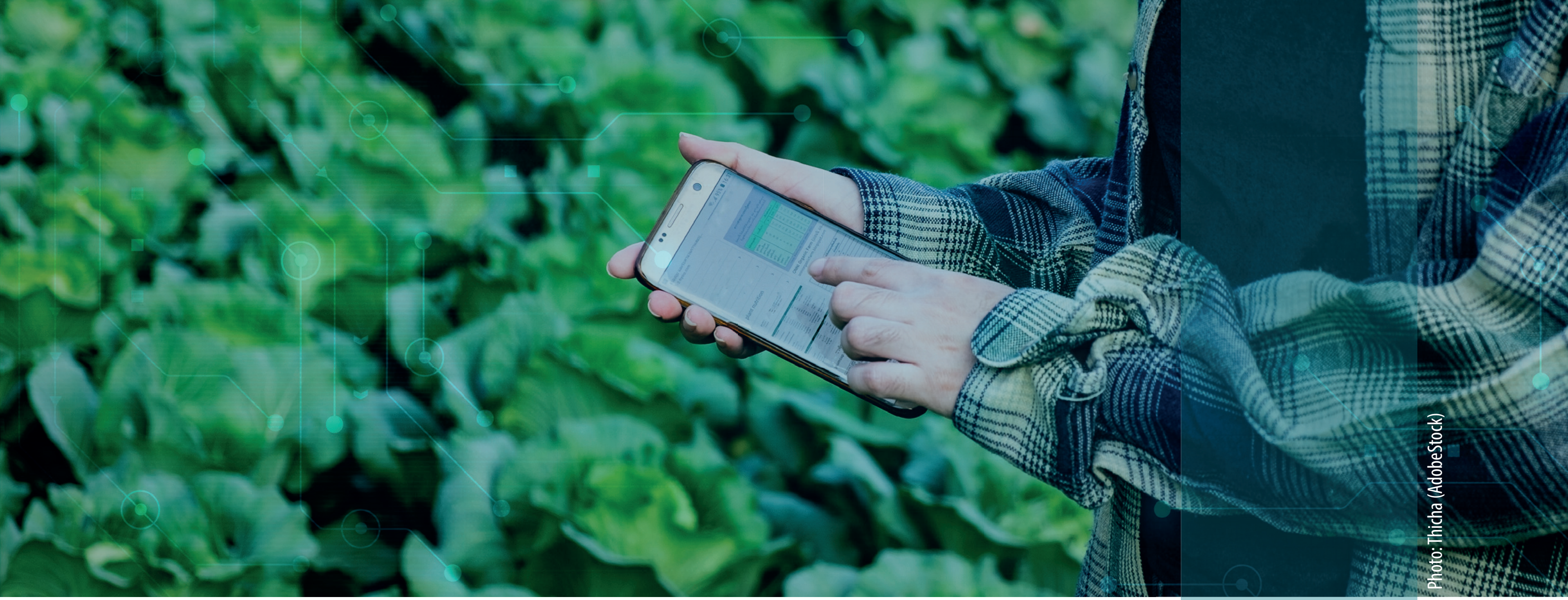
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Technologies developed in precision agriculture

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Introduction

Precision Agriculture (PA) is a management strategy that considers temporal and spatial variability to improve the sustainability of agricultural production (International Society of Precision Agriculture, 2020). Through it, temporal, individual, and spatial data are collected, then processed, analyzed, and combined with other information to support management decisions. These decisions are made according to estimated variability so as to improve the efficiency in resources use, productivity, quality, profitability, and sustainability of agricultural production.

Developing methodologies either in experimental fields or by inference in an ideal environment by agents without field experience can result in proposals that are very difficult for the productive sector to absorb. With that in consideration, we will develop the chapter as the first steps for implementing PA and focus on enabling technologies.

It is important to understand that the crop is not uniform and has variability. There are areas where crops are more prone to flood and others with good drainage, and plots that can vary from clayey to sandy soil, or from more acidic to less acidic soil, and so on. Such variation includes different characteristics that imply productivity variation in the same crop. It is intuitively understood that in areas that produce two to four times more, the need for input is different, and that perhaps there is an excessive application of input in one area, or productivity is being lost due to lack of this input in another. In both situations, the producer is losing an important economic return on his business and possibly an environmental return.

Despite the variability of productivity in the areas, conventional machines are rigid, their adjustments are mechanical and cannot be changed during a field operation. In the case of PA machines, as the adjustment is programmable, the input release can be adjusted according to a recommendation map. Its performance is flexible and is able to react to values obtained by sensors in real time.

Thus, when starting PA with machines able to map crop productivity and enable input application according to geographic coordinates, the cycle apparently closes – that is, the fundamental cycle of control: reading, analysis, and action, as illustrated in Figure 1.

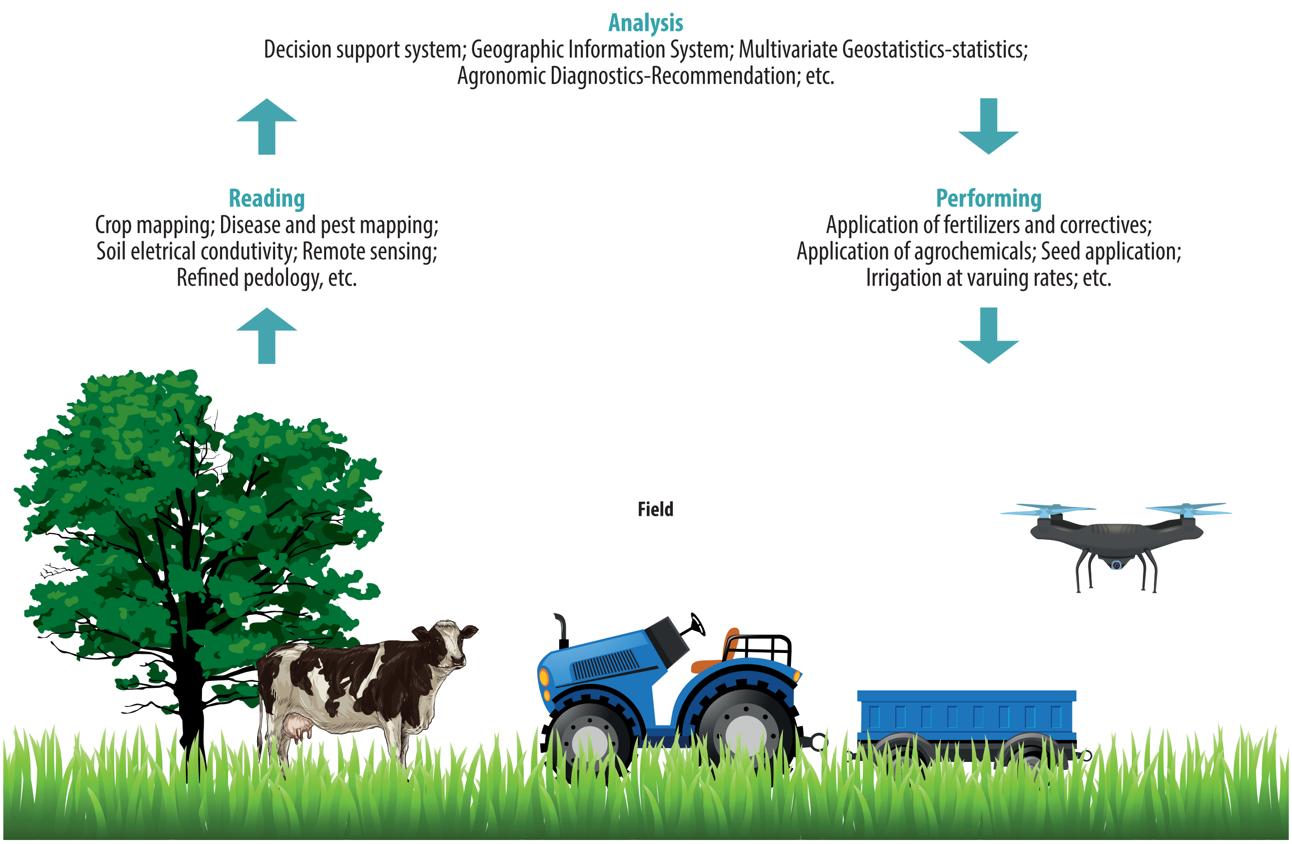


Figure 1. Control cycle used in Precision Agriculture.

It was at this point that PA moved forward, and likely surpassed the "inflated expectation" peak of the Gartner[1] hypercycle, plunging into the "disillusionment" stretch. It was often reported that the machines were being operated in the field with disabled electronic controls.

There were and still are operational problems. The various proprietary formats generated the lack of compatibility of digital systems, both for communication between equipment, such as file and data exchange, are problems recurring operations. But perhaps most important is the fact that the methodologies used in the analysis stage, the "heart" of the control cycle, still being planted in conventional agriculture. The methodologies of Conventional analysis does not take into account the variables that differentiate regions from the farm. The methodologies developed in this chapter, such as those created in onfarm system (procedures by experimentation according to planning inside the farm or on the farm), are an attempt to develop and surprise the absence of this information and methodologies.

[1] Cycle representing maturity, adoption, and social application of specific technologies.

Collecting, storing, and analyzing data in PA

An important part of the PA application cycle is obtaining data and relevant attribute maps that influence the spatial and temporal variability of crop yields. Productivity maps express natural and anthropic soil variations, such as topography, texture, fertility, compaction, and other variations, as well as plants, with responses to the attributes of soil, climate, and crop management.

There are, commercially, many equipment, sensors, techniques, and approaches that can be used to map crop variability in PA (Leroux; Tisseyre, 2019; Molin; Tavares, 2019). The number of information layers will depend on the variability level in the area and the user's interest. However, in general, a suitable approach should include mapping of the soil variability, another mapping of the plants, and at the end of the cycle, a harvest map. For the selection of the most suitable techniques and instruments, the production system, the availability of instrumentation, and the scale or dimension of the plots must be considered.

For soil mapping, the measurement of apparent electrical conductivity (ECa) has proved to be a very useful tool (Corwin; Plant, 2005), as it integrates mineralogical and physical factors such as texture, density, compaction, water retention; chemicals, Cation Exchange Capacity (CEC), and organic matter. Thus, it can identify global soil variability, which can lead to regions of higher (or lower) productivity within the stand. For plant mapping, Vegetation Indices (VI) obtained from satellite images, remotely piloted aircraft (RPA), and active canopy sensors (Lee et al., 2010) make it possible to trace crop vigor, both spatially and temporally (throughout the crop cycle). With these three attributes maps (CEa, IV and productivity) it is possible to establish management zones which can be used for more detailed sampling of additional attributes, such as diseases, pests, and soil compaction. Other variables of great importance in PA are plant nutrients (fertility) and soil texture, which can be obtained in a regular grid or by management zones defined from CEa, IV and productivity maps.

This section presents the procedures and instruments used in data collection in PA, as well as their storage and analysis.

Identification of soil spatial variability

Soil sampling

Soil sampling is an essential procedure in PA, as it enables knowledge on fertility and characteristics that influence productivity. The regular grid procedure is the most used. Therefore, it is recommended that the sampling density be one sample per stand in extensive areas of grain production, for example. In fruit-growing areas, commonly with plots of a few hectares, the sampling density can be a few dozen samples per hectare. Another criterion to be considered is prior knowledge and visual analysis of field variability. In plots with great variability, visually observed and recognized by the producer over the years, the sampling density must be greater than in those where little variability has already been verified. Figure 2A illustrates some real examples of sampling grids, where samples were collected for fertility and soil texture, both in a soil texture system, in soybean-cotton production areas in Mato Grosso (A), and soil potassium maps (B) of these two areas. The plot areas are 110 ha and 200 ha, and the numbers of samples collected were 70 and 135, respectively. That is, both with about 1a sample per hectare and a half. Figure 2B shows the potassium maps of these two areas, obtained by spatial interpolation.

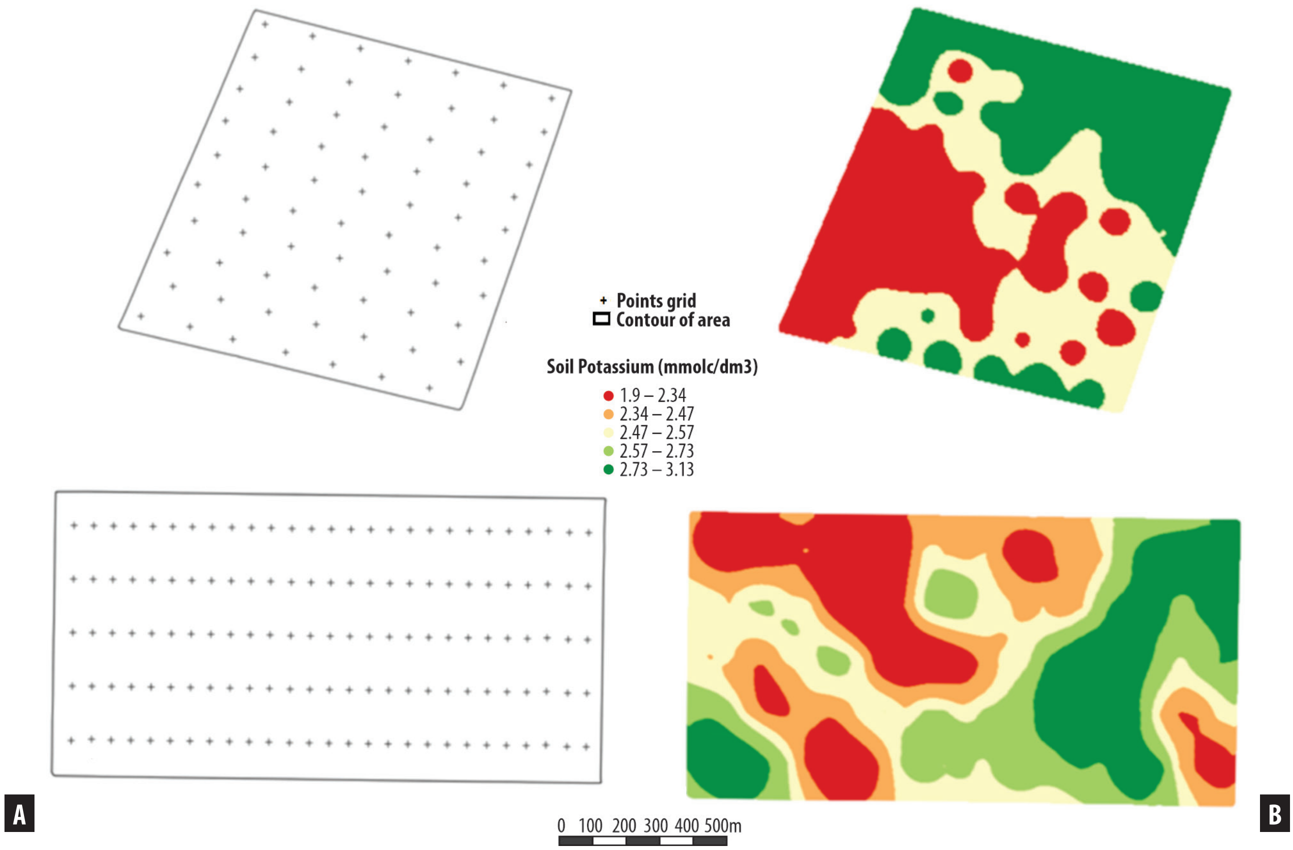


Figure 2. Examples of sample grids in Precision Agriculture, for the determination of fertility attributes and soybean-cotton production, in the municipalities of Pedra Preta, MT, and Sapezal,MT (A) and soil potassium maps (B).

Other important issues considered in PA sampling are related to the equipment used for collection and crop stage. In intensive production systems, where two or three crops are grown in a year, the time intervals between harvesting the first crop and planting the second crop are very short. For the use of quad bikes equipped with soil samplers, the sampling should be carried out after the first harvest (summer) or after the second harvest (winter), avoiding damage to plants when the quad bike is moving in the area. If collection is needed when the crop is in a well-developed phase, manual cutting should be used. In both cases, georeferencing of samples is always necessary. For collection with the quad bike, it is recommended to extract the soil in at least 9 subsamples, in a circle around the georeferenced point, at a depth of 0-20cm. As for sampling with Dutch augers, the number of sub-samples around the point can be reduced to five, since the amount of soil collected per hole is greater.

In the same way as for collecting soil samples, the soil compaction measurement can be done by penetrometers coupled to quad bikes or by manual devices. Equipment coupled to quad bikes are recommended for periods after the summer crop is harvested, since in the winter crop harvest, the soil will have very low moisture, which is inadequate for this type of determination. Figure 3 shows the penetration resistance maps, measured with a manual penetrometer and generated based on spatial interpolation, in plots with cotton crops in the municipality of Pedra Preta, MT, (Figure 3A) and Sapezal, MT, (Figure 3B).

Soil and root sampling for the quantification of phytonematodes should also be carried out during the crop cycle, therefore, the use of quad bike samplers is not recommended, but rather soil treatment and manual collection of roots. Figure 4 shows maps of *Rotylenchulus reniformis* phytonematodes in soil and root, obtained by kriging from 70 samples collected in a soybean production area, in Pedra Preta, MT.

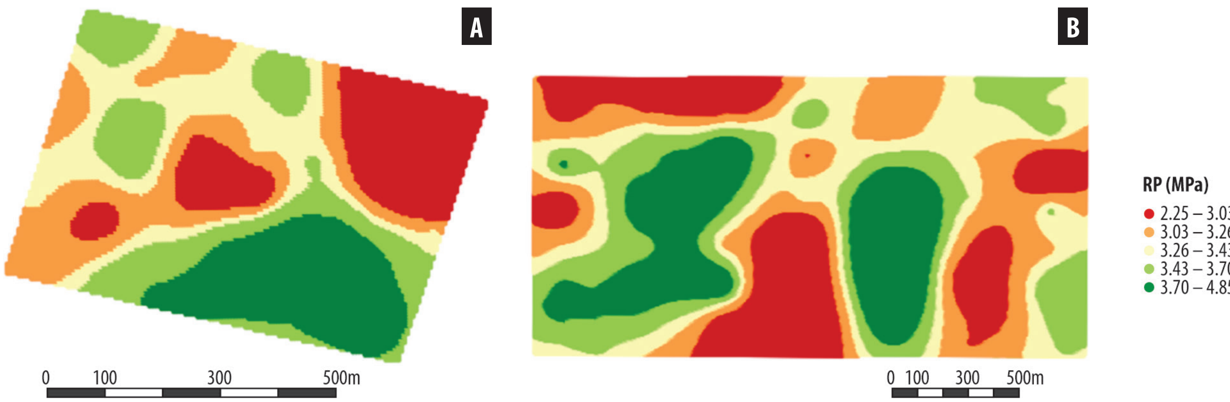


Figure 3. Penetration resistance maps in the 10-40cm layer in cotton planting area in Pedra Preta, MT (A) and Sapezal, MT (B).

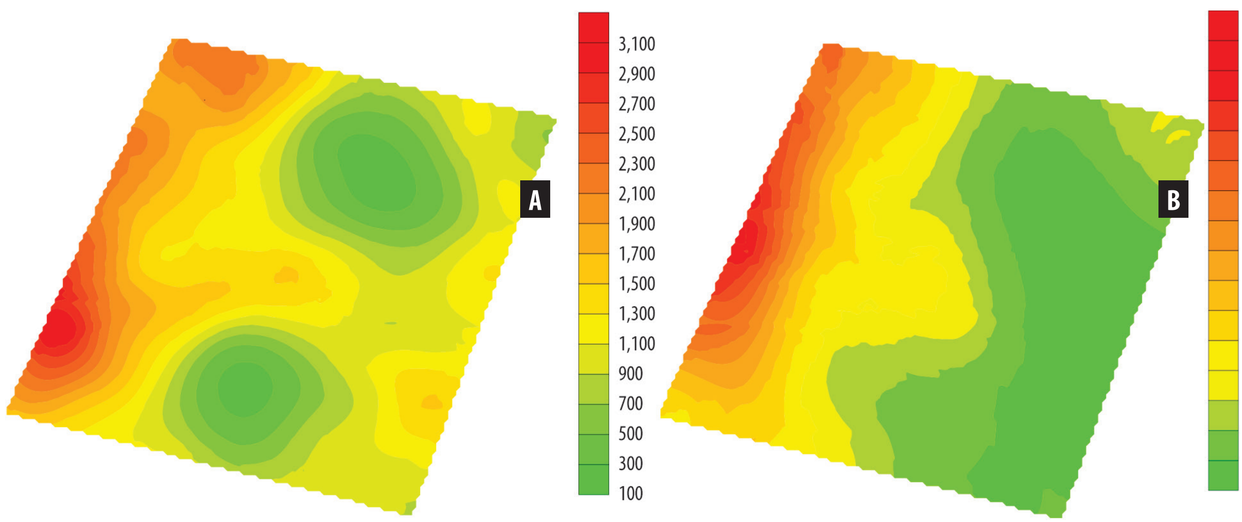


Figure 4. Nematode maps (*Rotylenchulus reniformis*) in soil (A) and in soybean root (B).

Electrical conductivity

Apparent soil electrical conductivity (AEC) is used at field scale to map the spatial variability of numerous edaphic properties, such as texture, salt concentration, and moisture. This tool is faster, more reliable, and easier to use compared to other techniques, and it is often correlated with crop yields. Therefore, it is widely used in PA research for the spatiotemporal characterization of edaphic and anthropogenic properties that influence crop productivity. AEC measurements are usually obtained from the method known as the four-point system (Smtis, 1958), which consists of using four metal electrodes sequentially aligned with known spacing (Figure 5).

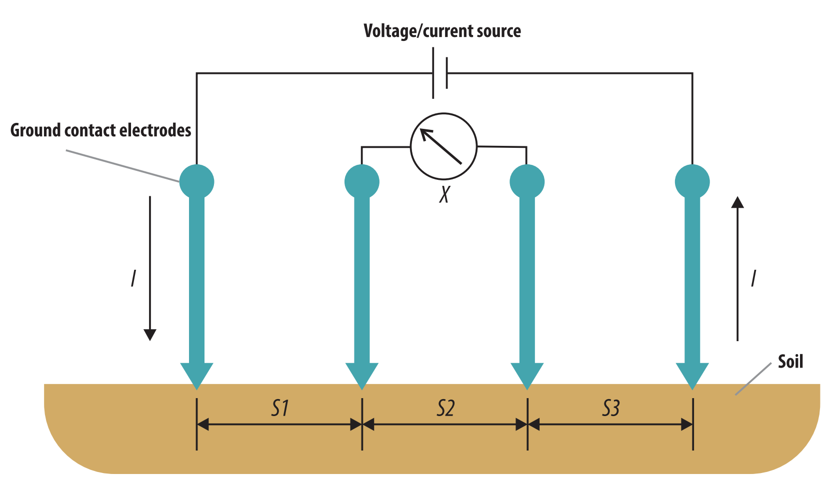


Figure 5. Four-point system for measuring apparent soil electrical conductivity.

Source: Rabello et al. (2014).

The market has systems that have already been developed for measuring AEC with the traditional four-point system and the magnetic induction system, both manufactured abroad. Embrapa has also developed an AEC measurement system based on the four-point system.

AEC provides high density data, enabling a quick overview of the area that allows dividing it into homogeneous regions, facilitating its interpretation and, consequently, management decision-making.

Identification of crop spatial variability

Productivity mapping

To analyze spatial variability of productivity using PA, a set of production values is registered in geographic coordinates and stored by the device during harvesting. System integration is conceptually simple. It consists of a mass sensor, a GNSS receiver, and a data logging system. The first system appeared in a grain harvester. Currently, a force sensor board (similar to electronic scales) located where the grains are loaded by elevators is used for mass measurement. The greater the grain flow, the greater the impact on the board. These values are accumulated in memory and, for each coordinate sent by the GNSS receiver, the accumulated values are integrated and recorded. Each manufacturer records this differently, and there is no standard. However, all of them store at least the geographic coordinate, the time, and the mass value. The force sensor is like an electronic scale and must be calibrated frequently. Some current harvester models perform self-calibration, but this process is commonly performed at each harvest.

Since each manufacturer has developed their own processes, many applications and file formats are proprietary. There are standardization efforts, and it is hoped that incompatibility between systems will no longer be a problem for the producer. There are difficulties in the field. In harvests carried out in fleets, which are common in exporting regions such as the Cerrado biome, the data composition is not possible if one or more machines do not have mapping capacity. The whole process hinders visualizing the production. Therefore, PA harvesting requires attention and, above all, dedication. In the case of the first crop harvest, this operation is tense, caused by waiting until grain moisture has reached the correct point, with the possibility of rain interrupting the operation (harvesting occurs in the middle of the rainy season), and the need to prepare the area to plant the following crop.

It should be noted that if the planting does not take place at the best time/moment, the crop will not express maximum productivity. There are other important factors to achieve differentiated productivity, but it is important to emphasize that the window of opportunity is narrow and time management is directly related to the efficiency of the crop. Therefore, it is understandable that a machine calibration operation may not be a priority for the vast majority of producers, especially in reduced, efficient and lean teams.

The first crops in which machine yield measurement took place commercially were grains such as corn, soybeans, and wheat. They are large machines. In addition to grains, coffee, and cotton also have harvesters capable of recording productivity – noting that, in the case of cotton, these are not impact sensors and are based on radars using infrared signals, and more recently, microwaves. For sugarcane, productivity sensors in machines are not yet commercial successes, since it is challenging and complex to measure this crop automatically. This is due to the difficulty in developing sensors that can accurately identify the biomass flow. In crop cultivars that do not have harvesting machines with a production sensor, maps have been obtained through sampling, similar to soil sampling. A collection protocol with the coordinates of each sample and its weighing is needed, and spatial dependence is also required to enable a precise interpolation process. Some academic works can be found, but not in the sugarcane crop, they are not yet available in the market. Camera sensing and 3D reconstruction are considered to be promising (Santos et al., 2017).

Pre-processing is essential for correct interpretation once harvest data are obtained. Figure 6 illustrates, in a geographic information system, actual cotton harvest productivity data collected from a machine. Each point illustrates the coordinate and the collected value, grouped into four classes, ranging from red (low production) to orange, light green and more intense green (maximum production). The first four Figures 6A, 6B, 6C and 6D, come from four different files, either collected from different machines or performed at different times; Figure 6E illustrates the composition of the four files in one. Harvesting is carried out interspersing planting lines. There is an interruption during the harvesting process, and maneuvering and displacement may also occur. In these cases, if the operator keeps the registration system turned on, there is zero productivity registration, so it is important to exclude these points.

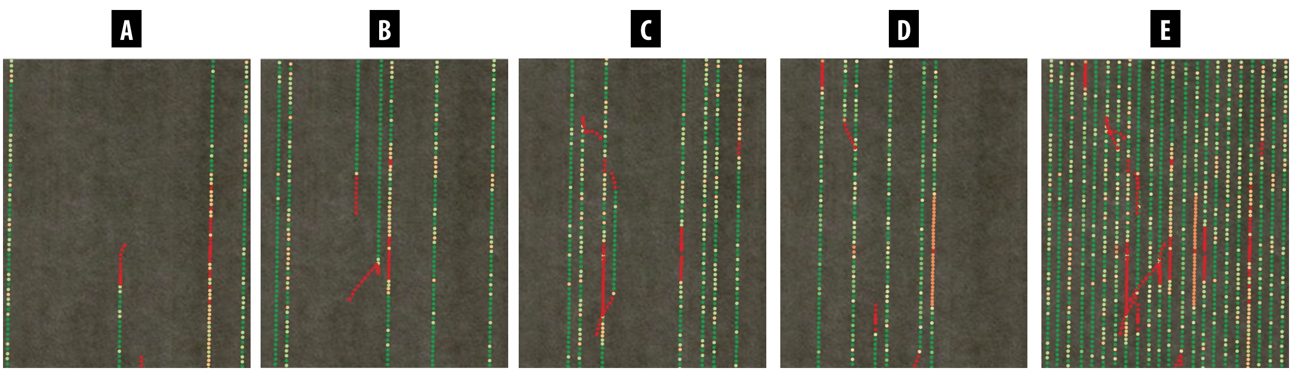


Figure 6. Illustration of harvest data (A, B, C, D) and its composition (E).

Proximal sensing

Various types of sensors have been developed for the acquisition of soil and plant monitoring data allowing efficient data generation a lower cost. These provide reliable estimates of crop development and improve the estimation of production potential. For the vegetative monitoring of plants, the vegetative indices (IV) NDVI and NDRE (Red Edge with normalized difference) can be obtained by reflectance sensors, such as Crop Circle® (Holland Scientific, Lincoln, USA).

Light Detection and Ranging (LiDAR) technology is a proximal remote sensing methodology based on optical concepts. The main objective is to identify distances to a target object, which are determined by time differences between the emission of a laser pulse to a target object and the detection of the signal reflected by that object (Reutebuch et al., 2005). Using a LiDAR sensor allows to quickly and accurately reconstruct three-dimension objects, which makes this technology feasible in various agricultural activities carried out by land implements equipped with automation. In PA, LiDAR sensors can be embedded in spray implements, together with reflectance sensors, for plant height detection and online application of growth regulators (Figure 7).

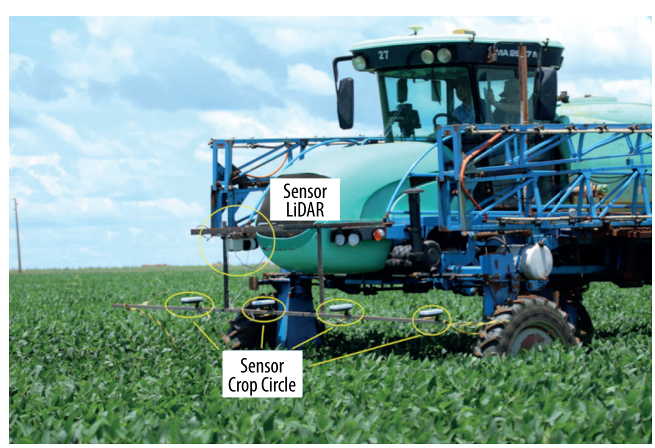


Photo: Ricardo Yassushi Inamasu

Figure 7. Use of LiDAR sensor in conjunction with Crop Circle® reflectance sensors, embedded in an implement for plant height detection.

Suborbital and remote sensing

Sensors with free images, available from the internet, with spatial resolutions between 10 m and 30 m, and temporal resolutions between 5 and 15 days, such as Sentinel-2/MSI and LandSat-8/OLI, can support various PA activities, mainly in more extensive plots. In Brazilian agriculture, these areas are concentrated in sugarcane and grain producing regions. For these regions, remote sensing can analyze stand spatial variability based on vegetation indices (VI), which can be obtained by combining the bands in the visible and infrared spectrum.

Analyses on biomass presence can be performed with VImaps obtained from combinations with infrared spectrum bands. Through these indices, it is possible to establish correlations with the availability of nitrogen and other nutrients in plants, monitor the evolution of crop growth, and perform productivity estimates in different regions within the same field (Candiago et al., 2015). The presence of water in plants can also be spatially assessed using index maps that combine visible spectrum bands with short-wave infrared spectrum bands, such as the Normalized Difference Water Index (NDWI) (Zhang et al., 2019). Combined with data related to soil variability and crop yield, VIs can be important for area subdivision strategies for specialized treatments, such as the design of management zones (Figure 8) and on-farm experimentation.

Remote sensing images with spatial resolutions below 10 m are not yet available for free. However, the need to obtain more accurate data for PA activities, which allow, for example, identifying pests, diseases, and the presence of invasive plants, and to estimate productivity, increased the use of multi and hyperspectral cameras onboard remotely piloted aircraft (RPA). The use of such devices has intensified in recent years (Jorge; Inamasu, 2014) due to the falling cost of this technology, gradually increasing its acceptance by producers.

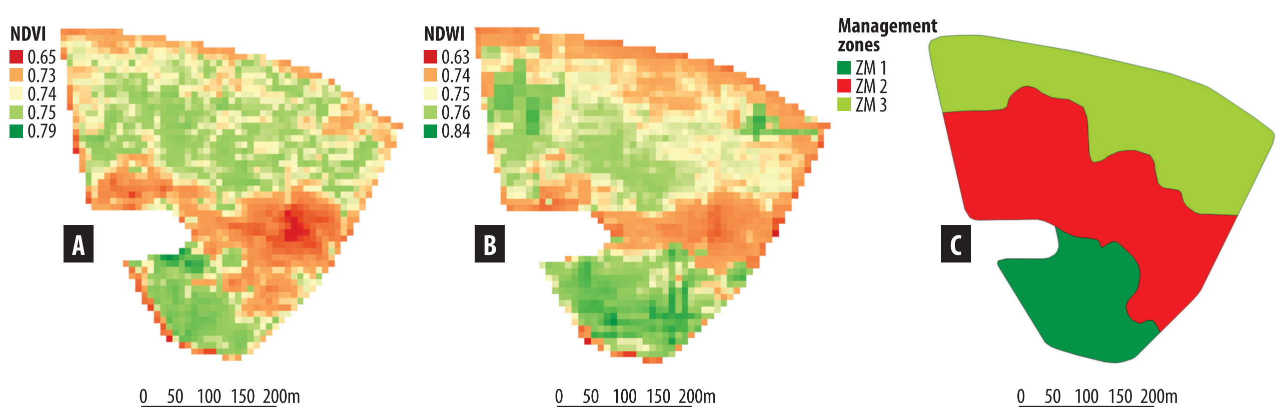


Figure 8. Sugarcane area maps: NDVI (A) and NDWI (B) composition from Sentinel-2/MSI satellite images between February and May 2017; also, management zones map (ZM) (C) from soil and crop attributes between 2012 and 2016.

In addition to reducing costs, the use of RPA in PA also gives the producer the advantage of planning the data collection time, thus avoiding problems with rainy days or high incidence of clouds that often occur with satellite data. Another important factor is the possibility of planning the height of the flight, which allows obtaining images with different spatial resolutions using the same camera. This allows to identify, for example, planting failures that remote sensing images cannot capture (Figure 9). RPAs that include performance functions also allow the producer to apply agricultural inputs and correctives in a localized manner, making them an interesting alternative to the conventional automation performed by traditional agricultural implements (Mogili; Deepak, 2018). However, the operationalization of RPA still needs to be performed by professionals specialized in most applications. Another negative point is the autonomy and imaging capacity of the equipment. A single RPA has the ability to generate images covering a few hundred hectares in a single day, images that must later be processed by high-performance computers in order to generate mosaics.

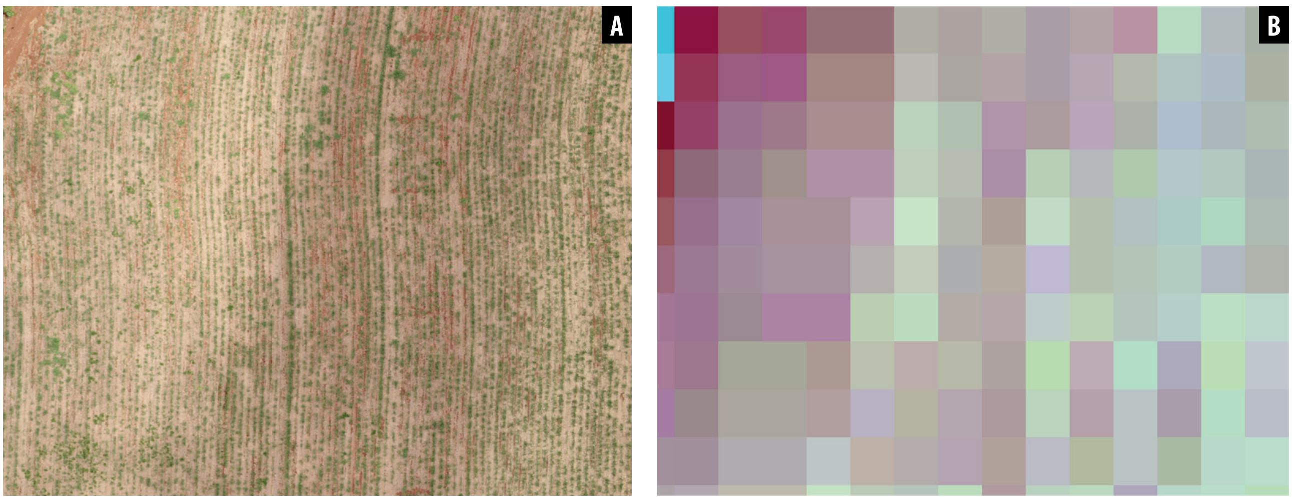


Figure 9. Example of cut-out images, with a sugarcane stand with an area of about 120 m × 120 m taken in October 2019 using: RPA with embedded camera, with a spatial resolution of 2 cm/pixel (A); and Sentinel-2/MSI satellite, with a 10 m/pixel resolution and cloud incidence (B).

Following the evolution of RPAs and multispectral cameras, aerospace technology private companies have placed satellites and, more recently, constellations of nanosatellites equipped with sensors capable of capturing images with a spatial resolution below 1 m, into orbit. The current market allows producer associations to different platforms for accessing these images, already in the form of ready-to-use products, usually at a high cost. However, unlike what happens with ARPs, it is possible to obtain images that cover large areas in one day. In summary, both satellite images with submetric spatial resolution and images captured by RPAs still require investments by the producer, which must make up a cost-benefit relationship, which depends on the application. In this relationship, issues such as the time when one wants to obtain the images and the need for spatial resolutions must be taken into account.

Cloud data storage

Embrapa's PA Network (Rede PA) is committed to raising awareness among researchers and partners in order to encourage the sharing of final data produced in their research. Thus, the GeoNode tool[2], a free and open-source software, was evaluated and adapted to absorb the specific requirements of the community, providing the development of a new version of the PA Network data repository[3]. Metadata cataloging is the main functionality of the repository to ensure data integrity over time. Based on the metadata, it is possible to verify authorship data, the equipment and methodologies used, the environmental conditions, and the difficulties encountered during data collection. This information is an important input for future reuse and analysis for any given dataset.

[2] Available at: http://geonode.org

[3] Available at: http ://www.redeap.cnptia.embrapa

Data analysis in PA

Data mining and pattern extraction

Computational techniques for data mining are extremely important for the data analysis process. The main objective of these techniques are to discover patterns in databases using tools made available by the use of artificial intelligence, machine learning, and statistics (Majumdar et al., 2017). In this context, unsupervised (grouping) and supervised (classification) learning methods are normally considered.

In PA, there is a growing popularization of algorithms derived from clustering and classification methods used for different analyses based on the data. Classifiers such as artificial and convolutional neural networks are used for the semi-automatic identification of various events that occur in crops, such as planting failures and the appearance of pests and invasive plants, based on images (Tang et al., 2017). The productivity of a crop can also be estimated from regressors and vegetation multispectral data (Al-Gaadi et al., 2016). Grouping methods, on the other hand, are fundamentally used for the subdivision of cultivated areas into regions with similar productive potential, known as management zones (Luchiari Júnior et al., 2000).

Regardless of the method used, this pattern extraction analysis is part of a broader process known as Knowledge Discovery in Databases (KDD). Thus, previous steps, such as filtering, cleaning, normalizing the data; as well as subsequent ones, such as the statistical validation of applied models must be performed before and after the use of data mining methods. The more complete the KDD process used to analyze the data, the greater the chance of obtaining more accurate and reality-consistent results.

Filtering tools and data cleaning

By means of data filtering and cleaning tools, data samples obtained in the field with positioning errors or associated outliers can be eliminated from the data set in order to be analyzed, thus avoiding interpretation errors in later steps. In PA, the greatest concern is with the productivity data obtained by harvesters, due to their high sampling density and the diversity of manufacturers. Thus, algorithms and software based on statistical methodologies and variability parameters informed by the user can be used for this task (Sudduth; Drummond, 2007; Vega et al., 2019). In addition to productivity data, any other dataset from proximal sensing subject to collection errors must go through this cleaning and filtering step before being used in the data-mining step.

Geostatistics and spatial interpolation

Geostatistical analyses applied to PA are essential to ensure better accuracy in the mapping of interpolated data. According to Vieira (2000), Geostatistics is a tool set that allows to analyze the degree of spatial dependence of varying data in space, whether in thousands of hectares or in a small plot, such as an experimental 30x30m-plot, as shown in Grego and Vieira (2005).

Geostatistics assumes that the greater the number of samples, the better the representation of the real spatial variability expressed by the tool. However, it is known that, in practice, it is necessary to meet the needs of the user, mainly considering available resources, labor, and operational time for sampling. To assist in this step, it is possible to use historical information about the area and data obtained from sensors and satellite images, thus optimizing the number of samples.

With the georeferenced data, an investigation is carried out as to the existence or not of spatial dependence, and, if so, it is possible to interpolate data by kriging, which guarantees minimum variance and non-bias in the interpolated values. The result is based on accurate maps in which spatial variability patches are observed, these can be correlated to form a spatial information platform during crop cycles. This mapping, as detailed in Bernardi et al. (2014), helps to identify differentiated management zones for localized application of inputs.

Outlining management zones

Under PA, activities like planting, interventions such as the application of inputs and irrigation can be uniformly managed, based on the delimitation of sub-areas known as management zones (MZ). A MZ can be defined as a portion of land that is stable over time, where the production potential, the efficiency of input use and the risk of environmental impact are essentially uniform (Doerge, 1999; Luchiari Júnior et al., 2000). In order to obtain MZs with these characteristics, the main prerequisite is using non-anthropogenic attributes related to the genesis and culture (Molin et al., 2015). Thus, factors such as relief, electrical conductivity, texture, physical attributes of the soil, biomass indices, and historical productivity must be used to support the delineation of ZMs (Kitchen et al., 2005; Li et al., 2007; Scudiero et al., 2013).

It is now possible to generate ZM maps by combining numerous datasets and machine learning algorithms, offering the producer greater precision and confidence. Due to the current high availability of data, it is necessary to adapt these algorithms so they can handle massive data sets and make the most of the computational processing capacity available in the environment in which they are executed. Despite this need, these efforts are at an embryonic stage.

On-farm experiments, spatial correlation, and recommendations

The on-farm experiment consists of defining virtual plots within an experimental cultivation area in order to evaluate different application rates with repetitions in interventions such as planting (population), nitrogen fertilization, and growth regulators. The plot procedures must be carried out according to the producer's planning and with the available agricultural implements – hence the use of the term on-farm (or on the farm) (Shiratsuchi et al., 2014). The experiments must be carried out for a few seasons, so when considering the crop yield as the final result, it is possible to establish adequate and spatially differentiated recommendations for population and input doses. Intervention recommendations can be obtained based on the use of spatial correlation analysis tools. In PA, the determination coefficient (Nagelkerke, 1991) is a result of a linear regression model that allows identifying the correlation and trend values (Figure 10).

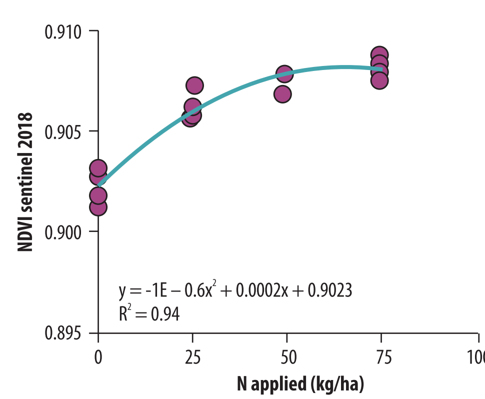


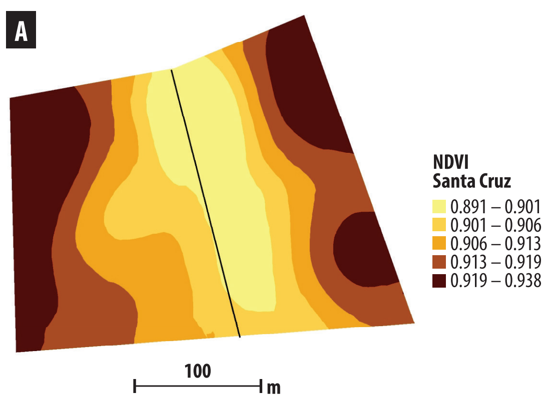
Figure 10. Example of correlation coefficient R^2, obtained from averages of NDVI and nitrogen (N) values, applied in on-farm experimental plots.

The correlation measures between attributes are an important support for establishing recommendations in areas with specific characteristics. In soil homogeneous areas free from pests, for example, it is possible to infer adequate nitrogen rates that should be applied until reaching a maximum yield threshold for the crop under those conditions.

Practical applications in precision agriculture

Characterization of the spatial variability in southern Minas Gerais specialty coffee production systems

In order to spatially assess the representative areas of Arabica coffee (*Coffea arabica*) production, which is classified as special in southern Minas Gerais, Rodrigues et al. (2019a) used the vegetative and chlorophyll indices to identify the existence of spatial variability for the application of Precision Coffee Growing. In the 2017 post-flowering period, data related to biomass, chlorophyll, and plant altitude were collected in two farms in southern Minas Gerais. The occurrence of spatial variability was observed, and at Fazenda Santa Cruz, an inverse relationship was observed between altitude and NDVI, with the highest NDVI values found in the lower areas of the field. These facts indicate that management techniques must be carried out due to this variability. At the Morro Alto Farm, the right-side sun exposure was more uniform (Figure 11).



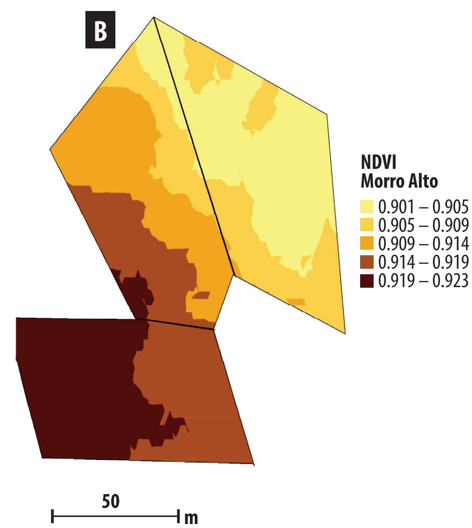


Figure 11. Ordinary kriging interpolated value maps for NDVI data from Santa Cruz (A) and Morro Alto (B) coffee farms.

Source: Rodrigues et al. (2019b).

In order to define which of the variables were able to assist in the delineation of the MZ in this study, Speranza et al. (2019a) correlated maps of ZM potentials with sun exposure maps in each area, allowing a differentiation of the coffee's quality. There was high correlation of sun exposure faces with the IRC index, and a better overall performance of the NDRE index in relation to the NDVI for this context. This difference can be explained by the fact that data were collected at the beginning of the reproductive period, right after flowering, when there was a mixture of fully expanded leaves and others with initial vegetative growth. Both Rodrigues et al. (2019b) and Speranza et al. (2019a) emphasize that the spatial responses of coffee in relation to vegetation and chlorophyll indices will be complemented in planned future analyses, considering the different phenological phases of the coffee tree. Productivity and beverage quality maps will also be generated and correlated with biophysical and microclimatic variables.

Spatial and spectral behavior in sugarcane and its correlation to soil electrical conductivity

Vegetation indices (VI), obtained from satellite images, are powerful tools that for years have been monitoring and providing near real-time information on agricultural crops, especially sugarcane. Soil AEC presents similar spatial behavior with VIs obtained both by remote sensing (Rodrigues et al., 2019a), by proximal and suborbital sensing (Speranza et al., 2019b), and also by sugarcane production (Sanches et al., 2019). In this context, Embrapa's Precision Agriculture Network, through a partnership with Usina Santa Cruz, belonging to the São Martinho group, develops on-farm experiments within a 15.7-hectare sugarcane plot (Grego et al., 2019; Rodrigues; Rodrigues et al., 2019a). Through geostatistics and machine learning algorithms, two simplified management zones (Mzs) were identified for the area, which reflect the soil texture: MZ 1 – clayiest area (55% of the area), in the lowest part, on the west side of the stand, but with greater variability in relation to AEC; and MZ 2 – sandy area (45%), in the highest part, on the east side of the stand and with less variability in relation to AEC (Figure 12). The difference between MZ 1 and MZ 2 for TCH was approximately 16 t/ha.

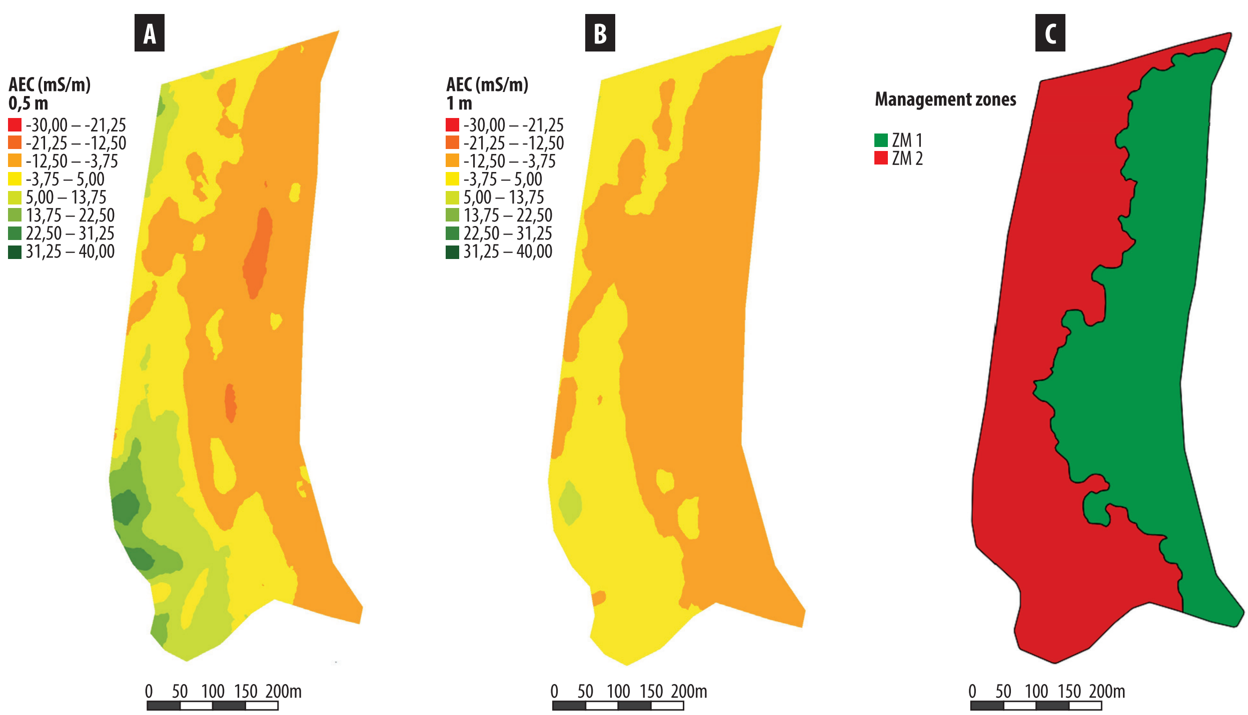


Figure 12. Apparent Electrical Conductivity (AEC) in two coil spacings: 0.5 m (A), and 1 m (B); delineated management zones (ZM 1 and ZM 2) (C).

Source: Adapted from Speranza et al. (2019b).

The MZ design for this area (Figure 12C) allowed programming more dense soil samples in MZ 1, with greater soil variability; and less density in MZ 2, with less soil variability, supporting the definition of onfarm experimentation. Measuring the AEC of the soil indirectly optimizes the spatial sampling of cultivated areas, promoting savings in the amount of collections and costs for soil analysis.

To correlate AEC to VIs from remote sensing images, 18 images were collected from the study area, between March 2018 (planting month) and July 2019, from the MSI/Sentinel-2A and 2B sensor. The results indicated a significant correlation between soil AEC (0.5 m and 1.0 m) and the VIs for most of the evaluated dates. The correlation between the VIs and AEC variables was positive from March to September 2018, that is, the VIs tended to move in the same relative direction (but not necessarily at a constant rate) until approximately 223 days after planting. From that period until the final date of sugarcane harvesting, the correlation was negative (Figure 13). There was similarity in spatial behavior and correlation values with the soil vegetation and AEC indices. Therefore, soil AEC can be an indicator for different managements in the same sugarcane crop.

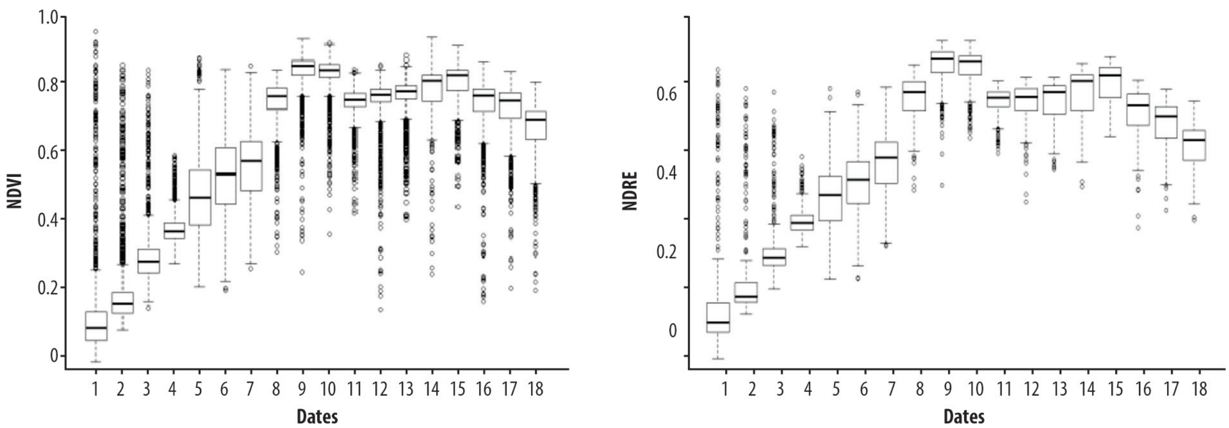


Figure 13. Boxplot of NDVI and NDre2 values on 18 observation dates of VIs in a sugarcane plantation in Ibaté, SP.

Source: Rodrigues et al. (2019a).

PA technologies in fiber and grain management systems in the state of Mato Grosso

The cotton-growing regions in the west and southeast of Mato Grosso are those that most use instruments: light bar, automatic pilot, and section control (sprinklers and seeders). The most used implements are the autopilot (61%) and the sprayer section control (58%). The average rate of PA instrumentalized techniques in this state is 42%, with the highest rate (54%) in the west region. The western region is also above average in the use of other management instruments under the PA approach. In it, 51% use fertility maps, 22% harvest maps, 27% maps of pests, diseases and invasive plants, 49% use variable rate application, and 49% applications use management zones.

Due to the large amount of equipment, there is an urgent concern to continuously train the field workforce in activities such as regulation, preventive, and corrective maintenance, machinery technology, and agricultural operations. After training, the mid-northern region of the state had the highest rate in efficiency (81%), compared to the average rate of 71% for the entire state. The study points out that most properties in the state use some of the PA techniques, however the lack of qualified labor not only for field operations, but also for data analysis represents a limitation for the maintenance and growth of this management approach.

Another important point refers to the systematic collection and storage of physicochemical soil analysis associated with stand productivity for soil management effectiveness. In Figure 14, the high correlation of CTC and organic matter, at both depths, reflects the importance of applying fertilizers in order to avoid sudden pH changes, which sometimes require higher doses of lime (Ronquim, 2010).

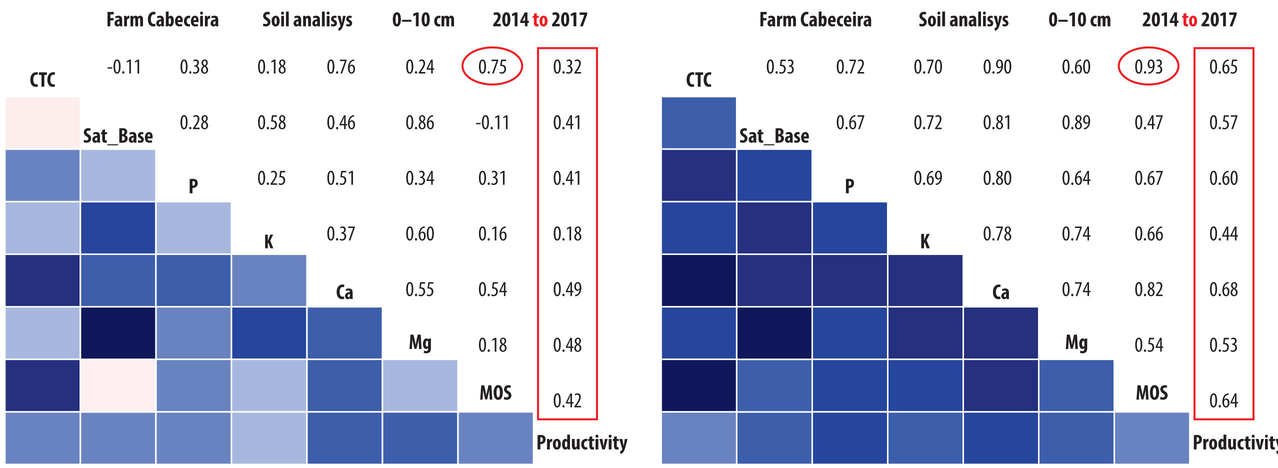


Figure 14. Correlation matrix of soil variables at depth of 0–10 cm (A) and 10–20 cm (B) in a property located in the north of Mato Grosso state.

As a way of optimizing the chemical control used for identification of weeds there is the use of processed images of ARPs, which allow specific use in areas with infestation of invasive plants (Figure 15). The use of herbicide application maps significantly reduces the number of shares, directly impacting the reduction of the cost of culture production.

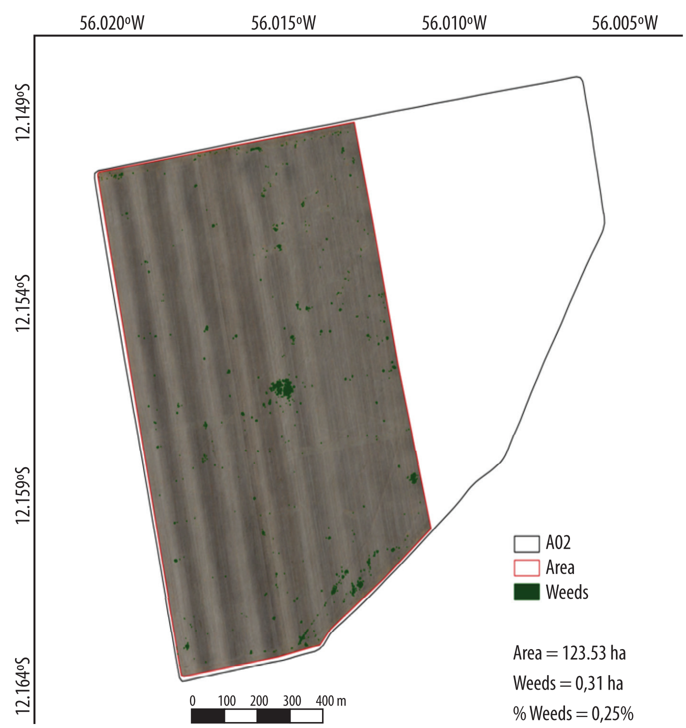


Figure 15. Processed ARP image for identification and geolocation of volunteer corn and bitter grass on a property located in northern Mato Grosso.

Despite having high-performance machines equipped with automatic pilot, managing variability for grain and fiber crops is not common. Flat areas have spatial variability that does not encourage producers to apply Precision Agriculture. Another factor that discourages producers relates to machine versions and models. In this region, two plantings are interspersed in a year. In the case of cotton, soybean is the crop used in the rotation. Each plot has an average size of 200 hectares. Soybean harvesting is carried out with a fleet of machines, and not all have a harvest monitor, therefore, maps are incomplete. This is not the case with cotton, where, due to good economic returns, it is possible to find similar models during harvest, allowing acquiring complete maps.

In 2018, Embrapa's Precision Agriculture Network began a partnership with the Instituto Mato-grossense do Algodão (IMAmt) for research in four large producer experimental plots in the municipalities of Sapezal and Rondonópolis, in the state of Mato Grosso. The 2018 and 2019 cotton crops were monitored by obtaining AEC, soil texture, fertility, phytonematode distribution; and productivity maps, IR maps came from remote and suborbital sensing. Currently, three of the four studied plots have adopted the on farm experimentation process, where it is now possible to visualize responses in relation to the application of different doses of nitrogen fertilization in the virtual plots (Figure 16).

The collected data are corrected, filtered, and made available in the cloud for access and analysis by the Embrapa and IMAmt work teams, as well as by the producers. Although the recommendations are applied in specific experimental plots, they can be extended to plots with similar characteristics, increasing the adoption of PA by producers in the region.

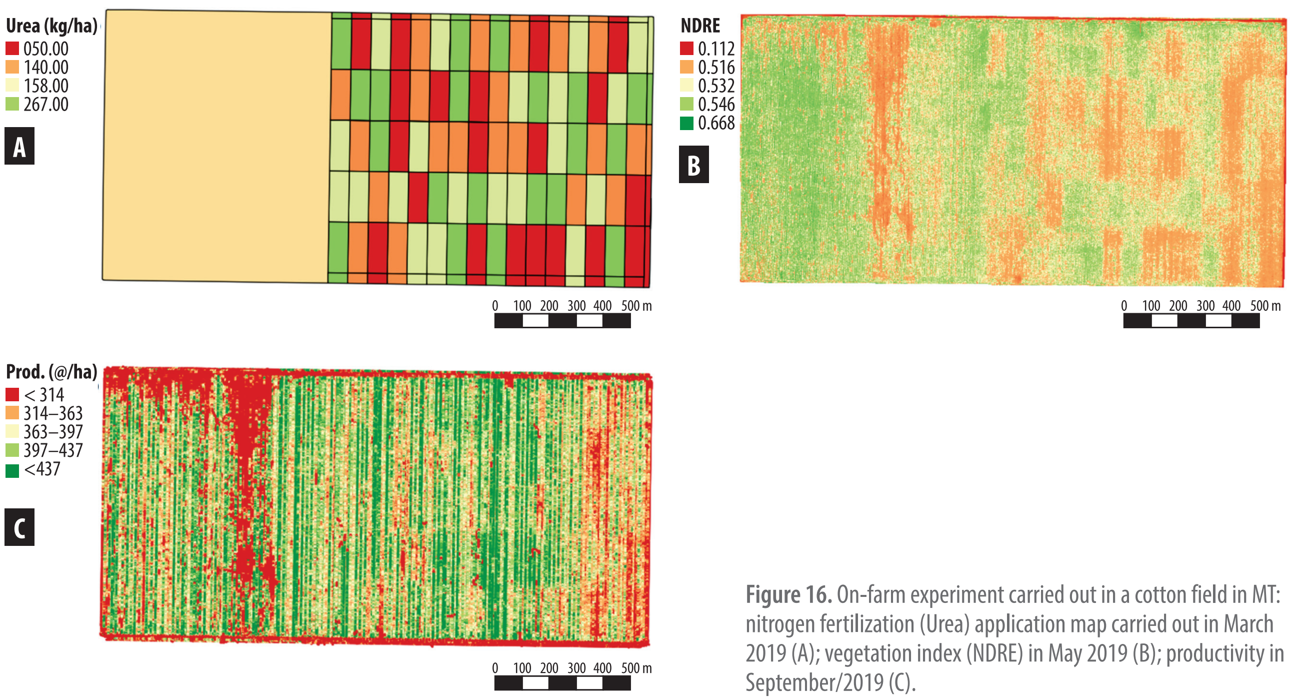


Figure 16. On-farm experiment carried out in a cotton field in MT: nitrogen fertilization (Urea) application map carried out in March 2019 (A); vegetation index (NDRE) in May 2019 (B); productivity in September/2019 (C).

RPA applications in different crops

The applications of RPAs in agriculture have increased with the advancement of technology and available sensors, highlighting the estimation of biomass and productivity, nutritional assessment, pest and disease detection, assessment of plant water requirement, and soil mapping with RGB, multispectral, hyperspectral, LIDAR, and thermal sensors, among others (Hatfield et al., 2008; d'Oliveira et al., 2020). By assessing reflectance values in certain regions of the electromagnetic spectrum it is possible to observe differences between plants and soil and between healthy green vegetation and vegetation with nutritional and water deficiency or attacked by pests and diseases (Jorge; Inamasu, 2014).

Some of the most prominent applications are the monitoring of plant vigor with vegetation indices, studies for nitrogen fertilization using RPAs equipped with sensors, the use of multispectral aerial images to assess the spatial variability of soil and biomass, as well as the cotton, soybean, and corn yield estimates. Also with the data obtained by RPAs equipped with image sensors and LiDAR, studies for plant counting stand out. Figure 17 shows an area of citrus with automatic counting by deep learning techniques, described by Osco et al. (2020a). Figure 18 shows the height determination of cotton plants by LIDAR in a Lidar-equipped RPA to develop a growth regulator application methodology.

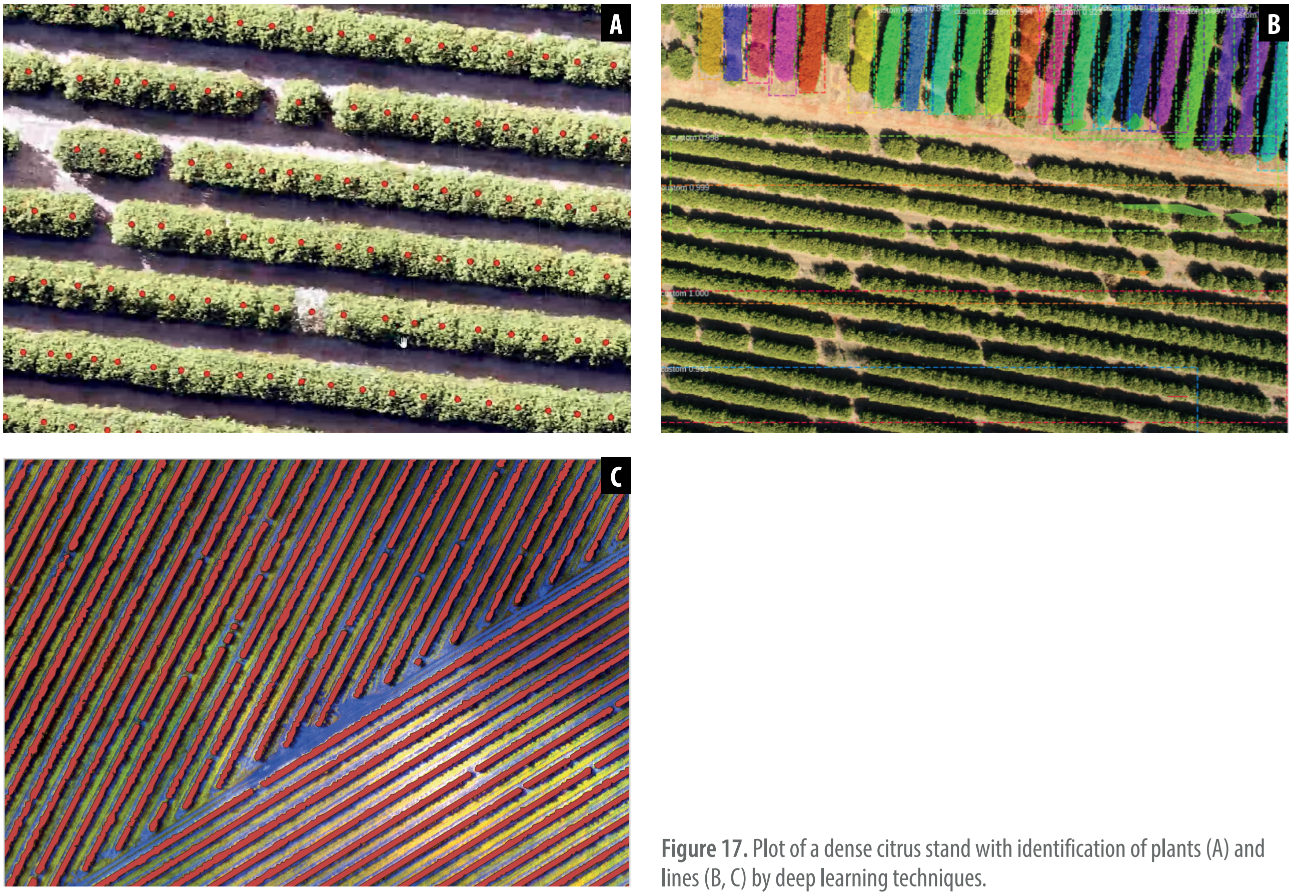


Figure 17. Plot of a dense citrus stand with identification of plants (A) and lines (B, C) by deep learning techniques.

Photo: Lucio André de Castro Jorge

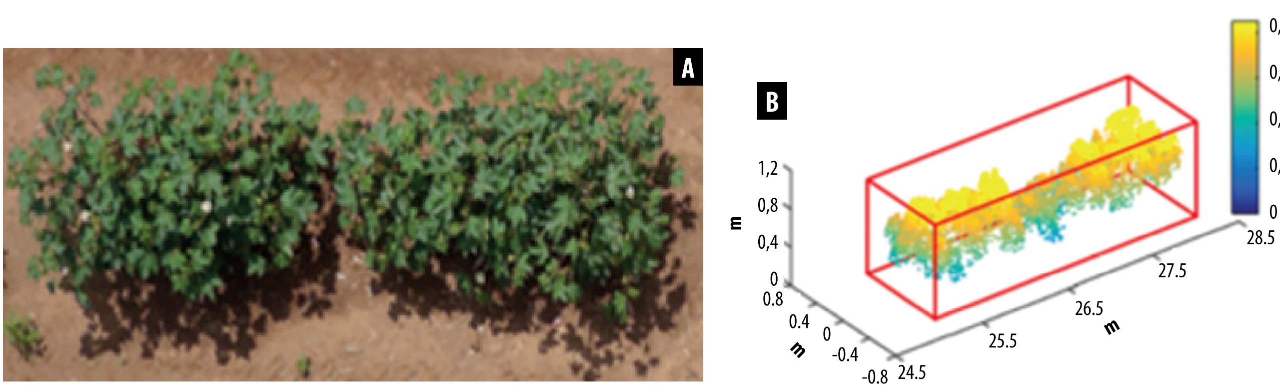


Figure 18. RPA image (A) and LIDAR point cloud (B).

Source: Adapted from Sun et al. (2018).

Sensor-equipped RPAs have evolved considerably and have enabled to study spectral crop signature based on hyperspectra, as in Figure 19A, while assessing the presence of pests in the crop right at the beginning of the infestation (Osco et al., 2020b). Figure 19B shows the result of the hyperspectral analysis when pod caterpillars (*Spodoptera eridania*) occur in the first few hours.

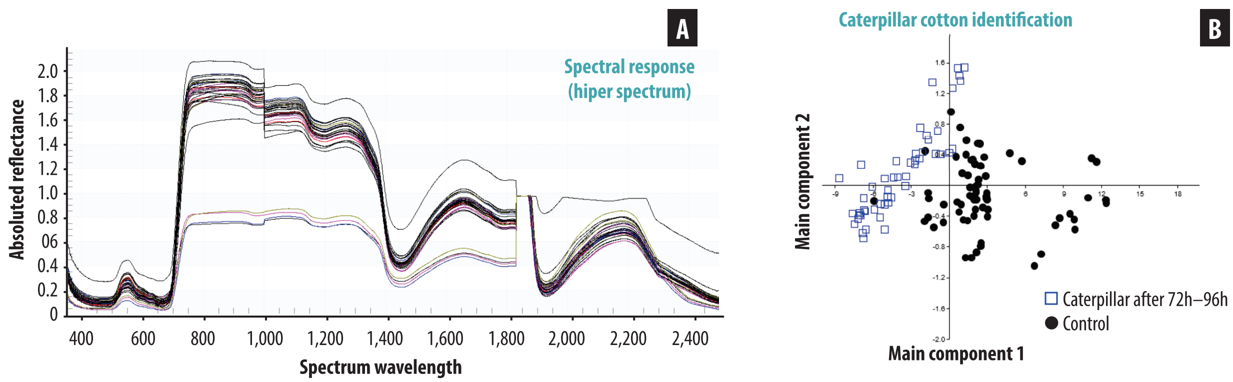


Figure 19. Pixel-by-pixel Hyperspectral RPA images (A) and hyperspectral analysis when pod caterpillars (*Spodoptera eridania*) occur in the first hours (B).

Final considerations

In summary, as regards PA, it is important to understand that crops are not uniform and, therefore, the spatial variability must be considered so that the producer has economic and environmental return on his property.

PA has advanced and exceeded expectations mainly in the use of field-operated machines. However, there are still operational problems due to the lack of digital system compatibility, both for communication between equipment and for exchanging files and data, rendering it still an operational challenge.

An important part of the PA application cycle is the stage of obtaining, storing, and analyzing relevant attribute data and maps that influence the spatial and temporal variability of crop productivity.

Yield maps express natural and anthropogenic soil variations. Various types of terrestrial, orbital, and suborbital sensors have been used to assist in the acquisition of soil and plant monitoring data, allowing efficient and low cost data generation, while providing reliable crop estimates to improve the production potential.

All these advances presented in this chapter lead to current agriculture innovations for detailed spatial management of the agricultural production system, in order to maximize economic returns and reduce environmental impacts.

The methodologies and results presented in this work were developed with the collaboration of several Embrapa Research Units, the management and technical teams of several partners such as the Gatto, 3D Engenharia, Amaggi, Scheffer, Sementes Petrovina, Sugarcane Plant Santa Cruz, Santa Cruz coffee farms and Morro Alto farm groups. In addition, we emphasize the technical field support of the Instituto Matogrossense do Algodão (IMAmt) and of the agronomist Guy Carvalho.

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