eISSN: 1984-3909
Coffee Science, e172007, 2022

Doi: https://doi.org/10.25186/.v17i.2007

REVIEW

Precision coffee growing: A review

Lucas Santos Santana[1], Gabriel Araújo e Silva Ferraz[1], Sthéfany Airane dos Santos[1], Jessica Ellen Lima Dias[2]

[1]Universidade Federal de Lavras/UFLA, Departamento de Engenharia Agrícola, Lavras, MG, Brasil
[2]Faculty of Agricultural and Life Sciences/MKK, Szent Istvan University SZIE, Gödöllő, Condado de Peste, Hungary
Corresponding authors: lucas.unemat@hotmail.com; gabriel.ferraz@ufla.br; thethsantos@hotmail.com; jessicaeldias@gmail.com
Received in January 24, 2022 and approved in May 31, 2022

ABSTRACT

Precision Agriculture (PA) technologies introduction in coffee-growing is becoming essential to advances in sustainable cultivation and increase in output. Applications that involve PA techniques in coffee production are defined now as Precision Coffee growing (PC). Systematically explored, studies on the subject contribute to improvements in the area, relating soil variability to its impacts on plants. The PC's scientific approach offers new forms of management and more security in coffee production. Aimed at reducing pesticides application and nutrients to the soil, contributing to sustainable development in coffee production. Initially, the research on coffee production had dealt with soil spatial variability, highlighting the geostatistical methods and specific ways to sample the soil. With technological advances in agriculture, new ways of monitoring spatial variability are available. In this context, studies are arising on spatial variability related to the plant, applying terrestrial, aerial and orbital sensors, possibly creating perspectives for monitoring and mapping coffee production. Artificial intelligence, Remotely Piloted Aircraft (ARP) products, harvesting yield sensors, automatic grain classifiers, and remote sensing stand out as new technologies under development in coffee production. These applications in PC involving multidisciplinary research demonstrate new relevant ways of improving crop managing and sustainability guaranteeing.

Key words: Digital agriculture; spatial variability; sustainability of cultivation; remote sensing; Sensors.

1 INTRODUCTION

Several regions of the world cultivate coffee plants, such as Africa, Asia, Oceania, North America, Central America, and South America. In Africa, the countries that stand out in coffee production are Ivory Coast, Rwanda, Burundi, Congo, Angola, and Kenya. In Asia and Oceania, these countries are Indonesia, Vietnam, Thailand, Yemen, and India. In North and Central America are Mexico and Costa Rica. In South America, the countries that stand out are Brazil and Colombia, revealing worldwide importance to production, exportation, and quality of the drink among countries like Venezuela, Ecuador, Peru, and Paraguay. A remarkable characteristic of coffee production in those regions listed above is that the rural properties are mainly composed of small areas with family agriculture. Brazil is highlighted as the world major coffee producer. It is possible to find greater areas that cultivate coffee related to agribusiness, and, also, it is possible to find small family farmers in this country. Due to these different worldwide coffee producers` characteristics, Precision Agriculture (PA) in the coffee field can be applied differently to other crops. In this way, PA application can be a differentiation for this cultivation.

Many pieces of research are being made focused on the application of PA to coffee cultivation. Nowadays, there is a noticeable tendency to study applications of 4.0 agriculture or digital agriculture in various cultivation, and it is clear that the scientific community has been pushing for research with PA in coffee production to move towards these new trends. However, in coffee production, some issues need to be corrected before following scientific and market trends so that PA can practically be applied on coffee farms.

In coffee production, the PA still needs to be developed and implemented. However, there is still a propensity to research, defunded, and adopted due to the benefits and adopted due to the benefits it can bring as efficiency, environmental and economic sustainability. Some technicians and producers sought solutions that were not comparable to grain production. Due to the importance of coffee production for exportation and world consumption, in addition to agronomics characteristics, coffee cultivation has gained a specific designation, which Alves, Queiroz and Pinto (2006) called precision coffee-growing (PC).

PC was defined by Ferraz et al. (2012a) as a conjuncture of techniques and technologies that aim to support the management of coffee crops. It bases on the spatial variability of soil and plant attributes, seeking to maximize profitability, the efficiency of fertilization, spraying treatments, and harvesting, resulting in elevated yield and best quality of the grain. From the development new technologies, those definitions can and should be updated as well as their ultimate goals. This way, PC can be defined as updated techniques and technologies use that aim to maximize crops profitability, increase operations efficiency, search for business sustainability, environmentally sustainable production, and unceasing search for maximizing yield and improving product final quality.

This literature review aims at demonstrating how research has been carried out with PC. Observing the technology use evolution and its degree of application and examining the PC applications and their trends. This review will address spatial variability topics for soil, plant, yield, pests, and diseases. Applications at variable rates, yield sensors, remote sensing in coffee growing, remotely piloted aircraft, new technologies, and economic studies, leading the reader to a deep understanding of the characteristics that make PC so different from other cultures.

2 SOIL SPATIAL VARIABILITY

Knowing the variability of soil attributes is essential for precise crop management, considering the application of fertilizers, sampling strategy and the field research project (Bhatti et al., 1991; Cambardella et al., 1994). Soil attributes generally vary over time and can also differ in space. This variation is due to the action of natural agents and human inference, manifesting itself with greater intensity in some attributes (Stolt et al., 2001).

Soil attributes variability mapping, especially those that control crop yield, is an important factor in a production system that aims for sustainability through localized management (Cora et al., 2004; Grego; Vieira 2005). Attributes variability in the soil studies is evidence of some findings of obtaining information by sampling collection through sampling grids. Melo et al. (2017) describe the challenges for work with PA and report the difficulty in defining the sample area size because larger grids may not reflect dependent attribute study and tiny grids up cost much for collection and laboratory analysis. Establishing a necessary number of samples to determine soil properties results in optimized work and allows a better representation of such attributes (Santos et al., 2017). The methodology to define the sample grid size depends on the investment of time and financial resources. The cost is one of the most significant limitations for collecting information on an adequate scale (Neto et al., 2006).

Companies and rural producers working in PA have used different grids and different sampling methods per grid. In coffee growing, the most used commercial grids used one point per hectare (Ferraz et al., 2011) and continue to be the most used nowadays. Some methodologies for soil sample collection were researched to enable the mapping of the soil spatial variability attributes in coffee growing. Assessment of soil attributes through regular grids was also available in work developed by Silva et al. (2007). From geostatistical analysis results, the authors concluded that all the soil variables analyzed showed remarkable spatial dependence.

Using the regular grid method, Sanchez et al. (2005) evaluated the spatial variability of soil properties, chemical, granulometric, and coffee yield. All variables analyzed showed spatial dependence, chemical and granulometric properties of intensively managed soils show spatial dependence in the face of variations in relief terrain.

The geomorphological variations influence on spatial distribution characteristics of soil attributes encouraged studies to define management zones related to terrain relief. (Sanchez et al., 2013) presented specific management mapping areas to predict soil attributes and coffee grain quality. In addition, they have studied the soil quality attributes and their relationship to relief. Their analyzes presented the soil-relief relationships in the Digital Elevation Model (DEM) and combined application for the hybrid mapping of areas, contributing to coffee production management.

Aiming to increase the soil sampling assertiveness, Ferraz et al. (2017a) developed the Accuracy Index (AI), the Precision Index (PI), and the Optimal Grid Indicator (OGI) that possibilities to choose the best soil sample grid for coffee crops. Using 20 different sample grids and the soil chemical attributes: phosphorus, remaining phosphorus, potassium, and potential CEC, the authors concluded that the OGI allowed the sampling grid choice of three points per hectare. Figueiredo et al. (2018) expanded the methodology proposed by Ferraz et al. (2017a) and tested the standardized (AI), standardized (PI), and the standardized (OGI) in smaller grids. The authors concluded that the 2 points per hectare grid best represented the coffee crop attributes.

2.1 Spatial variability of physical soil attributes

Spatial distribution mapping of granulometric soil fractions contributes to decision-making in coffee growing. These soil characteristics are considered in fertilizer application, mechanized practices, soil conservation and irrigation management.

The spatial variability of some physical attributes was investigated by Simões et al. (2006) that carried out a study in the soil layer from 0 to 20 cm to assess the density levels of clay, silt, sand, and particles. The authors concluded the influence of slope and soil variability management and found that the areas with greater soil overturning showed trends towards uniformity of the physical attributes. In addition, soil management can lead to an absence of spatial dependence for particle density. An experiment conducted by Lima, De Oliveira and Silva (2012) evaluated deeper soil layers to know the water use by the roots. The study was collected soil up to 0.40 m in depth. The authors concluded that the granulometric fractions presented from low to medium spatial variability since the contents of clay and total sand had divergent correlations to the sampling depth.

Management influence on the variability of soil physical attributes was identified in the study by Burak, Santos and Passos (2016). Using factor analysis and geostatistics, the authors identified groups of soil attributes, spatial variability and the relationship between yield and relief. The soil attributes related to particle aggregation were not associated with the relief and yield. It was observed that the spatial variability was influenced by the management, as it presented less continuity and less spatial dependence at the layer of 0 to 0.10 m and by the pure nugget effect puro at a depth of 0.10 to 0.20 m. Microporosity and humidity increased at higher altitudes and lower slopes.

Assessments searching to identify soil variability for the precise cultivation of coffee have become relevant with applications of PA techniques in coffee growing. Carvalho et al. (2013) have collected data on soil density, soil resistance to penetration, and clay content, at different depths and height and coffee plants yield. They observed that yield and plant height are higher in regions with higher soil densities. In addition, found higher yield and plant height in areas with lower clay contents and lower soil resistance values to penetration.

The distribution of soil physical attributes (granular sand, fine sand, silt, clay and soil density) and its spatial relationship with the coffee yield were evaluated by Silva and Lima (2013) that used multivariate geostatistics methods. In this study, the yield and the soil physical attributes presented spatial distribution with high continuity.

In different depth layers, Carvalho et al. (2014) evaluated the variability of gravimetric moisture and clay content of a coffee plantation. For all variables evaluated, it was impossible to identify the variability existing in the field only using descriptive statistics. Regarding geostatistical analysis, all variables showed strong spatial dependence, allowing the creation of thematic maps. Thematic maps comparing, it was observed in regions with the lowest clay lower gravimetric moisture values. This study highlighted the importance of applying geostatistical techniques for variability characterization.

Research using geostatistics was presented by Kamimura et al. (2013). Trenches were made at the intersections of a 40 x 150 m rectangular grid to characterize soil macroporosity, soil microporosity, soil density, soil penetration resistance and soil total porosity. The authors concluded that the soil physical attributes presented a spatial dependence structured in all layers, except for total porosity. In addition, it highlighted out that the 0 to 0.03 m layers showed a physical impediment to roots growth due to higher density and low soil porosity.

Use geostatistical analysis intensive influenced the proposal of a method that best fits the spatial variability characterization of soil physical properties. The study conducted by Santos et al. (2017) evaluated data of the soil physical properties by statistical and geostatistical analyses. It was observed that the physical properties have a better spatial dependence structure when adjusted to the spherical model, except for particle density. The authors also stated that establishing the number of samples and studying soil physics spatial variability is useful in sampling strategies. This can minimize costs for farmers within a tolerable and predictable level of error.

In order to identify critical zones of soil compaction through soil penetration resistance (SPR) using spatial distribution Andrade et al. (2018), conducted a survey, collecting data on positions within the coffee line and in certain depths of the soil. The data was interpreted based on geostatistical analysis to identify the spatial dependence on SPR and generate maps, which showed the spatial behavior of the variable. The authors proved the spatial dependence of SPR, based on the classes presented in the literature. The RSP values in the tractor's trail, for the layers of 0.10 to 0.20 m and 0.20 to 0.30 m, were classified as the high RSP class, which may cause crop damage. This information contributes to data collection strategies in mechanized crops due to the variations in compaction caused by agricultural machinery traffic.

Soil physical attributes mapping contribution for irrigation was researched by Jorge et al. (2019). They evaluated the plant yield spatial variability of nutrients in the saturation soil extract. They showed that the yield and soil chemistry varied over the study site. Thus, the authors concluded that maps generated from geostatistics are valuable tools for soil management in fertigated coffee crops.

Applications to identify soil attributes behaviour was also used in unconventional soil. In *Terra Preta de Índio* (TPI) soil Júnior et al. (2017) collected samples and analyzed particle size, aggregate stability, total organic carbon, carbon stock, macroporosity, microporosity, soil density, total porosity, soil resistance to penetration, and volumetric moisture. From the descriptive statistical and geostatistical analysis, they concluded that the soil physical attributes showed weak to moderate spatial dependence. This demonstrates the geostatistical analysis ability and grid sampling collection to characterize crops variables in unconventional soils.

2.2 Spatial variability of chemical soil attributes

Spatial variability evaluation of soil chemical properties has become an essential aspect of soil management strategies, aiming at greater yield Carvalho, Silveira and Vieira (2002). The knowledge of the spatial variations of chemical attributes of the soil can contribute to the rational application of resources, allowing economic and environmental gains.

Advanced statistics use allowed the efficient spatial characterization of soil chemical attributes. Evaluating the co-kriging interpolation efficiency to estimate calcium according to pH, Costa and Lima (2011) studied geostatistical analysis to quantify the attributes' spatial dependence degree and estimate values of chemical attributes. The authors stated that Ca and pH attributes showed high correlation and spatial dependence in the area, showing that the co-kriging technique is an efficient interpolation method to estimate spatial distribution accurately of calcium.

Chemical soil attributes spatial dependence by associating geostatistics and multivariate analysis (Exploratory

Factor Analysis), researched by Almeida and Guimarães (2016), performed in a grid of 63 sample points, arranged in *Coffea arabica* L. plantation in the cerrado vegetation. Showed that the association of geostatistics and multivariate analysis provides interesting results regarding the spatial distribution of the soil chemical attributes. This study facilitates or provides the interaction of soil attributes when these are spatially dependent.

Soil chemical variability after removing a coffee plantation was studied by Vieira et al. (2009). The chemical attributes measured were pH, organic matter, K+, P, Ca2+, Mg2+, potential acidity, NH4-N, and NO3-N. In the study, samples were collected in a grid, and the authors found moderate to strong degrees of spatial dependence from 31 to 60 m. Similar results were found by Santos et al. (2014) that collected soil sampling in a regular grid. The data was analysed by geostatistics, and all attributes showed a dependency structure, moderate to strong. A higher range was found for potential acidity (33.58 m). Lima et al. (2013) were collected soil samples in a grid with 50 points. The chemical attributes studied were available P, Na, S, exchangeable Ca, Mg, and Al, pH, H + Al, SB, t, T, V, m, MO, NaSI, P- remaining, and micronutrients (Zn, Fe, Mn, Cu, and B). Using multivariate analysis techniques in association with geostatistics, main components 1 and 2 showed moderate spatial dependence, with greater spatial continuity observed for component 1, which allowed better characterization of soil acidity. Using the same type of sampling grid and statistical techniques Silva S. A. et al. (2010) determined the spatial variability of attributes P, K, Ca, Mg, clay, sand and silt. They highlighted the interaction importance between physical and chemical attributes.

Geostatistical techniques applications and descriptive statistics to characterize the chemical variability in the soil are applied in conventional and organic cultivation areas. Silva, A. F et al. (2010) proved that all soil chemical attributes have spatial dependence in both managements. The soil's chemical characteristics presented less spatial variability in organic management than conventional management, indicating the possible homogeneous zones for applying fertilizers.

Variability mapping of soil chemical attributes was also analyzed by temporal variability. Ferraz et al. (2012a) used geostatistics to assess the soil chemical variables of phosphorus and potassium in three agricultural harvesting years. Through the analysis, the authors established that it was possible to characterize the extent of the spatial variability for the attributes under study, which showed greater variation in time and space.

Macronutrients spatial variability as calcium (Ca), magnesium (Mg), phosphorus (P) and potassium (K) in a conilon coffee crop was studied by Santos et al. (2015). Examining a quadrangular grid with 60 points and samples at each point were collected soil samples at a depth of 0 to 0.20 m. These analyzes showed that all macronutrients under study showed solid spatial dependence. The greatest range of spatial dependence was for Mg (32.4 m) and the smallest for Ca (8.1 m). Oliveira A.R. et al. (2018) performed this type of characterization, which observed better correlations between the attributes pH and Ca 0.65 and K and Mg 0.39. Ferraz et al. (2019) developed a study to spatial variability determine of soil pH in water, available phosphorus (P), sodium (Na), potassium (K), calcium (Ca), magnesium (Mg), aluminum (Al); acidity potential (H + Al), organic matter (OM), sum of bases (SB), cation exchange capacity (T), base saturation (V%) and Al saturation (m%). This study corroborates with others that concluded that it is possible to map the soil variables of a coffee field using geostatistics.

Almeida and Guimarães (2017) studied the chemical attributes: Boron (B), Zinc (Zn), Iron (Fe), Manganese (Mn), and Copper (Cu). They found that B and Zn showed spatial solid dependence, Cu and Fe moderate spatial dependence and manganese present a pure pepita effect. The authors stated that modelling the spatial distribution of micronutrients contributes to management decisions for these elements in coffee crops.

Characteristics of a collection can influence spatial variability mapping of the soil. In many cases, the attributes variability analysis is carried out individually to avoid spatialization errors. Ferraz et al. (2017b) investigated the spatial distribution magnitude of soil attributes and mapped chemical attributes by conventional and grid sampling. They recognized the differences presented in the contents of pH, P, Prem, K, Ca, Mg, Al, H + Al, m, T, t, SB, V, and MO in the soil, when compared to conventional sampling and georeferenced grid for application in precision coffee-growing.

3 SPATIAL VARIABILITY OF PLANT-RELATED ATTRIBUTES

The mapping of yield in a crop refers to an important phase of PA. Consequently, in the harvest, producers obtain the results of their efforts. For the cultivation of cereals, the necessary methods and equipment are relatively known, well-founded, and widespread. There are fewer studies on coffee in the literature, and there is still no specific technology for this culture available on the market, making it harder to collect yield data in real-time.

Yield maps can be used as a starting phase to assess the causes of variability in crop yield, as well as to verify the possible events or causes for changes in the managing system in specific locations. The yield map can be considered the completest information to visualize the spatial variability of crops (Molin, 2006).

Given these characteristics, some methodologies for mapping the yield spatial variability have been proposed. Coffee production allows the use of mapping methodologies not only in mechanized harvesting but also in manual harvesting, as it is possible to see in different studies. Sanchez et al. (2005) installed a grid with regular spacing of 50 m between points, totalling 68 points for each plot. They evaluated coffee yield by manually collecting coffee grains per plant. The coffee yield map was made based on the estimated values by kriging. The authors concluded that there is little variation in the pattern of the spatial distribution of yield in the two years evaluated, and despite the management activities, the kriging maps showed the same spatial behaviour in the different years of evaluation.

In their work, Silva et al. (2008) performed the manual harvesting in two cycles, on coffee in the cloths of 4 plants around sampling points, properly georeferenced using GPS. The volume harvested from each plant, after shaking, was measured in a container graduated in liters. The authors concluded that there was spatial variability in yield, and the spatial dependence of this variable was considered strong. Silva and Lima (2012) applied a sampling grid containing 50 points. After the harvest was done manually, the yield calculation was converted into yield per hectare. The quantification of the degree of spatial dependence was performed by geostatistical calculations. It was noticeable that the most significant proportion of the area under study had values between 6 and 8 $mg.ha^{-1}$, representing between 100 to 130 $bags.ha^{-1}$.

Miranda, Reinato and Da Silva (2014) created a yield estimator. Their research evaluated the plant's phenological attributes: height, number of fruits in the 4th and 5th internodes of the plagiotropic branches, length in meters of the coffee lines, and diameter measured in the lower region of the plants. Thus, the authors presented a model that considers the proportion of the coffee canopy volume closer to the real architecture of the plant, with a significant 0.83 coefficient determination. Rocha et al. (2016) mapped yield in 1 hectare by creating mathematical models for crop forecasting. In this area, 50 sample points were collected, and the differences (residues) between the observed yield and the yield obtained by the estimator models were analyzed. The attributes showed spatial dependence, making it reasonable to distinguish between areas with greater and lesser variability observed in the kriging maps.

Following the co-kriging methodology, Lima et al. (2016) estimated the yield using as a covariate the number of productive branches per plant and defining a sample grid with 109 georeferenced points (five plants per point). The yield and the number of productive branches per sampling point showed linear correlation and spatial dependence in the three harvests collected. They showed that the covariable productive branch is efficient in estimating yield. Carvalho et al. (2017) georeferenced 100 sampling points. From geostatistical analyzes, they identified and characterized the spatial dependence of yield by adjusting semivariograms. The maps created made it possible to observe the spatial distribution of the yield, the non-uniformity of yield in the experimental area, and the difference between the two studied years.

Ferraz et al. (2017a) studied the yield spatial variability in an area of 22 hectares cultivating Coffea arabica. The coffee yield ($L.plant^{-1}$) was obtained through manual harvesting on the cloths of the four plants around the georeferenced sampling point. The data were adjusted using a spherical model semivariogram and ordinary kriging interpolation. The authors characterized magnitude and spatial dependence structure of coffee crop yield by adjusting the semivariogram. Besides, they described that geostatistics is an important methodology for data analysis in PA field. Ferraz et al. (2019) also carried out the manual harvesting of coffee fruits in an area of 10 ha of arabica coffee, applying geostatistics to map the yield in L $plant^{-1}$. Demonstrating the capability of geostatistical techniques for use in precision coffee-growing.

Applying the descriptive analysis method, followed by Pearson's correlation analysis between soil attributes, plant agronomic characteristics, and altitude Jacintho et al. (2017) defined management zones for precision coffee growing, which, through correlation analysis, observed that altitude was the variable that most correlated with yield. Thus, this was the most favourable variable for generating management zones and thematic maps to assist coffee producers. Defining management zones for selective harvesting based on coffee fruit yield and maturation was proposed by Kazama et al. (2021). The authors concluded that it was not possible to carry out the selective harvesting of the fruits even though maps for management zones were successfully done.

Thus, it is possible to conclude that in this subtopic, a wide range of studies used manual harvesting to coffee crops map. Still, this review will also contemplate studies that used sensors to measure the yield of coffee crops.

Some studies were developed in coffee plantations to characterize the nitrogen content variability and map its presence in the plants. For this, chlorophyll analysis is performed mainly using digital chlorophylls, which allow reading directly in the field, without the need to remove leaves and send them to the laboratory.

Alves, Queiroz and Pinto (2006) monitored the chlorophyll content of 818 coffee plants using a portable digital chlorophyll meter. The readings were performed monthly between September 2003 and March 2004, in four leaves per plant, at the average height of the plant, in four opposed branches selected. Prado, Machado and Prado (2015) conducted a study georeferencing sampling chlorophyll content in an area of irrigated coffee with a central pivot to generate management zones for irrigated coffee farming, based on measurements with chlorophyll sensor (SPAD) and apparent electrical conductivity (CEA) of the soil. The authors concluded that management zones generated by the chlorophyll sensor SPAD and CEA values of the soil presented a weak positive correlation. Likewise, they defined three different management zones for water and soil, maximizing natural resources use and minimizing production costs with the appropriate application of fertilizers and agricultural corrective supplies.

Research by Zanella et al. (2020) presented a spatial correction between chlorophyll indices and NPK leaf contents. This study evaluated spatial correlations between the chlorophyll index (CI) and the leaf levels of nitrogen, phosphorus, and potassium (NPK) in coffee culture. Furthermore, the authors estimated the potential use of this index as a tool for managing site-specific nutrients in an irrigated coffee plantation. The study was carried out in an area of 2.1 ha under cultivation of arabica coffee. For the analysis, geostatistical tools were used under the inferences made. In this research, the potential of the chlorophyll meter was demonstrated as effective for the management of site-specific nitrogen in coffee cultivation, as opposed to the CI, which was not recommended for P and K management, since they were not well correlated. Finally, as a tool that performs indirect measurements, the results of the chlorophyll meter must be validated by field measurements for local calibrations.

The structure characterization, spatial distribution magnitude biophysical characteristics of the plant is essential information for precision coffee-growing. This mapping contributes to the application of pesticides, pruning management and harvesters regulation.

Analyzing defoliation through the effects of manual harvesting and biennial production of coffee Silva, F. M. et al. (2010) conducted an irregular grid of 25 x 25 m collecting 67 points. Defoliation was quantified based on leaf weight (F) (kg Plant-1) after manual harvest. The variability and pattern of spatial dependence on coffee yield and defoliation were analyzed using geostatistics. The kriging maps directly correlated the spatial variability of plants with higher yield and bigger defoliation in the same year. They were verifying alternation in this behaviour, characterized by the biennial production of coffee crops over space and time.

Carvalho et al. (2013) assessed the spatial variability of the coffee plants' physical soil attributes and growth characteristics. The data was collected in an irregular grid of 24 georeferenced points. The coffee plants height from the soil surface was measured using a scale in millimetres, and the results were expressed in meters. Variables spatial dependence was analyzed by adjusting the semivariograms using the classic estimator. Through geostatistical analysis, the authors observed that the height variable has a strong degree of spatial dependence.

Mapping the plant foliation and spatial distribution demonstrating in coffee plantations, Ferraz et al. (2017b) conducted a survey applying a sampling grid of 100 georeferenced points. For the assessment of foliation, a visual scale was used, with variations ranging from 0 to 20%, 21 to 40%, 41 to 60%, 61 to 80%, and from 81 to 100%. Analyzing the spatial variability on the map of the foliation, the authors observed that a large part of the area presented foliation ranging from 81 to 100%. The analysis of these data using statistical and geostatistical techniques made it possible to characterize the spatial variability of the foliation, allowing the mapping of this variable.

Canopy Diameter and Plant Height are important growth characteristics of the plant that indicate its development. These features are closely related to the management imposed on crops. Therefore, identifying the spatial variability of these attributes and their consequent mapping can collaborate with coffee producers to identify growth distortions occurring in the field, facilitating their correction Ferraz et al. (2017b). These authors have studied the canopy diameter and plant height by geostatistical analyses. The canopy diameter was obtained by measuring the most extended branch. A scale was used to measure the plant height from the soil surface to the top of the plant. The authors concluded that it was possible to map both variables and find out their spatial variability.

Coffee producers face challenges for is determining the appropriate time to start harvesting coffee due to the plant's shape, lack of uniform maturation, and high moisture content of the fruits. Since the mechanized harvest operations are carried out by vibration Santinato et al. (2015), spatial variation maps of the fruit's detachment force, for example, can assist farmers in identifying the areas where harvesting should start Ferraz et al. (2012c).

Using geostatistical analysis, Ferraz et al. (2014) studied the coffee fruit detachment force. It was used an irregular grid with 48 georeferenced sampling points. A portable dynamometer obtained the fruit's detachment force. The authors concluded that the semivariograms provided a satisfactory approach to model the detachment force of mature and green fruits. Kriging maps showed that, in general, the detachment force of mature and green fruits is directly related. The detachment force for mature and green fruits was inversely related to coffee yield in most parts of the field. Therefore, it was possible to identify the best place to start harvesting mechanically and selectively using the fruit detachment force maps.

In coffee crops irrigated by the central pivot, Figueiredo et al. (2017) analyzed the spatial variability of the fruit's detachment force using a sample grid with 100 georeferenced points. The portable dynamometer was used to sample fruits in two maturation stages (green and mature). Kriging maps analysis of the variables studied confirmed that the force for removing green coffee fruits is greater than the force required for removing mature fruits.

Baesso et al. (2019) analyzed the soluble solids spatial variability in coffee. Mature fruits were collected from four branches, one pair on each side of the plants. Using a portable digital refractometer, Brix level was read on fifteen fruits from each sample. Two tasters performed the drink tests. The author found spatial variability in Brix level values and proved that this variability is related to drink quality.

Despite the contribution of assertive research on identifying variability in plant characteristics, this mapping for applications in precision coffee growing is still considered costly. Since collections are carried out manually, this lack of equipment for simultaneous and continuous collections is considered a gap to be implemented in precision coffee-growing.

4 SPATIAL VARIABILITY OF PESTS AND DISEASES

Mapping the spatial variability of pest and disease damage is necessary for precision coffee-growing for efficient control planning and targeted spraying. Contributing to the reduction in the application of chemical products and cost reduction in coffee growing.

Alves et al. (2009) conducted an experiment to identify the magnitude and structure of the spatial dependence of coffee rust and cercosporiosis, in a 6.6-hectare coffee plantation, over three years. The authors aimed to identify the incidence and severity of these diseases in 67 georeferenced points. The authors made kriging maps for rust and cercosporiosis that allowed the observation of disease intensity, distribution pattern, and outbreaks of phytopathogens throughout the crop, indicating that a located control can replace control strategies based on the total area.

Employing statistical analysis techniques, Alves et al. (2011) characterized the spatial structure and mapped the spatial variation of the damage caused by the *Hypothenemus hampei* and *Leucoptera Coffeella* in a coffee plantation. They monitored 67 georeferenced points in three years and found that mapping signals in fruit and coffee leaves caused by pests can be useful in inferring the ecology and infestation of pests in crops at different times of the year. With this, the establishment of control strategies and tactics can be improved, enabling a more effective control with less environmental impacts and greater sustainability.

5 VARIABLE RATE APPLICATIONS IN COFFEE CROPS

A variable-rate application system was first used in the 1990s in the United States and then gradually developed (Lan et al., 2010). Providing the necessary inputs is essential for the plant's physiological maintenance and offers sustainable agriculture. Besides, fertilizers, pesticides, and seeds are the main sources of production costs (Bennur; Taylor, 2010; Tekin 2010). Some studies prove the variable rate application efficiency, such as Irrigation at a variable rate (West; Kovacs, 2017; Pugh et al. 2019); Variable-rate spraying (Walklate; Cross; Pergher, 2011; Wang et al., 2019); Planting at a variable rate (Virk et al., 2020) in different crops. Although various research has shown efficiency for application at variable rates in several stages and segments, this technique is still more explored in fertilizer applications.

Chemical and physical attributes characterization spatial variability of the soil made through sampling is indispensable to apply PA. This mapping guides an application zones managing system by variable rates, aiming to meet the specific necessities of each location (Bottega et al., 2013). Slightly inserted into coffee production, variable-rate fertilizers application is still a technology to be studied deeply and has a great potential for application, gaining more supporters every day. Comparing the application in variable and fixed rates in coffee production, Molin et al. (2010) observed a 34% increase in yield in areas that applied fertilizers at variable rates. Phosphorus consumption decreased by 23%, and potassium increased by 13% in the dose applied at a variable rate.

Ferraz et al. (2015) presented a form of mapping using geostatistics for soil attributes, phosphorus and potassium, and recommendations for application and evaluated the application of fertilizers based on conventional methods and in a grid form. The results demonstrated the variations of recommendations due to the method. In spatial variability research, Silva et al. (2014) evaluated Ca, Mg, P, K, and S levels in coffee plantations with a PA system. The authors examined over three years that variable-rate fertilizers application promotes the homogenization of nutrients in the soil. Therefore, Valente et al. (2012) defined management zones for coffee plantations based on the apparent electrical conductivity spatial variability soil.

In a performance survey for variable rates application in coffee culture, Barros et al. (2015) achieved important results when testing a variable rate machine's. The authors concluded that system application at variable rates in field conditions showed low variation and good accuracy. Andrade et al. (2020) research evaluated the transversal application of fertilizers in a centrifugal spreader. The study also compared the efficiency between two methods of operation in applying fertilizers using different doses of product and spreading at different rotation speeds. The authors attested that the transversal application proved practical and efficient, and the best results were found in the applications on one side of the plants with a disk rotation of 750 Rotations Per Minute (RPM).

Researching the variable rate application system sustainability Angnes et al. (2021) analyzed how variable-rate fertilization influences energy efficiency in coffee growing. Their results indicated that the application of fertilizers at a variable rate has a slight difference, meaning greater energy efficiency about applied fertilization and coffee production per crop. But the energy balance was more efficient at variable rates, as it provided fertilizer savings without compromising productivity.

Accordingly, variable rate applications contribute to increased yield and, consequently, to reduced costs. In coffee production, it is important to evince that the adoption of variable rate application techniques is still limited since coffee production is undergoing considerable transitions regarding agricultural mechanization, as it requires specific machines for handling. Few machines are adapted to carry out fertilizer applications at a variable rate in coffee crops. It is important to note that this review found no studies for spraying at a variable rate applied to coffee production.

6 YIELD SENSORS IN COFFEE GROWING

The Jacto Company (Máquinas Agrícolas Jacto S.A, Brazil) tested a productivity yield monitor for self-propelled harvesters in mechanised coffee harvesting. They have characterized a volumetric sensor integrated with the collector on the furrow located at the end of the internal transport system. Yield per hectare was obtained by manual sampling, necessary to determine the correction factor volume. The getting yield data proved appropriate, practical, accurate, and possible to be incorporated into the harvester planning (Queiroz et al., 2021).

Martello, Molin and Bazame (2022) evaluated yield data quality obtained through a yield monitor on board a coffee harvester over three seasons. They showed a high correlation between productivity data obtained by the monitor (above R2 0.968) about data from an instrumented wagon with load cells. They also presented yield maps for three consecutive seasons, identifying their internal variability and classifying them by regions. This result demonstrates that knowledge of the spatial variability of productivity and the formation of biennial variance must be considered in site-specific management strategies.

The great challenge for obtaining accurate yield data via sensors is directly related to cultivation characteristics, such as varieties and different species, plant heights, diameters and crowns, uneven maturation during fruit harvest and plant ages. In addition, elements related to plantings, such as spacing between plants and planting lines, mechanization and planting system surfaced, circular or rectilinear, must be considered. This low development is related to the interest of companies in investing in the development of sensors and the acceptance of producers with new technologies, which tend to be less reactive.

7 REMOTE SENSING IN COFFEE GROWING

Precision agriculture, in recent decades, presented new monitoring techniques. Significant advances are seen in the introduction of Remote Sensing (RS) technologies (Huang et al., 2018). These are techniques from sensors coupled to terrestrial vehicles, aircraft, satellites, and portable radiometers that provide spectral, spatial information on the surface of objects (Chlingaryan; Sukkarieh; Whelan, 2018). Products derived from RS can offer data and information in a short space of time (Seelan et al., 2003). Adapting to PA needs (Haboudane et al., 2002; Chemura et al., 2018). Collecting information about the occupied area, location, spectral responses of the installed crops, vegetation indexes, recognizing unusual problems and economic sectors (Atzberger, 2013).

Applications of remote sensors in agriculture are already important allies in monitoring and detecting anomalies (Weiss; Jacob; Duveiller, 2020). Orbital or platform sensors can identify fundamental vegetative properties, link physical properties to ecological theory and provide spatial and temporal databases (Ustin; Gamon, 2010). Improvements in orbital sensors have marked significant advances in remote sensing of vegetation over the past 50 years. Enabling identifying phenological and biochemical structures in spatial and temporal scales (Houborg; Fischer; Skidmore, 2015). Quality spatial production and spectral information can contribute to agricultural planning and decision-making (Moriya et al., 2017; Wolfert et al., 2017). In coffee plantations, monitoring using remote sensors is systematically explored. This statement was supported by studies by Devi and Kumar (2008), in which it showed the positive insertion of satellite images for use in precision coffee growing. Endorsing that the use of remote sensing improves the efficiency and accuracy of the data in the crop.

RS technologies inclusion in coffee production has become useful in macro and micro scale decision-making (Almeida; Sediyama; De Alencar, 2017). In monitoring, expansion, and quantification of coffee areas, orbital sensors are used in several regions. In identifying altimetric characteristics in coffee growing, Trabaquini et al. (2010) showed orbital sensors used for macro-region studies is highly accurate and can be compared with agricultural surveys conducted by government agencies. Takahashi and Todo (2017) processed Landsat images using automatic classifiers to identify coffee characteristics for certification in Ethiopia. Sarmiento et al. (2014) compared supervised classifiers, using object-oriented image analysis and pixel-by-pixel image analysis, in coffee areas' discrimination in Quickbird images. These authors demonstrated the potential of the Maxver classifier algorithm for separating coffee areas in high spatial resolution images and recommending the use of this pixel-by-pixel image analysis algorithm.

In studies that used regression techniques by multitemporal analysis in Landsat satellite images, Ortega-Huerta et al. (2012) presented the RS's potential for mapping coffee areas in El Salvador. Also studying mapping techniques, Souza et al. (2019) proposed a new methodology for mapping coffee fields, including multitemporal data as input parameters in the classification process, through a Landsat TM NDVI time series.

Kawakubo and Machado (2016) identified coffee fields using multispectral images with a spatial resolution of 23.5 m. From Linear Imaging Self Scanner Instrument (LISS III) onboard the Indian Remote Sensing Satellite System (IRS). The method was efficient in isolating the coffee classes, with an accuracy greater than 70%, from other categories of soil use. Comparing the results obtained in this research with a maximum conventional probability (ML) classification revealed that when using the described methodology, the confusions between the classes were less dispersed, and an improvement of approximately 10% was observed in the mapping of the coffee production classes. Using high-resolution spectral data (WordView-2) in Hawaii, Gaertner et al. (2017) evaluated two methods for detecting coffee plantations. The study presented satisfactory results in applications of the object-based image analysis (OBIA) methods, presenting an accuracy of 81% in the identifications. In the study by Kelley et al. (2018), techniques for detecting coffee plantation fields cultivated in the shade were presented using the Google Earth Engine platform.

Although the RS contributes significantly to coffee plantations geolocation, this technology has emerged strongly for monitoring and detecting anomalies. They are contributing directly to decision-making and offering new forms of monitoring in precision coffee growing.

Among these contributions, we can mention the identification of crop vigor, phytopathogens symptoms, nutritional deficiencies, yield, quality of planting, management zones, among others. However, in coffee production, some barriers are found in surveys handled using orbital images. Yet, some orbital sensors have low spatial resolutions.

Coffee crop reflectance values are variable due to heterogeneous surface coverage, influenced by planting directions, crop spacing, time of year and plant age. Even with those obstacles, some authors obtained satisfactory results in research with orbital sensors and vegetation indices, as explained in the study by Bernardes et al. (2012), who evaluated coffee production for eight years. Through vegetation indices in images from the Moderate Resolution Imaging Spectroradiometer - MODIS sensor, the authors understood biennial effects and found good relationships between vegetation indices and production. From vegetation indices obtained through images Landsat 8, Nogueira, Moreira and Volpato (2018) concluded that SAVI and NDWI indices showed a correlation in the flowering phase in the year with high yield. Marin et al. (2019a) identified the stress caused by biotic and abiotic factors in coffee crops through vegetation indices in Landsat 5 TM images. Ramirez and Júnior (2010), using the green and blue bands of the Quickbird images, concluded that the use of images with the high spatial resolution is promising in the study of coffee areas and showed greater detail of the site, additionally to the detection of critical biophysical characteristics for the crop. Pereira et al. (2013) carried analyzes on vegetation indices based on GeoEye images in coffee plantations and biomass measurement. Using data from Sentinel-2, Jaramillo-Giraldo et al. (2019) analyzed the relationship between the spatial-temporal variability of the Leaf Area Index (IAF) and the crop coefficient (Kc) for coffee crops. Thus, they demonstrated that the variable IAF could replace Kc and is used to monitor water conditions in the production area and analyze the spatial variability within that area.

Spectral behaviour rates change of plants are altered under attack by pests and diseases. High spectral resolutions of the remote sensors, was used to detect and predict anomalies. Marin et al. (2019b) presented an evaluation of the Landsat 8 OLI/TIRS multispectral sensor for monitoring the spatial and temporal progress of bacterial burning in coffee. Relationships between spectral radiometry, irrigation systems and coffee rust were showed in research carried out by Pires, Alvesa and Pozza (2020) from the Landsat-7 / ETM + and Landsat-8 / OLI-TIRS satellite images. These authors obtained spectral, spatial, and temporal patterns of the disease. Katsuhama et al. (2018) focused on the standard deviation of NDVI values (σNDVI), not as an index of statistical error, but as a new effective indicator for monitoring the occurrence of rust in coffee plants in the mountain regions of Guatemala. Sentinel 2B data is used to characterize nitrogen in coffee cultivation. From the Random forest classification, these products present satisfactory results in predicting nitrogen in coffee (Chemura et al., 2018). Based on spectral responses of coffee leaves in the fields, Martins, Galo and Vieira (2017) proposed monitoring through RS in areas infested by nematodes, concluding that this tool can be used in precision monitoring. Remote sensing in a coffee plantation, using orbital sensors, has proven to be an essential technology in several stages of cultivation. Therefore, it still has some limitations, such as spatial and temporal resolution. Given the need to obtain information with high spatial resolution and in short time intervals, other platforms are studied.

8 REMOTELY PILOTED AIRCRAFT (RPA) IN COFFEE GROWING

Significant advances in sensors coupled to satellites for platforms now offer spatial resolutions in centimeters order. However, in emerging crop monitoring cases, such as nutritional deficit analysis, crop forecast, anomalies, orbital data may not be helpful, presenting low temporal resolution (Zhang; Kovacs, 2012; Mateen; Zhu, 2019). Moreover, limitations such as high costs, lack of operational flexibility, and low spatial and temporal resolution are encountered. At the orbital level, the presence of clouds is another factor that intervenes with the acquisition of images. On cloudy days, the passage of solar energy is blocked. Consequently, the surface loses data from the image (Honkavaara et al., 2013).

Due to these characteristics, researchers explored innovation on different platforms, which proved to be efficient in obtaining remote data at minimal costs, such as airships (Vericat et al., 2009; Inoue et al., 2010) balloons (Vierling et al., 2006) and kites (Aber et al., 2009). Although these are low-cost platforms concerning the orbitals, their maneuvers are manuals operationally impractical for some regions, making the cultivations challenging to monitor. (Whitehead et al., 2014)

Those restrictions were the starting point for new technology insertion, the Remote Piloted Aircraft (RPAs). However, there are several terminologies found in the literature, such as Unmanned Aerial Vehicles – UAV (Peña et al., 2013; Candiago et al., 2015; López-Granados et al., 2016; Tokekar et al., 2016), Remotely Piloted Aircraft Systems - RPAS (Barry; Coakley, 2013), Remotely Piloted Aircraft - RPA (Giles, 2016; Zajkowski et al., 2016), Remotely Piloted Vehicles – RPV (Hardin; Hardin, 2010; Siebert; Teizer, 2014), Unmanned Aircraft Systems – UAS (Whitehead et al., 2014) and Remotely Operated Aircraft – ROA (Uysal; Toprak; Polat, 2015).

Faced with various terminologies that have emerged to represent these aircraft, (Swann, 2016) designated RPA as the standard terminology. RPA concept refers to any aircraft that can be remotely piloted to schedule and execute previously planned autonomous flights (Santana et al., 2021b). This technology has been gaining renown in several segments recently (Bereta et al., 2018), explored for presenting images with high temporal, spatial resolution, and low operating costs compared to piloted aircraft and high-resolution satellites. (Laliberte; Rango, 2011; Xiang; Tian, 2011). Low cost, autonomous data collection, operation in climatic conditions, a process in unfavorable climatic conditions, orbital collection, image capture in dangerous environments, and high flight stability are characteristics that make RPA a potential technology (Torrado; Jiménez; Díaz, 2016). In addition to being considered a new way of obtaining spatial, spectral, and temporal quality parameters, they are lightweight equipment and are versatile in coupling sensors (Hassler; Baysal-Gurel, 2019).

In agricultural fields monitoring, RPA technologies are being introduced through PA, with advanced altitude and positioning control systems, carrying high-resolution digital cameras on board. These tools combined with remote sensing techniques form a set to improve remote agricultural monitoring (Lelong et al., 2008; Santana et al., 2019). They provide valuable and specific information in a short period of adapting to PA needs (Chemura; Mutanga; Dube, 2017a). They also offer detailed information about biophysical properties, such as monitoring nutrients, phenology, pests and diseases; production; and other activities in the planting areas (Putra et al., 2020).

RPAs technologies, allied to precision farming techniques, provide frequent monitoring in different cultivations, improving managing quality and agricultural applications (Santos et al., 2019b). Thus, it appears that there are studies in the literature regarding technology in some perennial cultures. Despite conclusive evidence on RPA applications in coffee growing, few techniques are found about this technology. RPA for coffee areas mapping can produce fast products with low cost, high technological value, and high precision. Applications of RPAs can be of fundamental importance for coffee growing since they comprise mostly small growing areas (Garcia-Freites et al., 2020).

Although few studies have already shown satisfactory results for RPAs insertion in precision coffee growing, the first approaches were conducted by (Johnson et al., 2004). The authors collected geo-referenced images of the coffee crop in 2002 harvest, using RPA, and compared the image pixels with the reflectance data collected in the field, creating an index of maturation of the crop. Herwitz et al. (2004) used RPA to collect images to monitor and support decisions in coffee plantations. The authors found several aspects of crop management that benefit from aerial observation. The study demonstrated the ability to monitor RPA over a prolonged period, in addition to obtaining images with high spatial resolution, mapping outbreaks of grass growing, and differentiating the ground cover in the monitored areas. Thus, RPA is a comprehensive tool that complements satellites and piloted aircraft to support agriculture.

Current studies are being developed in coffee production due to sensors evolution and the accentuated remotely piloted aircraft application. As discussed in the research by Oliveira, H. C et al. (2018), the authors presented a technique for detecting defects in coffee plants, based on the processing in RGB images and morphological operators, with individual identification and the total length of the defects. Santos et al. (2019a) have proven the potential of the techniques to improve the geometric errors of RPA images, with applicability in coffee crops. Barbosa et al. (2021) demonstrated that the use of low-cost UVAs and RGB cameras could monitor coffee production through image classification processes (vegetation indices). Studies by Cunha et al. (2019) shown a method to estimate the volume of vegetation in coffee crops, using RPA images, in addition to not finding significant differences with the traditional survey method. Chemura, Mutanga and Dube, (2017b) tested the ability of multispectral photos to assess the water content of the plants, using algorithms as a way of detecting and monitoring water stress.

In an experiment with multispectral cameras, Velásquez et al. (2020) tested a simulator for accurate detection of rust in coffee. Its results showed significant correlations, proving the model as excellent in terms of certainty and usefulness of its diagnosis. The authors highlighted cameras similarity used in RPA and the technological integration occurring for the actual practice of coffee rust identification.

In images collected using RPA and manual field measurements, Santos et al. (2020b) evaluated biophysical meters and measures of height and diameter of the coffee plant for twelve months. The authors attested that photogrammetric products have significant capacity in estimating the size and diameter of coffee plants. Additionally, it is used to analyze biophysical attributes avoiding the need for sample collection in the soil. In leaf area index evaluation (LAI), Santos, F. F. L et al. (2020) aimed to monitor LAI evolution and the percentage of soil cover (% COV) in coffee plants, using plant equations and measurements obtained from 3D generated point clouds, combined with the SfM algorithm application for digital images recorded by a camera coupled to a UAV. This study made it possible to determine a new way of monitoring LAI's temporal and spatial behaviour and % COV. In studies to analyze mechanized planting quality in regions with high slopes, Santana et al. (2021a) performed flights with ARP in an area six months after transplanting. Their results demonstrated the digital elevation model maps effectiveness obtained by ARP applied in this type of monitoring. In addition to presenting statistical process controls on plants and planting lines alignment.

Using RGB camera coupled in RPA, Mincato et al. (2020) developed research to evaluate the vegetation indices potential based on spectral bands and visible wavelength to nitrogen concentration monitoring in coffee leaves. However, the authors concluded that it was not possible to distinguish the different levels of nitrogen concentration in coffee plants. Marin et al. (2021a) determined the spatial variability of nitrogen (N) in coffee leaves by evaluating the potential of the Random Forest (RF) machine learning method applied to vegetation indices (VI). From images of Remotely Piloted Aircraft (RPA), ten vegetation indices (VI) were obtained. The suggested model presented global accuracy and kappa coefficient of 0.91 and 0.86 for N classification in coffee leaves.

Applications of Unmanned Aerial Vehicle (UAV) in coffee plants shown by Soela et al. (2020) obtained results in flight height evaluations for spraying, analyzing the amount of spray solution deposited on the leaf. Thus, employing control charts did not detect negative patterns within the treatments, ensuring the quality of applications in the coffee growing. Additionally, all treatments were within the area limits, but at 1.0-meter flight height and A1 genotype showed the best results for upper and lower deposition. As seen in this topic, there are still several possibilities to explore using RPAs in precision coffee-growing, which is a technology in full expansion with great potential.

9 NEW TECHNOLOGIES

Coffee production has been incorporating new technologies every day, even if it is not at the same speed as other cultivations, to improve assertive decision-making, yield and higher quality coffee fruits.

Coffee fruits harvesting is an essential step in cycle growing, considered the final production stage process and the moment for obtaining profits to farm. As explained in the yield sensors topic, sensors type still have a weak insertion in coffee production. Thus, other research aims to include technologies to contribute to the producers defining the harvest best time. According to the detachment force, Barros et al. (2018) developed a classifier based on neural networks to determine the moment coffee fruits harvesting. The classifier differentiated between green and cherry fruits in the five study moments and indicated the best time to perform the harvest. Furfaro et al. (2007) developed a model based on neural networks to obtain maturation percentage of coffee fruits using multi-spectral images collected by a remotely piloted aircraft. The errors found by the model used were considered lower than the conventional methods based on field sampling.

Kazama et al. (2021) developed an automatic and non-destructive method for counting coffee fruits and classifying them in different maturation stages based on images. This methodology evaluated two types of image collection, directly in the field and collecting the branches and taking them to a laboratory. This algorithm was based on neural networks and predicted approximately one-third of the productivity in the area. Avendano, Ramos and Prieto (2017) developed a system to classify the vegetative structures in the coffee branches: leaves, branches, flowers, green fruits, cane, and ripe. The authors used 3D reconstruction using Structure from Motion (SfM) and Patch-based multi-view stereo (PMVS) techniques. However, the system was slow to process each branch and confused fruits between mature, green, and green fruits with coffee leaves.

Another essential factor of mechanized harvesting is to correct the harvester's correct adjustment, which must be done for the presenting conditions of the crop. Ferreira Júnior et al. (2016) used a system to detect the vibration amplitudes of the rods in the vertical direction of mechanized harvesting, finding occurrences for the adjustments of 8 and 10Kgf in the brake, in the vibration of 950 cycles min-1 of the cylinder, and with rods of 570mm in length. The study by Ferreira Júnior et al. (2018) developed a low-cost system based on the Arduino platform and accelerometers to track the trajectory of the vibrating rods on a self-propelled coffee fruit harvester. With the development of this study, the authors understood the vertical and horizontal behaviour of the coffee stems and related to the greater detachment of the coffee grains.

Research by Ferreira Júnior et al. (2020) presented a way displacement observing of coffee branches. Considering the frequency and amplitude of vibration, the authors developed a low-cost system utilizing instrumentation and signal processing techniques. This analysis observed the complete two-dimensional displacement of the coffee branches to different configurations of harvesters during mechanized harvesting and dynamic interaction between the machine and the coffee plants.

Coffee prices are established mainly on grain quality. Analyzing defects in grains and fruits is extremely important to orient the separation at a higher rate. A computer vision model to detect, classify and map the ripening stage of fruits during harvest was developed by Bazame et al. (2021). The detection and classification of coffee pods were carried out using the object detection system called YOLOv3-tiny, coupled to the discharge conveyor. They enabled video detection and classification during harvesting and mapping qualitative attributes related to the coffee maturation stage along the cultivation lines. Santos F. F. L. et al. (2020), also focusing on coffee beans quality, developed a work testing different machine learning techniques, such as Support Vector Machine (SVM), Deep Neural Network (DNN), and Random Forest (RF), to identify grains defects. The study demonstrated excellent performance of the classifiers similar to those offered computer vision and machine learning algorithms. In RGB (Red, Green, Blue) images obtained by ARPS and computer vision algorithms, Barbosa et al. (2021) estimated the height and diameter of canopy and coffee yield prediction. In addition to proving the use of these techniques for yield prediction models, they reduced the need for extensive data collection (e.g. monthly data collection). Marin et al. (2021b) developed a methodology for identifying coffee rust using multispectral magnets and machine learning techniques in vegetation indices.

Sott et al. (2020) made a bibliometric study on the use of Agriculture 4.0 technologies and PA in coffee production. For this study, 87 documents published since 2011 were used, extracted from the Scopus and Web of Science databases and processed through the protocol of preferred report items for systematic reviews and meta-analyses (PRISMA). The themes: Internet of Things, Machine Learning, and Geostatistics are the most used technologies in the coffee sector, presenting the main challenges and trends related to technology adoption in coffee systems.

10 ECONOMIC STUDIES OF PRECISION COFFEE PRODUCTION

PA is closely associated with highly technological resources. However, experiences show that PA is not limited to procedures that require highly sophisticated equipment and investments. Any farm, including family, can adopt low-cost actions and equipment (Inamasu et al., 2009). Besides, according to Oliveira et al. (2016), PA can be adopted by parts, initially in operations considered essential to a given crop, for example, soil correction, fertilization, pest, and disease identification, among others. Therefore, studies related to the costs of implanting and using PA techniques on a farm is very relevant. Ferraz et al. (2011) performed a comparative analysis between the differentiated and conventional fertilization methods in coffee production. The authors evaluated three different plots in two consecutive years, concluding that there was a difference in phosphorus and potassium application between the two fertilization assessed systems. Variable fertilization was advantageous for 22 ha and 10.52 ha in the two crops under study. The size of 6.23 ha was only beneficial in the 2008/09 harvest, with less loss.

Investigating the performance parameters and related costs in a set of machines, Andrade et al. (2020) researched two operational modes in a 7.5 ha coffee plantation. The first mode of operation (OM1) considered the recommended total dose on only one side of the plants and covering only half of the plot lines. In the second mode of operation (OM2), the machinery applied half the recommended dose on each side of the plants and covered all lines between plots. Performance parameters included effective field capacity and effective time. The authors concluded that OM1 implies greater effective

Assessing the technical and economic variability of manual coffee crop maps, the research by Faria et al. (2020) aimed to generate a linear regression model to estimate the harvesting needed time and labour costs. These analyses were by georeferenced sampling points and generating maps of coffee yield. Four rural workers conducted manual harvesting of the issues with experience in coffee harvesting. The volume was measured through a graduated container and a digital stopwatch obtained the period. Through this analysis, the authors established a linear correlation model between harvest time and yield, for which the R^2 value was 78.27, and the cost was BRL 8.92 by point.

11 CONCLUSIONS

This literature review showed precision coffee growing has been developing over the last decades, even though this evolution has not followed the advancement of other annuals crops.

The studies on soil spatial variability and plant attribute variability are still widespread and have great relevance. Besides, it observed that Remote Sensing had been successfully applied for some years in coffee cultivation, mainly in different countries.

In coffee-growing management, improvements are also attributed to the gradual application of several sensor models, incorporated and expanded into the coffee crop. Moreover, new techniques and technologies have been applied in precision coffee production, such as Remotely Piloted Aircraft, Yield

Sensors, Algorithms based on machine learning and image analysis that are slowly becoming more frequent in the literature.

Therefore, precision coffee growing is renewed every year, gaining new researchers, relevant studies, participants, and users, making it a new focus for farmers. Furthermore, the techniques presented in this review are important for achieving sustainable forms of coffee production.

12 ACKNOWLEDGEMENTS

This research was supported by Embrapa Café—Consórcio Pesquisa Café, project approved n◦ 234/2019, Foundation for Research of the State of Minas Gerais (FAPEMIG), National Council for Scientific and Technological Development (CNPq), Coordination for the Improvement of Higher Education Personnel (CAPES) and Agricultural Engineering Department - Federal University of Lavras (UFLA).

13 AUTHORS' CONTRIBUTION

LSS, GASF and SAS wrote the manuscript and performed the article searches, GASF and JELD supervised the experiment and co-worked the manuscript, GASF reviewed and approved the final paper version.

14 REFERENCES

ABER, J. S. et al. Challenge of infrared kite aerial photography: A digital update. **Transactions of the Kansas Academy of Science**, 112 (1/2): 31-39, 2009.

ALMEIDA, L. DA S.; GUIMARÃES, E. C. Geostatistics and exploratory factor analysis for spacial representation of soil chemical attribute in coffee growing. **Coffee Science**, 11(2):195-203, 2016.

ALMEIDA, L. S. da.; GUIMARÃES, E. C. Geostatistics for determination and modeling of spatial variability space of micronutrients in cultivated soil with coffee tree in the municipality of Araguari-MG. **Cultura Agronômica**, 26(2):58-66, 2017.

ALMEIDA, T. S.; SEDIYAMA, G. C.; DE ALENCAR, L. P. Estimativa da produtividade de cafeeiros irrigados pelo método zona agroecológica espectral. **Revista Engenharia Na Agricultura - Reveng**, 25(1):1-11, 2017.

ALVES, M. C. de. et al. Geostatistical analysis of the spatial variation of the berry borer and leaf miner in a coffee agroecosystem. **Precision Agriculture**, 12(1):18-31, 2011.

ALVES, E. A.; QUEIROZ, D. M.; PINTO, F. A. C. Cafeicultura de precisão. In: ZAMBOLIM, L. (Ed.). **Boas práticas agrícolas na produção de café**. Viçosa MG: Editora UFV, 2006. p. 190.

ALVES, M. C. et al. Modeling spatial variability and pattern of rust and brown eye spot in coffee agroecosystem. **Journal of Pest Science**, 82(2):137-148, 2009.

ANDRADE, A. D. et al. Spatial variability of soil penetration resistanacnder in coffee growing. **Coffee Science**, 13(3):341-348, 2018.

ANDRADE, A. D. et al. Technical and economic evaluation of different operating modes for mechanized fertilizer application in coffee plantations. **Coffee Science**, 15e151748, 2020.

ANGNES, G. et al. Energy efficiency of variable rate fertilizer application in coffee production in Brazil. **AgriEngineering**, 3(4):815-826, 2021.

ATZBERGER, C. Advances in remote sensing of agriculture: Context description, existing operational monitoring systems and major information needs. **Remote Sensing**, 5(2):949-981, 2013.

AVENDANO, J.; RAMOS, P. J.; PRIETO, F. A. A system for classifying vegetative structures on coffee branches based on videos recorded in the field by a mobile device. **Expert Systems with Applications**, 88:178-192, 2017.

BAESSO, M. M. et al. Variabilidade espacial da qualidade do café cereja. **Revista Brasileira de Engenharia de Biossistemas**, 13(2): 109-115, 2019.

BARBOSA, B. D. S. et al. Application of rgb images obtained by uav in coffee farming. **Remote Sensing**, 13(12):2397, 2021.

BARROS, M. M. de. et al. Use of classifier to determine coffee harvest time by detachment force. **Revista Brasileira de Engenharia Agrícola e Ambiental**, 22(5):366-370, 2018.

BARROS, M. M. et al. Avaliação de um sistema de aplicação de fertilizantes a taxa variável adaptado à cultura cafeeira. **Coffee Science**, 10(2):223-232, 2015.

BARRY, P.; COAKLEY, R. Field accuracy test of RPAS photogrammetry. **International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences**, 40(1):27-31, 2013.

BAZAME, H. C. et al. Detection, classification, and mapping of coffee fruits during harvest with computer vision. **Computers and Electronics in Agriculture**, 183:106066, 2021.

BENNUR, P. J.; TAYLOR, R. K. Evaluating the response time of a rate controller used with a sensor-based, variable rate application system. **Applied Engineering in Agriculture**, 26(6):1069-1076, 2010.

BERETA, F. et al. Topographic modelling using UAVs compared with traditional survey methods in mining. **Mining**, 71(3):463-470, 2018.

BERNARDES, T. et al. Monitoring biennial bearing effect on coffee yield using MODIS remote sensing imagery. **Remote Sensing**, 4(9):2492-2509, 2012.

BHATTI, A. U.; MULLA, D. J.; FRAZIER, B. E. Estimation of soil properties and wheat yields on complex eroded hills using geostatistics and thematic mapper images. **Remote Sensing of Environment**, 37(3):181-191, 1991.

BOTTEGA, E. L. et al. Spatial variability of soil attributes in no a no-tillage system with crop rotation in the brazilian savannah. **Revista Ciencia Agronomica**, 44(1):1-9, 2013.

BURAK, D. L.; SANTOS, D. A.; PASSOS, R. R. Spatial variability of physical properties: relationship with relief, organic matter and productivity in conilon coffee. **Coffee Science**, 11(4):455-466, 2016.

CAMBARDELLA, C. A. et al. Field-scale variability of soil properties in central iowa soils. **Soil Science Society of America Journal**, 58(5):1501-1511, 1994.

CANDIAGO, S. et al. Evaluating multispectral images and vegetation indices for precision farming applications from UAV images. **Remote Sensing**, 7(4):4026-4047, 2015.

CARVALHO, J. R. P. de.; SILVEIRA, P. M. da.; VIEIRA, S. R. Geoestatística na determinação da variabilidade espacial de características químicas do solo sob diferentes preparos. **Pesquisa Agropecuária Brasileira**, 37(8):1151-1159, 2002.

CARVALHO, L. C. C. et al. Variabilidade espacial de atributos físicos do solo e características agronômicas da cultura do café. **Coffee Science**, 8(3):265-275, 2013.

CARVALHO, L. C. C. et al. Space analysis of clay content and humidity gravimetric, in different depth of layers in a red latosol dystrophic. **Nucleus**, 11(2):379-384, 2014.

CARVALHO, L. C. C. et al. Geostatistical analysis of arabic coffee yield in two crop seasons [Análise geoestatística da produtividade do cafeeiro arábica em duas safras]. **Revista Brasileira de Engenharia Agricola e Ambiental**, 21(6):410-414, 2017.

CHEMURA, A. et al. Mapping spatial variability of foliar nitrogen in coffee (*Coffea arabica* L.) plantations with multispectral Sentinel-2 MSI data. **ISPRS Journal of Photogrammetry and Remote Sensing**, 138:1-11, 2018.

CHEMURA, A.; MUTANGA, O.; DUBE, T. Integrating age in the detection and mapping of incongruous patches in coffee (Coffea arabica) plantations using multi-temporal Landsat 8 NDVI anomalies. **International Journal of Applied Earth Observations and Geoinformation**, 57:1-13, 2017a.

CHEMURA, A.; MUTANGA, O.; DUBE, T. Remote sensing leaf water stress in coffee (Coffea arabica) using secondary effects of water absorption and random forests. **Physics and Chemistry of the Earth**, 100:317-324, 2017b.

CHLINGARYAN, A.; SUKKARIEH, S.; WHELAN, B. Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. **Computers and Electronics in Agriculture**, 151:61-69, 2018.

CORA, J. E. et al. Assessment of spatial variability of soil attributes as a basis for the adoption of precision agriculture in sugarcane plantations. **Revista Brasileira de Ciencia do Solo**, 28(6):1013-1021, 2004.

COSTA, F. P.; LIMA, J. S. S. de. Cokrigagem na distribuição espacial do cálcio em um latossolo cultivado com café conilon. **Nucleus**, 8(1):269-276, 2011.

CUNHA, J. P. A. R.; NETO, M. A. S.; HURTADO, S. M. C. Estimating vegetation volume of coffee crops using images from unmanned aerial vehicles system , digital image tree crops, such as arabica coffee (*Coffea arabica* L .), present enormous technical challenges in terms. **Precision Agriculture**, 4430:41-47, 2019.

DEVI, G. M. S.; KUMAR, K. S. A. Remote sensing and GIS application for land quality assessment for coffee growing areas of Karnataka. **Journal of the Indian Society of Remote Sensing**, 36(1):89-97, 2008.

FARIA, R. O. de. et al. Technical and economic viability of manual harvesting coffee yield maps. **Coffee Science**, 15:e151674, 2020.

FERRAZ, G. A. E. S. et al. Viabilidade econômica do sistema de adubação diferenciado comparado ao sistema de adubação convencional em lavoura cafeeira: Um estudo de caso. **Engenharia Agricola**, 31(5):906-915, 2011.

FERRAZ, G. A. E. S. et al. Variabilidade espacial e temporal do fósforo, potássio e da produtividade de uma lavoura cafeeira. **Engenharia Agricola**, 32:(1):140-150, 2012a.

FERRAZ, G. A. E. S. et al. Geostatistical analysis of fruit yield and detachment force in coffee. **Precision Agriculture**,13(1):76-89, 2012b.

FERRAZ, G. A. S. et al. Variabilidade espacial dos atributos da planta de uma lavoura cafeeira. **Revista Ciencia Agronomica**, 48(1):81-91, 2017c.

FERRAZ, G. A. E. S. et al. Spatial variability of the dosage of P2O5 and K2O to fertilize in a variable rate and in a conventional way in a coffee field. **Coffee Science**, 10(3):346-356, 2015.

FERRAZ, G. A. E. S. et al. Metodología para determinar la cuadrícula de muestreo del suelo para la agricultura de precisión en un campo de café. **DYNA (Colombia)**, 84(200):316-325, 2017a.

FERRAZ, G. A. E. S. et al. Comparison between the soil chemical atributes sampled comventionaly and in grid. **Coffee Science**, 12(1):17-29, 2017b.

FERRAZ, G. A. E S. et al. Spatial variability of the detachment force of coffee fruit. **Engenharia Agricola**, 34(6):1210-1223, 2014.

FERRAZ, G. A. S. et al. Spatial variability of soil fertility attributes and productivity in a coffee crop farm. **Agronomy Research**, 17(4):1630-1638, 2019.

FERREIRA JÚNIOR, L. G. de. et al. Recomendação para colheita mecânica do café baseado no comportamento de vibração das hastes derriçadoras. **Ciencia Rural**, 46(2):273-278, 2016.

FERREIRA JÚNIOR, L. G. de. et al. Characterization of the coffee fruit detachment force in crop subjected to mechanized harvesting. **Coffee Science**, 13(1):71-79, 2018.

FERREIRA JÚNIOR, L. G. de. et al. Dynamic behavior of coffee tree branches during mechanical harvest. **Computers and Electronics in Agriculture**, 173:105415, 2020.

FIGUEIREDO, V. C. et al. Analysis of spatial variability of force detachment of coffee fruits in central pivot. **Coffee Science**, 12(2):84-92, 2017.

FIGUEIREDO, V. C. et al. Development of a methodology to determine the best grid sampling precision coffee growing. **Coffee Science**, 13(3):312-323, 2018.

FURFARO, R. et al. Neural network algorithm for coffee ripeness evaluation using airborne images. **Applied Engineering in Agriculture**, 23(3):379-387, 2007.

GAERTNER, J. Vegetation classification of *Coffea* on Hawaii Island using WorldView-2 satellite imagery. **Journal of Applied Remote Sensing**, 11(4):046005, 2017.

GARCIA-FREITES, S. et al. The potential of coffee stems gasification to provide bioenergy for coffee farms: a case study in the Colombian coffee sector. **Biomass Conversion and Biorefinery**, 10(4):1137-1152, 2020.

GILES, D. Use of remotely piloted aircraft for pesticide applications: Issues and outlook. **Outlooks on Pest Management**, 27(5):196-197, 2016.

GREGO, C. R.; VIEIRA, S. R. Variabilidade espacial de propriedades físicas do solo em uma parcela experimental. **Revista Brasileira de Ciência do Solo**, 29(2):169-177, 2005.

HABOUDANE, D. et al. Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. **Remote Sensing of Environment**, 81:416-426, 2002.

HARDIN, P. J.; HARDIN, T. J. Small-scale remotely piloted vehicles in environmental research. **Geography Compass**, 4(9):1297-1311, 2010.

HASSLER, S. C.; BAYSAL-GUREL, F. Unmanned aircraft system (UAS) technology and applications in agriculture. **Agronomy**, 9(10):618, 2019.

HERWITZ, S. R. et al. Imaging from an unmanned aerial vehicle: Agricultural surveillance and decision support. **Computers and Electronics in Agriculture**, 44(1):49-61, 2004.

HONKAVAARA, E. et al. Processing and assessment of spectrometric, stereoscopic imagery collected using a lightweight UAV spectral camera for precision agriculture. **Remote Sensing**, 5(10):5006-5039, 2013.

HOUBORG, R.; FISCHER, J. B.; SKIDMORE, A. K. Advances in remote sensing of vegetation function and traits. **International Journal of Applied Earth Observation and Geoinformation**, 43:1-6, 2015.

HUANG, Y. et al. Agricultural remote sensing big data: Management and applications. **Journal of Integrative Agriculture**, 17(9):1915-1931, 2018.

INAMASU, R. Y. et al. Strategies for the implementation, management and operation of the Precision Agriculture Network. In: INAMASU, R. Y. et al. **Agricultura de precisão: Um novo olhar**. São Carlos, SP: Embrapa Instrumentação, p. 31-40, 2009.

INOUE, Y. et al. Assessing land-use and carbon stock in slash-and-burn ecosystems in tropical mountain of laos based on time-series satellite images. **International Journal of Applied Earth Observation and Geoinformation**, 12(4):287-297, 2010.

JACINTHO, J. L. et al. Management zones in coffee cultivation. **Revista Brasileira de Engenharia Agricola e Ambiental**, 21(2):94-99, 2017.

JARAMILLO-GIRALDO, C. et al. Relationship between spatio-temporal leaf area index and crop coefficient when monitoring coffee plots in Brazil using the Sentine-2. **Journal of Agricultural Science**, 11(15):187-199, 2019.

JOHNSON, L. F. et al. Feasibility of monitoring coffee field ripeness with airborne multispectral imagery. **Applied Engineering in Agriculture**, 20(6):845-850, 2004.

JORGE, R. F. et al. Spatial variability in fertigated coffee yields and plant nutrients in soil saturation extracts. **International Journal for Innovation Education and Research**, 7(11):347-360, 2019.

JÚNIOR, P. C. M. et al. Spatial variability of physical attributes of the soil in amazonian black soil under coffee cultivation. **Coffee Science**, 12(2):260-271, 2017.

KAMIMURA, K. M. et al. Variabilidade espacial de atributos físicos de um latossolo vermelho-amarelo, sob lavoura cafeeira. **Revista Brasileira de Ciencia do Solo**, 37(4):877-888, 2013.

KATSUHAMA, N. et al. Discrimination of areas infected with coffee leaf rust using a vegetation index. **Remote Sensing Letters**, 9(12):1168-1194, 2018.

KAWAKUBO, F. S.; PÉREZ MACHADO, R. P. Mapping coffee crops in southeastern Brazil using spectral mixture analysis and data mining classification. **International Journal of Remote Sensing**, 37(14):3414-3436, 2016.

KAZAMA, E. H. et al. Methodology for selective coffee harvesting in management zones of yield and maturation. **Precision Agriculture**, 22(3):711-733, 2021.

KELLEY, L. C.; PITCHER, L.; BACON, C. Using google earth engine to map complex shade-grown coffee landscapes in northern Nicaragua. **Remote Sensing**, 10(6):952, 2018.

LALIBERTE, A.; RANGO, A. Image processing and classification procedures for analysis of sub-decimeter imagery acquired with an unmanned aircraft over arid rangelands. **GIScience and Remote Sensing**, 48(1):4-23, 2011.

LAN, Y. et al. Current status and future directions of precision aerial application for site-specific crop management in the USA. **Computers and Electronics in Agriculture**, 74(1):34-38, 2010.

LELONG, C. C. D. et al. Assessment of unmanned aerial vehicles imagery for quantitative monitoring of wheat crop in small plots. **Sensors**, 8(5):3557-3585, 2008.

LIMA, J. S. S. de. et al. Estimativa da produtividade de café conilon utilizando técnicas de cokrigagem. **Revista Ceres**, 63(1):54-61, 2016.

LIMA, J. S. S. de.; DE OLIVEIRA, R. B.; SILVA, S. A. de. Spatial variability of particle size fractions of an Oxisol cultivated with conilon coffee. **Revista Ceres**, 59(6):867-872, 2012.

LIMA, J. S. S. de.; SILVA, S. A. de.; SILVA, J. M. da. Variabilidade espacial de atributos químicos de um latossolo vermelho-amarelo cultivado em plantio direto. **Revista Ciência Agronômica**, 44(1):16-23, 2013.

LÓPEZ-GRANADOS, F. et al. Early season weed mapping in sunflower using UAV technology: Variability of herbicide treatment maps against weed thresholds. **Precision Agriculture**, 17(2):183-199, 2016.

MARIN, D. B. et al. Sensoriamento remoto multiespectral na identificação e mapeamento das variáveis bióticas e abióticas do cafeeiro. **Revista Ceres**, 66(2):142-153, 2019a.

MARIN, D. B. et al. Multispectral radiometric monitoring of bacterial blight of coffee. **Precision Agriculture**, 20(5):959-982, 2019b.

MARIN, D. B. et al. Remotely piloted aircraft and random forest in the evaluation of the spatial variability of foliar nitrogen in coffee crop. **Remote Sensing**, 13(8):1471, 2021a.

MARIN, D. B. et al. Detecting coffee leaf rust with UAV-based vegetation indices and decision tree machine learning models. **Computers and Electronics in Agriculture**, 190:106476, 2021b.

MARTELLO, M.; MOLIN, J. P.; BAZAME, H. C. Obtaining and validating high-density coffee yield data. **Horticulturae**, 8(5):421, 2022.

MARTINS, G. D.; GALO, M. D. L. B. T.; VIEIRA, B. S. Detecting and mapping root-knot nematode infection in coffee crop using remote sensing measurements. **IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing**, 10(12):5395-5403, 2017.

MATEEN, A.; ZHU, Q. Weed detection in wheat crop using uav for precision agriculture. **Pakistan Journal of Agricultural Sciences**, 56(3):775-784, 2019.

MELO, B. M. R. de. et al. Zonas de manejo em função de propriedades de solo, relevo e produtividade da lavoura cafeeira. **Revista Agrogeoambiental**, 9(2):49-59, 2017.

MIRANDA, J. M.; REINATO, R. A. O.; DA SILVA, A. B. Mathematical model for predicting coffee yield. **Revista Brasileira de Engenharia Agricola e Ambiental**, 18(4):353-361, 2014.

MOLIN, J. P. Agricultura de precisão aprimora gerenciamento. **Visão Agrícola**, p. 115-118, 2006.

MOLIN, J. P. et al. Método para avaliação de aplicaç ão de fertilizantes em taxa variávelem café. **Acta Scientiarum - Agronomy**, 32(4):569-575, 2010.

MORIYA, E. A. S. et al. Mapping mosaic virus in sugarcane based on hyperspectral images. **IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing**, 10(2):740-748, 2017.

NETO, P. H. W. et al. Um estudo da variabilidade espacial do conteúdo de areia do solo, utilizando diferentes métodos de interpolação. **Publicatio UEPG: Ciências Exatas e da Terra, Agrárias e Engenharias**, 12 (1):41-49, 2006.

NOGUEIRA, S. M. C.; MOREIRA, M. A.; VOLPATO, M. M. L. Evaluating precipitation estimates from Eta, TRMM and CHRIPS data in the south-southeast region of Minas Gerais state-Brazil. **Remote Sensing**, 10(2):313, 2018.

OLIVEIRA, A. R. de. et al. Geoestatistical interpolation applied in the spatialization of chemical attributes of a red-yellow latosol. **Journal of Physical Therapy Science**, 9(1):1-11, 2018.

OLIVEIRA, H. C. et al. Failure Detection in Row Crops from UAV Images Using Morphological Operators. **IEEE Geoscience and Remote Sensing Letters**, v. 15, n. 7, p. 991–995, 2018.

OLIVEIRA, W. J. C. das. et al. Estimativa do custo horário de equipamentos e serviços em diferentes níveis de tecnificação em agricultura de precisão. **Revista de Ciências Agrarias - Amazon Journal of Agricultural and Environmental Sciences**, 59(4):378-385, 2016.

ORTEGA-HUERTA, M. A. et al. Mapping coffee plantations with land sat imagery: An example from El Salvador. **International Journal of Remote Sensing**, 33(1):220-242, 2012.

MINCATO, R. L. et al. Using unmanned aerial vehicle and machine learning algorithm to monitor leaf nitrogen in coffee. **Coffee Science**, 15:e151736, 2020.

PEÑA, J. M. et al. Weed mapping in early-season maize fields using object-based analysis of unmanned aerial vehicle (UAV) Images. **PLoS ONE**, 8(10):1-11, 2013.

PEREIRA, C. P. et al. Coffee crop's biomass and carbon stock estimation with usage of high resolution satellites images. **IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing**, 6(3):1786-1795, 2013.

PIRES, M. S. O. de.; ALVESA, M. C. de.; POZZA, E. A. Multispectral radiometric characterization of coffee rust epidemic in different irrigation management systems. **International Journal of Applied Earth Observation and Geoinformation**, 86:102016, 2020.

PRADO, E. V. do.; MACHADO, T. D. A.; PRADO, F. M. T. Geração e correlação de zonas de manejo usando sensor Spad e condutividade elétrica aparente do solo para a cafeicultura irrigada na zona da mata mineira. **Revista Científica Eletrônica de Agronomia**, (27):1-7, 2015.

PUGH, S. et al. Spatiotemporal lagged models for variable rate irrigation in agriculture. **Journal of Agricultural, Biological, and Environmental Statistics**, 24(4):634-650, 2019.

PUTRA, B. T. W. et al. Using information from images for plantation monitoring: A review of solutions for smallholders. **Information Processing in Agriculture**, 7(1):109-119, 2020.

QUEIROZ, D. M. D. et al. Sensors applied to digital agriculture: A review. **Revista Ciência Agronômica**, 51:e20207751, 2021.

RAMIREZ, G. M.; JÚNIOR, J. Z. Estimation of biophysical parameters of coffee fields based on high-resolution satellite images. **Engenharia Agricola**, 30(3):468-479, 2010.

ROCHA, H. G. et al. Coffee productivity mapping from mathematical models for prediction of harvest. **Coffee Science**, 11(1):108-116, 2016.

SANCHEZ, M. G. B. et al. Delineation of specific management areas for coffee cultivation based on the soil-relief relationship and numerical classification. **Precision Agriculture**, 14(2):201-214, 2013.

SANCHEZ, R. B. et al. Variabilidade espacial de propriedades de Latossolo e da produção de café em diferentes superfícies geomórficas. **Revista Brasileira de Engenharia Agrícola e Ambiental**, 9(4):489-495, 2005.

SANTANA, L. S. et al. Vegetative vigor of maize crop obtained through vegetation indexes in orbital and aerial sensors images. **Brazilian Journal of Biosystems Engineering**, 13(3):195-206, 2019.

SANTANA, L. S. et al. Influence of flight altitude and control points in the georeferencing of images obtained by unmanned aerial vehicle. **European Journal of Remote Sensing**, 54(1):59-71, 2021a.

SANTANA, L. S. et al. Monitoring errors of semi-mechanized coffee planting by remotely piloted aircraft. **Agronomy**, 11(6):1224, 2021b.

SANTINATO, F. et al. Número de operações mecanizadas na colheita do café. **Ciencia Rural**, 45(10):1809-1814, 2015.

SANTOS, E. O. J. de.; GONTIJO, I.; SILVA, M. B. da. Spatial variability of soil acidity attributes and liming requirement for conilon. **Coffee Science**, 9(2):275-283, 2014.

SANTOS, E. O. J. de. et al. Variabilidade espacial de macronutrientes em uma lavoura de café conilon no Norte do Espírito Santo. **Revista Ciencia Agronomica**, 46(3):469-476, 2015.

SANTOS, E. O. J. de. et al. Sampling design of soil physical properties in a Conilon coffee field. **Revista Brasileira de Ciencia do Solo**, 41:e0160426, 2017.

SANTOS, L. M. dos. et al. Use of remotely piloted aircraft in precision agriculture: A review. **DYNA** 86(210):284-291, 2019a.

SANTOS, L. M. dos. et al. Analysis of flight parameters and georeferencing of images with different control points obtained by RPA. **Agronomy Research**, 17(5):2054-2063, 2019b.

SANTOS, F. F. L. dos. et al. Quality assessment of coffee beans through computer vision and machine learning algorithms. **Coffee Science**, 15:e151752, 2020.

SANTOS, L. M. dos. et al. Determining the leaf area index and percentage of area covered by coffee crops using uav rgb images. **IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing**, 13:6401-6409, 2020a.

SANTOS, L. M. et al. Biophysical parameters of coffee crop estimated by UAV RGB images. **Precision Agriculture**, v. 21, n. 6, p. 1227–1241, 2020b.

SARMIENTO, C. M. et al. Comparação de classificadores supervisionados na discriminação de áreas cafeeiras em Campos Gerais - Minas Gerais. **Coffee Science**, 9(4):546-557, 2014.

SEELAN, S. K. et al . Remote sensing applications for precision agriculture: A learning community approach. **Remote sensing of environment**, 88(1-2), 157-169, 2003.

SIEBERT, S.; TEIZER, J. Mobile 3D mapping for surveying earthwork projects using an unmanned aerial vehicle (UAV) system. **Automation in Construction**, 41:1-14, 2014.

SILVA, A. et al. Mapas de fertilidade de solo em área manejada com agricultura de precisão cultivada com café. **Brazilian Geographical Journal - Geosciences and Humanities Research Medium**, 5(1):194-204, 2014.

SILVA, A. F. da. et al. Variabilidade espacial de atributos químicos do solo cultivado com café arábica (*Coffea arabica* L.) sob diferentes manejos. **Coffee Science**, 5(2):173-182, 2010.

SILVA, F. M. da. et al. Variabilidade espacial de atributos químicos e de produtividade na cultura do café. **Ciência Rural**, 37(2):401-407, 2007.

SILVA, F. M. da. et al. Efeitos da colheita manual na bienalidade do cafeeiro em Ijaci, Minas Gerais. **Ciência e Agrotecnologia**, 34(3):625-632, 2010.

SILVA, F. M. et al. Spatial variability of chemical attributes and coffee productivity in two harvests. **Ciencia e Agrotecnologia**, 32(1):231-241, 2008.

SILVA, S. A. de. et al. Spatial variability of chemical attributes of an oxisol under coffee cultivation. **Revista Brasileira de Ciência do Solo**, 34(1):16-23, 2010.

SILVA, S. A. de.; LIMA, J. S. de. Avaliação da variabilidade do estado nutricional e produtividade de café por meio da análise de componentes principais e geoestatística. **Revista Ceres**, 59(2):271-277, 2012.

SILVA, S. A. de.; LIMA, J. S. S. Physical attributes of soil and its relation with space productivity of Coffee Arabic. **Coffee Science**, 8(4):395-403, 2013.

SIMÕES, W. L. et al. Variabilidade espacial de atributos físicos de um latossolo vermelho distroférrico, submetido a diferentes manejos. **Revista Brasileira de Ciência do Solo**, 30(6):1061-1068, 2006.

SOELA, D. M. et al. Control spraying process statistics using uniproved air vehicle in conilon coffee culture. **Brazilian Journal of Production Engineering**, 6(4):52-63, 2020.

SOTT, M. K. et al. Precision techniques and agriculture 4.0 technologies to promote sustainability in the coffee sector: State of the art, challenges and future trends. **IEEE Access**, 8:149854-149867, 2020.

SOUZA, C. G. et al. Multitemporal variables for the mapping of coffee cultivation areas. **Pesquisa Agropecuaria Brasileira**, 54:e00017, 2019.

STOLT, M. H. et al. Spatial variability in palustrine wetlands. **Soil Science Society of America Journal**, 65(2):527-535, 2001.

SWANN, L. **Unmanned Aircraft Systems (UAS),** Quebec, Canada, 2016. 54p.

TAKAHASHI, R.; TODO, Y. Coffee certification and forest quality: Evidence from a wild coffee Forest in Ethiopia. **World Development**, 92(25):158-166, 2017.

TEKIN, A. B. Variable rate fertilizer application in Turkish wheat agriculture: Economic assessment. **African Journal of Agricultural Research**, 5(8):647-652, 2010.

TOKEKAR, P. et al. Sensor planning for a symbiotic UAV and UGV system for precision agriculture. **IEEE Transactions on Robotics**, 32(6):1498-1511, 2016.

TORRADO, J. O. E.; JIMÉNEZ, J. J. C.; DÍAZ, H. P. Ortomosaicos y modelos digitales de elevación generados a partir de imágenes tomadas con sistemas UAV. **Tecnura**, 20(50):119-140, 2016.

TRABAQUINI, K. et al. Uso da Geotenologia para caracterizar os cafezais no municipio de Londrina-PR, em relação à altimetria, declividade e tipo de solo. **Engenharia Agrícola**, 30(6):1136-1147, 2010.

USTIN, S. L.; GAMON, J. A. Remote sensing of plant functional types. **New Phytologist**, 186(4):795-816, 2010.

UYSAL, M.; TOPRAK, A. S.; POLAT, N. DEM generation with UAV Photogrammetry and accuracy analysis in Sahitler hill. **Measurement: Journal of the International Measurement Confederation**, 73:539-543, 2015.

VALENTE, D. S. M. et al. Definition of management zones in coffee production fields based on apparent soil electrical conductivity. **Scientia Agricola**, 69(3):173-179, 2012.

VELÁSQUEZ, D. et al. A method for detecting coffee leaf rust through wireless sensor networks, remote sensing, and deep learning: Case study of the Caturra variety in Colombia. **Applied Sciences (Switzerland)**, 10(2):1-27, 2020.

VERICAT, D. et al. Accuracy assessment of aerial photographs acquired using lighter-than-air blimps: Low-cost tools for mapping river corridors. **River Research and Applications**, 25:985-1000, 2009.

VIEIRA, S. R. et al. Spatial variability of soil chemical properties after coffee tree removal. **Revista Brasileira de Ciencia do Solo**, 33(5):1507-1514, 2009.

VIERLING, L. A. et al. The Short wave aerostat-mounted imager (SWAMI): A novel platform for acquiring remotely sensed data from a tethered balloon. **Remote Sensing of Environment**, 103(3):255-264, 2006.

VIRK, S. S. et al. Row-crop planter performance to support variable-rate seeding of maize. **Precision Agriculture**, 21(3):603-619, 2020.

WALKLATE, P. J.; CROSS, J. V.; PERGHER, G. Support system for efficient dosage of orchard and vineyard spraying products. **Computers and Electronics in Agriculture**, 75(2):355-362, 2011.

WANG, L. et al. Vision-based adaptive variable rate spraying approach for unmanned aerial vehicles. **International Journal of Agricultural and Biological Engineering**, 12(3):18-26, 2019.

WEISS, M.; JACOB, F.; DUVEILLER, G. Remote sensing for agricultural applications: A meta-review. **Remote Sensing of Environment**, 236:111402, 2020.

WEST, G. H.; KOVACS, K. Addressing groundwater declines with precision agriculture: An economic comparison of monitoring methods for variable-rate irrigation. **Water**, 9(1):28, 2017.

WHITEHEAD, K. et al. Remote sensing of the environment with small unmanned aircraft systems (Uass), part 2: Scientific and commercial applications. **Journal of Unmanned Vehicle Systems**, 2(3):86-102, 2014.

WOLFERT, S. et al. Big data in smart farming - A review. **Agricultural Systems**, 153:69-80, 2017.

XIANG, H.; TIAN, L. Method for automatic georeferencing aerial remote sensing (RS) images from an unmanned aerial vehicle (UAV) platform. **Biosystems Engineering**, 108(2):104-113, 2011.

ZAJKOWSKI, T. J. et al. Evaluation and use of remotely piloted aircraft systems for operations and research - RxCADRE 2012. **International Journal of Wildland Fire**, 25(1):114-128, 2016.

ZANELLA, M. A. et al. Spatial correlation between the chlorophyll index and foliar npk levels in coffee crop. **Coffee Science**, 15:e151765, 2020.

ZHANG, C.; KOVACS, J. M. The application of small unmanned aerial systems for precision agriculture: A review. **Precision Agriculture**, 13(6):693-712, 2012.