UNIVERSIDADE ESTADUAL DE CAMPINAS
FACULDADE DE ENGENHARIA DE ALIMENTOS

GUILHERME MARTINELI SANCHES

SPATIAL AND TEMPORAL VARIABILITY OF SOIL ATTRIBUTES AND THEIR RELATIONSHIP WITH CROP YIELD, TOPOGRAPHIC PARAMETERS AND APPARENT ELECTRICAL CONDUCTIVITY (ECa) IN SUGARCANE FIELDS

VARIABILIDADE ESPACIAL E TEMPORAL DOS ATRIBUTOS DO SOLO E SUA RELAÇÃO COM A PRODUTIVIDADE AGRÍCOLA, PARÂMETROS TOPOGRÁFICOS E CONDUTIVIDADE ELÉTRICA APARENTE (CEa) EM LAVOURAS DE CANA-DE-AÇÚCAR

CAMPINAS-SP
2018

GUILHERME MARTINELI SANCHES

SPATIAL AND TEMPORAL VARIABILITY OF SOIL ATTRIBUTES AND THEIR RELATIONSHIP WITH CROP YIELD, TOPOGRAPHIC PARAMETERS AND APPARENT ELECTRICAL CONDUCTIVITY (ECA) IN SUGARCANE FIELDS

VARIABILIDADE ESPACIAL E TEMPORAL DOS ATRIBUTOS DO SOLO E SUA RELAÇÃO COM A PRODUTIVIDADE AGRÍCOLA, PARÂMETROS TOPOGRÁFICOS E CONDUTIVIDADE ELÉTRICA APARENTE (CEA) EM LAVOURAS DE CANA-DE-AÇÚCAR

Thesis presented to the Faculty of Food Engineering of the University of Campinas in partial fulfillment of the requirements for the degree of Doctor in Sciences.

Tese apresentada à Faculdade de Engenharia de Alimentos da Universidade Estadual de Campinas como parte dos requisitos exigidos para a obtenção do título de Doutor em Ciências.

Orientador: Prof. Dr. Paulo Sérgio Graziano Magalhães

Este exemplar corresponde à versão final da tese defendida pelo aluno Guilherme Martineli Sanches, e orientada pelo prof. Dr. Paulo Sérgio Graziano Magalhães.

CAMPINAS-SP

2018

FICHA CATALOGRÁFICA

Agência(s) de fomento e nº(s) de processo(s): FAPESP, 2014/14965-0
ORCID: orcid.org/0000-0001-7718-8142

Ficha catalográfica
Universidade Estadual de Campinas
Biblioteca da Faculdade de Engenharia de Alimentos
Márcia Regina Garbelini Sevillano - CRB 8/3647

Sa55s	Sanches, Guilherme Martineli, 1989- Spatial and temporal variability of soil attributes and their relationship with crop yield, topographic parameters and apparent electrical conductivity (ECa) in sugarcane fields / Guilherme Martineli Sanches. – Campinas, SP : [s.n.], 2018. Orientador: Paulo Sérgio Graziano Magalhães. Tese (doutorado) – Universidade Estadual de Campinas, Faculdade de Engenharia de Alimentos. 1. Agricultura de Precisão. 2. Solos - Manejo. 3. Solos - Produtividade. 4. Cana-de-açúcar. 5. Plantas açucareiras - Cultivo. I. Magalhães, Paulo Sérgio Graziano. II. Universidade Estadual de Campinas. Faculdade de Engenharia de Alimentos. III. Título.

<u>Informações para Biblioteca Digital</u>

Título em outro idioma: Variabilidade espacial e temporal dos atributos do solo e sua relação com a produtividade agrícola, parâmetros topográficos e condutividade elétrica aparente (CEa) em lavouras de cana-de-açúcar
Palavras-chave em inglês:
Precision agriculture
Soils management
Soils productivity
Sugarcane
Sugar growing
Área de concentração: Bioenergia
Titulação: Doutor em Ciências
Banca examinadora:
Paulo Sérgio Graziano Magalhães [Orientador]
João Luís Nunes Carvalho
Claudio Leones Bazzi
Lucas Rios do Amaral
Stanley Robson de Medeiros Oliveira
Data de defesa: 17-09-2018
Programa de Pós-Graduação: Bioenergia

FOLHA DE APROVAÇÃO DA BANCA EXAMINADORA

Prof. Dr. Paulo Sérgio Graziano Magalhães - Presidente

FEAGRI - UNICAMP

Dr. Stanley Robson de Medeiros Oliveira – Membro Titular

CNPTIA - EMBRAPA

Dr. João Luís Nunes Carvalho – Membro Titular

CTBE - CNPEM

Prof. Dr. Claudio Leone Bazzi – Membro Titular

UTFPR

Prof. Dr. Lucas Rios do Amaral – Membro Titular

FEAGRI - UNICAMP

Ata da defesa com as respectivas assinaturas dos membros encontra-se no SIGA/Sistema de Fluxo de Dissertação/Tese e na Secretaria do Programa da Unidade

À minha estimada esposa Priscilla Sanches e ao meu amado filho Pedro Henrique pelo apoio, companheirismo, paciência e amor demonstrados ao longo desta jornada.

Com imenso carinho,

Dedico

Aos meus amados pais, Affonso e Malu, e irmão Gustavo e à toda minha família,

Ofereço

ACKNOWLEDGMENTS

There are countless people who I would like to express my gratitude, so I apologize if I forget some of them, but you are in my heart. First, I would like to thank Professor Paulo S. Graziano Magalhães for the support, patience, dedication and wisdom with me throughout my thesis journey. Second, to all friends from Brazilian Bioethanol Science and Technology Laboratory (CTBE) (Ana Claudia, Angélica Pontes, Antonio Bonomi, Bernardo Borges, Carlos Driemeier, Daniel Duft, Douglas Forchezatto, Fabio Makoto, Felipe Oliveira, Gisela Maira, Gonçalo Amarante, João Luis Nunes, João Neto, Jorge Neves, José Eliseu Débia, Karina Berbert, Larissa Cruz, Lauren Menandro, Leandro Barbosa, Liu Lin, Luana Moraes, Marcela Bruscagin, Maria Nonato, Mariana Stevanatto, Mateus Chagas, Oriel Kolln, Oscar Braunbeck, Raquel Scatolin, Ricardo Bordonal, Sergio Castro, Tatiane Morais, Terezinha Cardoso) who helped me most of time and provide to me a lovely work environment. To my Family (Auro, Isis, Felipe, Affonso, Adilson, Iara, Eldritch, Edwin, Inácio, Angelita, Rebeca, Isaque and, in memorian, Avós Affonso, Aurelina, Maria and Francisco). To my wife's Family (Carlos, Telma, Giovanna, Vó Eulina e Vó Dalva). To the true friends (Alice Hamamoto, Bruno e Carla Macedo, Bruno e Fernanda Palumbo, Cleso e Fabíola Andrade, Eicke e Eliana Bucholtz, Pr. Sauro, Pr. Cilas, Romulo e Priscilla Akemi, Victor Petri) who shared with me, with immense love, the days of anguish, anxiety, sorrows and joys. My acknowledgements to Henrique Franco, Thiago Brasco, Professor Lucas Amaral, Professor Paulo Molin, and all my 'scientific' colleagues along of my thesis journey. Finally, I thank God for my health and for the moments in which He reestablished me when I didn't have more strength, to give me a beautiful family and a loving wife (Priscilla) and son (Pedro Henrique) and for the grace of my life. I also thanks to São Paulo Research Foundation (FAPESP – Process 2014/14965-0). This study was fincanced in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001.

RESUMO

A produção de etanol no Brasil deverá ser de 54 bilhões de litros em 2030 para atender ao acordo firmado na COP21, o que representa o dobro da produção de etanol verificada em 2016. Do ponto de vista agronômico há duas alternativas: ou aumenta-se a área plantada com a cultura ou aumenta-se a produtividade por área. Ambientalmente não há dúvidas que o aumento da produtividade é a melhor alternativa, sendo que a agricultura de precisão (AP) será fundamental para contribuir com a sustentabilidade da produção. Atualmente a AP nas lavouras de cana-de-açúcar no Brasil está longe do potencial que as tecnologias disponíveis podem proporcionar para o manejo adequado da cultura. O principal objetivo da presente tese é demonstrar como as tecnologias de PA, mais especificamente, monitores de rendimento, parâmetros topográficos e sensores de condutividade elétrica aparente (CEa), podem ajudar os agricultores a gerenciar os campos de forma específica do local. Para tanto, os atributos do solo que impactam diretamente a produtividade das culturas foram avaliados espacial e temporalmente, associando esses elementos do solo com parâmetros topográficos e CEa. Os objetivos são fornecer indicadores qualitativos e quantitativos para uma caracterização espacial precisa dos campos, mostrando o potencial dos parâmetros topográficos e CEa para melhorar o manejo específico do local dos campos de cana-de-açúcar. Para aumentar a produtividade, os resultados mostraram que a matéria orgânica (MO) disponível no solo, teor de argila e capacidade de troca catiônica (CTC) são os fatores que impactam diretamente a produtividade da cana-de-açúcar. Além disso, a variabilidade temporal na produtividade foi causada principalmente pela variabilidade no pH do solo. Uma avaliação abrangente da variabilidade espacial dos atributos do solo relacionados aos parâmetros topográficos evidenciou padrões espaciais que foram temporalmente remanescentes. Os resultados mostraram que as classes morfométricas horizontais (H_{Conv}, H_{Plan} e H_{Div}), associadas às áreas côncavas (V_{conc}), apresentaram maiores teores de MO, Soma de Bases (SB) e CTC, indicando que essas áreas apresentam maior fertilidade do solo, onde a formação $V_{Conc}H_{Div}$ apresentou a maior fertilidade do solo. Para todas as classes morfométricas verticais (V_{Conc}, V_{Ret} e V_{Conv}), os níveis de pH do solo foram maiores quando associados a áreas divergentes (H_{Div}) e menores quando associados a áreas convergentes (H_{Conv}), sugerindo um manejo mais rigoroso da acidez do solo nas áreas H_{Conv}. As áreas $V_{Conv}H_{Conv}$, onde a menor fertilidade do solo foi observada, devem ser amostradas com maior acurácia para adequada caracterização espacial do solo, devido ao alto Coeficiente de Variação (CV) observado quando comparado a outras classes morfométricas avaliadas. Além disso, as classes de CEa, divididas pelo método do quantil, mostraram que os locais de menor condutividade elétrica apresentam menores teores de MO e CTC. As classes de CEa mais altas mostraram CV menor para todos os atributos do solo avaliados, ou seja, locais que podem ser caracterizados com menores quantidades de amostras para um mapeamento de solo adequado. A variabilidade do conteúdo de argila foi diretamente proporcional à variabilidade da CEa (R^2 = 0,97). MO (R^2 = 0,65) e CTC (R^2 = 0,76) também apresentaram boa correlação com a variabilidade da CEa. Com alta estabilidade espacial e temporal, os parâmetros topográficos e da CEa são excelentes fontes de informação (economicamente viáveis e de fácil avaliação) para apoiar os processos de amostragem do solo e mapear as zonas de fertilidade nos campos. **Palavras-chave:** agricultura de precisão; indução eletromagnética; manejo localizado da cultura; agricultura.

ABSTRACT

The ethanol production should be 54 billion liters in 2030, almost double of the current production. From the agronomic point of view, two alternatives are possible; increase the planted area and/or agricultural yield to reach the goals. Environmentally, increase the yield is a more sustainable option, and the adoption of Precision Agriculture (PA) will be essential. The current use of PA in Brazilian sugarcane industry is very far from its full potential. The main objective of the present thesis is to demonstrate how PA technologies, more specifically yield monitors, topographic parameters and apparent electrical conductivity (ECa) sensors, can help farmers to manage fields in a site-specific way. For this purpose, soil attributes that directly impact crop yield were spatially and temporally evaluated, associating these soil elements with topographic and ECa parameters. The aims are to provide qualitative and quantitative indicators for a precise soil spatial characterization of fields, showing the potential of topographic and ECa parameters to improve the site-specific management of sugarcane fields. To increase the yield, the findings showed that the amount of available soil organic matter (OM), clay content and cation exchange capacity (CEC) are important factors that directly impact sugarcane yield. Furthermore, the temporal variability in the yield is caused mainly by the variability in the soil pH. A comprehensive assessment of the spatial variability of soil attributes related to topographic parameters evidencing spatial patterns that were temporally remained. The results showed that the horizontal morphometric classes (H_{Conv}, H_{Plan} and H_{Div}), associated with vertical concave areas (V_{Conc}), presented higher levels of OM, Sum of Bases (SB) and CEC, which indicated that these areas have higher soil fertility, where $V_{Conc}H_{Div}$ showed the highest soil fertility. For all vertical morphometric classes (V_{Conc}, V_{Ret} and V_{Conv}), soil pH levels were higher when associated with horizontal divergent areas (H_{Div}) and lower when associated with convergent areas (H_{Conv}), suggesting that stricter soil acidity management was needed in the H_{Conv} areas. The $V_{Conv}H_{Conv}$ areas, where the lower soil fertility was observed, should be sampled with greater accuracy for adequate soil spatial characterization due to the high CV observed when compared to other morphometric classes assessed. Furthermore, ECa classes, defined by quantil method, showed that the low electrical conductivity sites present lower OM and CEC contents. The higher ECa classes showed smaller CV for all soil attributes assessed, i.e., sites that can be characterized with smaller amounts of samples to an adequate soil mapping than lower ECa classes. The clay content variability was directly proportional to the ECa variability ($R^2 = 0.97$). OM ($R^2 = 0.65$) and CEC ($R^2 = 0.76$) showed great correlation with ECa variability too. With high spatial and temporal stability, topographic and ECa parameters could be excellent (economically feasible and easily assessed) sources of information to support soil sampling processes and to map fertility zones within fields.
 Keywords: precision agriculture; electromagnetic induction; site specific crop management; agriculture.

FIGURES LIST

TABLES LIST

Summary

I. General Introduction

December 12, 2015 was a historic day for the world. More than 195 nations in Paris-France decided to combat global climate change (COP-21, Paris, France). This agreement provided an international engagement to limit the global temperature changes. One of the main focus of the agreement is the low-carbon economy. Then, Brazil plays a fundamental key for nations around the world, through the ethanol production; a renewable fuel that can mitigate the climate change. Thus, the production and export of Brazilian ethanol, which is increasing every year (OECD-FAO Agricultural Outlook 2015-2024, 2015), may suffer even more significant changes that projected earlier.

Brazil has the most renewable energy matrix in the industrialized world. About 41.2% of its production coming from renewable sources such as water resources, biomass and ethanol, wind and solar energy. The world energy matrix is composed of 13.5% of renewable sources in industrialized countries, decreasing to 6% in developing nations. The Brazilian biomass from sugarcane represents 16.9% of the national energy matrix. In the agreement signed during COP-21, Brazil committed to reduce the greenhouse gas (GHG) emissions by 37% and 43%, compared to the 2005 levels, by 2025 and 2030 respectively. The agreement will promote an irreversible change in the current Brazilian energy framework, and the sugarcane industry has a huge potential to replace the fossil fuels import with ethanol to meet the established demands.

Brazil is the world's largest producer of sugarcane and the second largest producer of ethanol, only behind of the United States of America. In 2017, Brazil produced 657.18 million tons of sugarcane in 9.05 million hectares (CONAB, 2017). To meet the COP-21 goals, the ethanol production is expected to reach 54 billion of liters in 2030, almost double of the 2016 production. The sugar production is expected to increase from 38.7 million tons to 46.4 million tons by 2030. To meet these demands for ethanol and sugar production, National Confederation of Industry (CNI), in partnership with the University of São Paulo (FEA/USP), estimated that it will be necessary 942 million tons of sugarcane per season in 2030 (CNI, 2017). To meet these demands, the Brazilian southeast region (especially São Paulo state) should still be the main pole of production, since the other Brazilian regions suffer with lack of investments in new research and technologies to increase their productions capacity.

From the agronomic point of view, two alternatives are possible. If the area expansion is possible, the increase of agricultural yield is also an alternative. Despite of the many controversies over the sugarcane fields expansion and their impact on food production

(Popp et al., 2014), studies showed that there is still potential for the crop expansion, especially in pasture fields (Loarie et al., 2011). However, a more sustainable alternative from the economic and environmental point of view is increase the crop yield. To accomplish that, it will be necessary to invest in technologies that allow to produce more in the same area, i.e., the crop yield should reach new levels and exceed the current Brazilian average of 73 Mg ha^{-1} (CONAB, 2017). In this context, precision agriculture (PA) is an approach that includes several technologies and tools that can contribute significantly to these challenges.

The PA is an approach that seeks to increase yield through a site-specific management of soil and crops, optimizing the inputs and environmental impacts (Bullock et al., 2007). The main technologies available to PA users are yield monitors, remote and proximal soil/plant sensors associated with Global Navigation Systems (GNSS) and several Geographic Information Systems (GIS) packages. Although these technologies are available worldwide, the Brazilian sugar and ethanol industry lacks the effective adoption of them. The adoption of PA is still far from its potential for localized management of sugarcane fields (Silva et al., 2011). One reasons for that is that the sugarcane fields lack a long-term assessment that supply producers with robustness results from technologies application in a site-specific level.

To ensure an adequate site-specific management of sugarcane fields, the soil variability characterization, at spatial and temporal level, is essential to guarantee economic and environmental returns of production. The precise mapping of soil attributes variability should be made in an efficient way, that is, economically and physically feasible. Among the technologies available, many studies in literature evidence that soil apparent electrical conductivity (ECa) and topographic parameters are source of information with great potential to help soil characterization. In this context, the hypothesis of the present thesis is that the main soil attributes, that direct affect sugarcane yield at spatial and temporal level, will be characterized by topographic and ECa information obtained thought SRTM data em EMI sensor, respectively. Sources of information economically feasible and easily assessed could help farmers to manage sugarcane fields in a sustainable way, enable the increase adoption of PA in sugarcane fields. We expected that, through the present study, it will be possible to visualize the main challenges that Brazil will face in the next decade, providing indicators to guide public policies that will overcome the technological bottlenecks for a sustainable sugarcane production expansion.

II. Objectives

The main objective is to provide a comprehensive assessment of the spatial and temporal variability of soil attributes and its relationship with sugarcane yield, topographic parameters and ECa information. The present thesis aims to provide qualitative and quantitative indicators for a precise soil spatial characterization of fields, showing the potential of PA technologies (yield monitor, ECa and remote sensing) to improve the production profitability in the Brazilian sugarcane industry. The specific objectives are as follows:

i. Provide a site-specific assessment of spatial and temporal variability of sugarcane yield and the soil attributes to identify the main soil factors that directly affect the crop yield;
ii. Provide a comprehensive assessment of spatial variability of soil attributes related to topographic parameters, providing indicators that can be used to guide the soil spatial characterization and soil sampling process;
iii. Provide a wide-ranging assessment of the relationship among soil attributes, that directly impact the sugarcane yield, and ECa at spatial and temporal level in Brazilian sugarcane fields by an EMI sensor.

The following topics are divided in chapters, where each one corresponds with a specific objective of this thesis. At the end of the last chapter, we will present the general discussions and conclusions. Figure 1 shows a general overview of how chapters were organized.

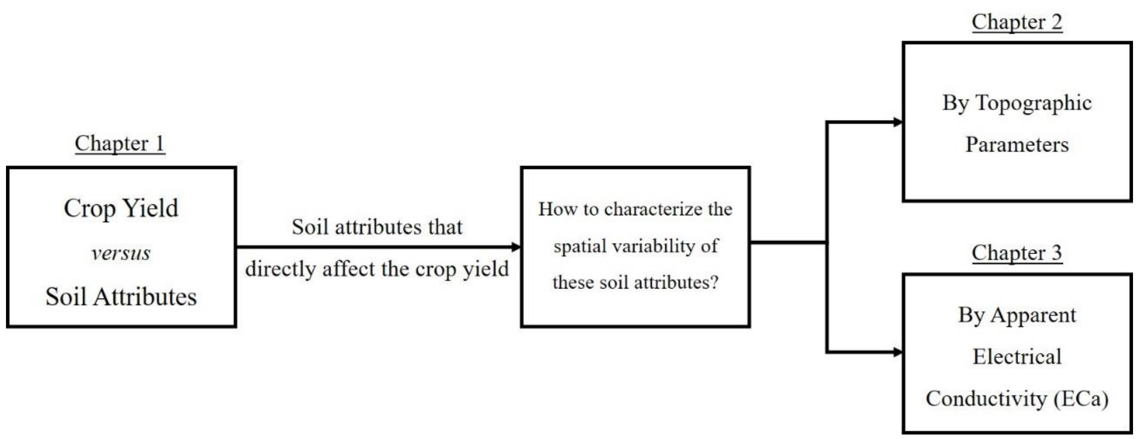


Figure 1. General overview of chapters.

Chapter 1: Site-specific assessment of spatial and temporal variability of sugarcane yield related to soil attributes (*Geoderma 334, 90-98, 2019*)

Guilherme M. Sanches[1*], Paulo S. Graziano Magalhães[1] and Henrique C. Junqueira Franco[1]

[1] University of Campinas – UNICAMP - Ph.D. Program in Bioenergy – Interdisciplinary Center for Energy Planning.

[*]Corresponding author – guilherme.sanches@cropman.com.br/+55 14 991648711

Abstract: The adoption of information technology (IT) and precision agriculture (PA) has converted agricultural fields into data sources. However, the transformation of data into decision making knowledge remains a major challenge. In the Brazilian sugarcane industry, the current use of PA technology is very far from its full potential for site-specific management, mainly because yields are not temporally or spatially monitored. The objective of the present study was to investigate the relationship between the physical and chemical properties of soils and sugarcane yield, thereby identifying the soil parameters that determine the final productivity. Two sugarcane fields were monitored from 2011 to 2014. During the crop season, soil samples and yield data were collected annually. The random forest algorithm was applied to investigate the influence of different soil attributes on yield using data that were collected spatially over the study period. The results showed that the amount of available soil organic matter (OM), clay content and cation exchange capacity (CEC) are important factors impacting sugarcane yield variation. Furthermore, it was found that the temporal variability in the yield is caused mainly by the variability in the pH over the study period. The results indicated that when OM increased over time, there was greater phosphorus availability. Large volumes of spatial and temporal data, together with data mining techniques, allowed for the extraction of knowledge and the creation of specific management zones in the field that support the decision-making process for producers. **Keywords:** precision farming; data mining; random forest; yield monitor; *Saccharum spp*.

1.1. Introduction

According to the goals set by the Brazilian government at COP21, ethanol production in 2030 is expected to be 54 billion of litres, almost double the current production levels. Sugar production will increase from 38.7 million tons to 46.4 million tons. To achieve these ethanol and sugar production goals, it will be necessary to produce 942 million tons of sugarcane per season in 2030 (CNI, 2017). These demands will promote an irreversible change in the current Brazilian sugar and ethanol framework. The sugarcane industry has great potential to replace part of the expected imports of fossil fuel with ethanol and to meet the established greenhouse gas (GHG) reduction targets. Thus, increasing the agricultural yield of sugarcane provides a more economically and environmentally sustainable alternative as producing more yield in the same planted area reduces production costs and avoids the need for new fields expansions. The current Brazilian average sugarcane yield is 72.6 Mg ha^{-1} (CONAB, 2017), far from the genetic potential of the crop, which is 300 Mg ha^{-1} (Waclawovsky et al., 2010). Achieving this yield threshold seems to be a distant possibility, but investments in technology and research can contribute significantly to reaching this goal.

The adoption of precision agriculture (PA) technologies represents a promising approach to increasing agricultural yields and reducing production costs. PA comprises several techniques and technologies for managing the spatial and temporal variability of crops, and these approaches seek to improve the yield, profitability and environmental management of fields. These benefits are essentially obtained through site-specific management that considers the spatial and temporal variability of fields. The main technologies available to PA users are yield monitors, remote and proximal soil and plant sensors associated with Global Navigation Satellite System (GNSS) positioning and geographic information systems (GIS). Among the fundamental PA tools are yield monitors, which can spatially map yields and identify problems in the fields. Although widely developed and used in grain crops (Silva et al., 2011, Arslan and Colvin, 2002), yield monitors are still rarely used in the Brazilian sugarcane industry. Examples of yield monitor applications come mainly from the academy, with the first works having been produced by Magalhães and Cerri (2007).

One of the technological bottlenecks preventing PA advances in the Brazilian sugarcane industry is the lack of applicable knowledge to help farmers make the right decisions. Moreover, the literature offers fewer long-term economic and environmental studies on the adoption of site-specific management of sugarcane fields compared to those that evaluate grains (Yost et al., 2016) and citrus (Colaço and Molin, 2017). The development of appropriate decision support systems for decision making remains a major hindrance to the full adoption of PA (McBratney et al., 2006). At the strategic and tactical levels, the data gathered on the performance of various farm management systems should be grouped by time to build a systematic database, allowing for "quick and preliminary" assessments of the effects of management strategies based on experiences obtained elsewhere in similar soil conditions (Bouma et al., 1999). To overcome this challenge, information technology (IT) has been widely applied in all aspects of agriculture, making it an effective tool to increase agricultural yield (Yan-e, 2011).

The acquisition of data and the extraction of agronomic knowledge on the spatial and temporal variability of crops can contribute significantly to the expansion of PA in sugarcane fields. Some studies have demonstrated the influence of soil attributes on sugarcane yield (spatially monitored). Using a yield monitor and decision trees algorithms, Souza et al. (2010) found that potassium and altitude were the most important attributes determining high yields. Cerri and Magalhães (2012) evaluated the correlations between sugarcane yield and some chemical and physical soil attributes. These correlations were found to be generally weak (<0.5), and the authors concluded that a simple correlation is not enough to explain the spatial variability in yield, suggesting that characteristics other than soil attributes should be analysed. Working with sugarcane yield mapping, soil fertility attributes and attributes of sugarcane quality over 3 years, Johnson and Richard Jr. (2005) obtained non-significant, low and moderate correlations using linear Pearson correlations, suggesting that future studies should verify the influence of micronutrients on crop quality and yield. Rodrigues Jr. et al. (2013) also did not find patterns in the temporal stability of sugarcane quality parameters, suggesting that more crop cycles should be included in future assessments. Although few studies in the literature have reported on using of yield monitors in sugarcane fields to investigate the causes of spatial and temporal variability, some plot-scale studies have addressed the influence of soil attributes on yield (Bordonal et al., 2017; Rossi Neto et al., 2017; Dias et al., 1999).

As suggested by Cerri and Magalhães (2012), a simple Pearson's correlation between soil and plant parameters is not enough to explain yield. Advancements in data science and big data (Wolfert et al., 2017) may be able to address this bottleneck. Some studies reported in the literature have used data mining techniques, such as random forest (RF) algorithms (Breiman, 2001), to estimate sugarcane yields (Everingham et al., 2016; Bocca et al., 2016; Bocca et al., 2015), showing the potential of these tools. RF methods have been widely adopted for certain agricultural problems, such as remote sensing analysis (Lebourgeois et al., 2017; Parente et al., 2017), leaf nitrogen levels (Abdel-Rahman et al., 2008) and classifying sugarcane varieties (Everingham et al., 2007). RF were used in many problems of yield estimation (Park et al., 2005; Tulbure et al., 2012; Fukuda et al., 2013; Newlands et al., 2014; Jeong et al., 2016), particularly in sugarcane fields (Everingham et al., 2009; Everingham et al., 2015a;

Everingham et al., 2015b; Everingham et al., 2016). RF algorithms can handle large volumes of data, use categorical variables as predictors, measure the degree of importance of the predictive variables, and output the class probability and is robust against overfitting, even for slightly imbalanced datasets (Khoshgoftaar et al., 2007). Although previous studies have addressed sugarcane crops, none of them use yield monitor data spanning multiple years to assess the influence of soil attributes on sugarcane yield.

In this context, the objective of this paper was to investigate the relationship between physical and chemical soil attributes and sugarcane yield in order to identify the determinant parameters that define the spatial and temporal variability of yields. Thus, we used the computational environment created to support agricultural research, data acquisition, data formatting, data verification, data storage and analysis that was described in Driemeier et al. (2016) and developed with the objective of assisting PA studies. From large volumes of data obtained through soil and plant monitoring, it is possible to obtain new and relevant agronomic knowledge that can help producers increase yields and production profitability, thereby increasing the efficiency and sustainability of the sugarcane industry based on site-specific crop management.

1.2. Materials and Methods

The data used in this paper are derived from two experimental sugarcane fields used for PA projects and are stored in the Agricultural Database (BDAgro) of the Brazilian Bioethanol Science and Technology Laboratory (CTBE/CNPEM). The first experimental area, with an area of 30 hectares, is located at the Pedra Mill (PeM - São Paulo - Brazil - 21°16’36.94”S, 47°18’31.31”W - 583 m), and the second, with an area of 10 hectares, is located at São João Mill (SJM - São Paulo - Brazil - 22°23’37.21”S, 47°18’31.31”W - 640 m). The slope of the areas is 10% and 2% for PeM and SJM fields, respectively. The sugarcane varieties, chosen according to the local climatic conditions and the soil type, were CTC09 and SP80-3280 for PeM and SJM, respectively. The full details and initial objectives of the PeM and SJM project experiments were reported by Magalhães et al. (2014) and Rodrigues Jr. et al. (2012), respectively. The main difference in the management of the two experimental fields is related to soil fertilization. At PeM, nitrogen (according to expected yield), phosphorus and potassium (according to the laboratory soil analyses) were applied at variable rates throughout the entire crop cycle (3 crop seasons), while at SJM, fertilizers were not applied during the experimental period (2 crop seasons). The areas were sampled in a regular grid of 50x50 m and 30x30 m for the PeM and SJM with a total of 107 and 117 soil sampling points, respectively (Figure 1.1). Soil samples collected in the superficial layer (0.00 to 0.20 m) were submitted for wet-chemical laboratory analysis. The soil attributes assessed were soil organic matter (OM), pH, phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), hydrogen + aluminium (H+Al), the sum of bases (SB), cation exchange capacity (CEC) and base saturation (BS). PeM was evaluated during the crop seasons of 2012 to 2014, and SJM was evaluated in 2011 and 2012. The first year of sugarcane production (lasting from 12 to 18 months) is defined as the cane plant, and successive years (12 months) are defined as ratoon. In Brazil, the length of the average sugarcane cycle, from one planting to the next, is approximately five years. In the present experiment, the sugarcane crops corresponding to the evaluated years were the cane plant, 1st ratoon, and 2nd ratoon for PeM and the 2nd and 3rd ratoons for SJM. The experimental fields were harvested using a yield monitor coupled to the sugarcane harvest (SIMPROCANA®, ENALTA, São Carlos, Brazil).

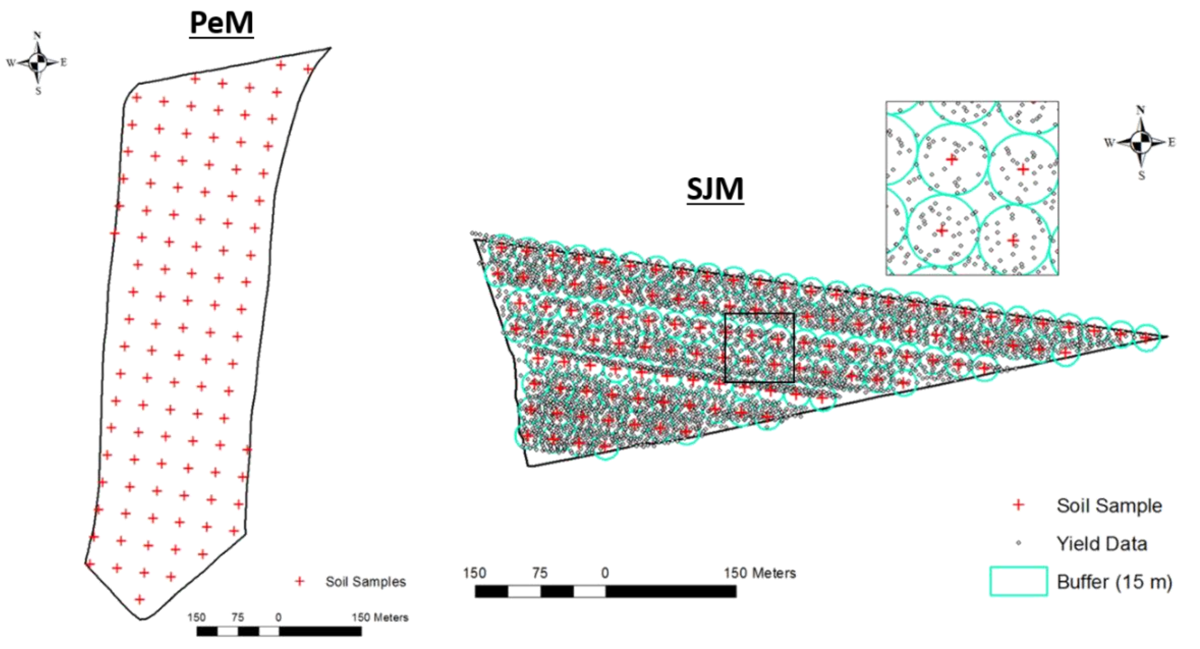


Figure 1.1. Grid soil sampling in the experimental fields of Pedra Mill (PeM – left) and São João Mill (SJM – right). Buffer zone (in detail) used to assign the yield data to the soil sampling grid.

1.2.1. Data analysis

The yield data were reduced to a soil sample grid by linear polynomial surface regression (*fittype fuction*) using Matlab software (MathWorks, Natick, Massachusetts) in the buffer zone (Figure 1.1 – detail) according to the linearization method described by Driemeier et al. (2016). The soil chemical attributes were converted to logarithms of the concentrations. The logarithmic scale reduced the positive asymmetry of the distribution, which was both physically and chemically justifiable (Atkins and Paula, 2010). The next step was to remove extreme values, which could cause detrimental biases for correlations, covariance, and subsequent analyses, from the datasets. Any input that deviated from the mean by more than three standard deviations (for a given attribute) was treated as an outlier (Driemeier et al., 2016). Pearson’s correlation and principal component analysis were performed to identify relationship patterns between soil attributes and yield. RF was applied to identify the major soil attributes that influence sugarcane yield at spatial and temporal level. To assess the soil and yield through time, annual differences at each sampling point were calculated (Eq. 1). The objective was to investigate the variation in soil attributes over the years associated with variations in yield. In Eq. 1, a positive value indicates an increase in the attribute evaluated in the following year, and a negative value indicates the opposite. This analysis allows for the effective interpretation of the evaluated parameters through time. For the present paper, we assumed that the spatial and temporal variability levels can be determined by applying the analysis to the original and transformed (Eq 1) data values.

$$C^{N}_{(\boldsymbol{x},\boldsymbol{y})} = C^{i+1}_{(\boldsymbol{x},\boldsymbol{y})} - C^{i}_{(\boldsymbol{x},\boldsymbol{y})} \qquad \text{[Eq 1]}$$

where $C^{N}_{(x,y)}$ is the new content evaluated at the [X,Y] coordinates and i is the evaluation year.

i. *Principal component analysis (PCA)*

Principal component analysis simplifies the description of a set of interrelated variables by reducing the dimensionality and enabling the interpretation of components. This analysis does not treat the variables as dependent or independent, as in the regression analyses; rather, all evaluated attributes are treated as variables. In this way, this technique can be understood as a method to transform the original variables into new uncorrelated variables, where each main principal component (PC) is a linear combination of the original variables (Johnson and Wichern, 2007). PCA was used to observe the correlation structure between soil attributes and crop yield. PCA allows for an effective qualitative interpretation of several evaluated parameters, resulting in a robust and simple means of identifying the relationship between the variables assessed.

ii. *Decision trees*

The principle behind classification/regression trees is to "divide-to-conquer". At each level of a tree, a more complex prediction/classification problem (where there is a greater heterogeneity of target variable values) is decomposed into simpler subproblems. This approach generates descendants in which the heterogeneity of the variables to be predicted (and explained) is more attenuated, and predictions can be made with lower risk for each of these nodes. The present paper applied an RF algorithm to identify the soil attributes (independent variables) that best explain the spatial and temporal variability in sugarcane yield (dependent variable). RF belongs to the class of supervised algorithms in which a dependent variable is explained in terms of *n* independent variables measured at any scale. RF is an ensemble learning method (Breiman, 2001) that can be applied to classification and regression problems. RF has certain advantages in that it can handle large volumes of data; it can use categorical variables as predictors; it can measure the degree of importance of the predictive variables in the final model; and it has only two main parameters to set: the number of classification trees (*n*trees) and the number of prediction variables (*m*try). RF algorithms operate with several decision trees at the time of training and allow for the identification and ranking of the most significant attributes in describing the dependent variable. For the assessment, 100 trees and all soil attributes were used. For training and testing, 70% and 30% of the total data were used, respectively. A classification and regression approach were applied in the spatial and temporal assessments, respectively. For classification, all soil attributes evaluated were discretized according to Raij et al. (1997). The yield data were classified into five classes: very high ($y \geq 110$ Mg ha^{-1}); high ($90 \leq y < 110$ Mg ha^{-1}); medium ($70 \leq y < 90$ Mg ha^{-1}); low ($50 \leq y < 70$ Mg ha^{-1}) and very low ($y < 50$ Mg ha^{-1}). Finally, a chi-squared automatic interaction detector (CHAID) decision tree (Kass, 1980) was applied to distinguish the yield potential of the experimental fields according to the most important soil attributes, aiming to visualize the yield differences by soil limiting factors.

1.3. Results

From the sample data (N = 555), 35 discrepant values were identified, corresponding to 6% of the dataset. These instances were eliminated in an attempt to avoid bias in the analyses. The experimental fields exhibit differences in the average clay and sand contents (Figure 1.2).

The PeM soils are more clayey (~458 g kg^{-1}) than the SJM soils (~232 g kg^{-1}), and the silt content is roughly equal (~90 g kg^{-1}).

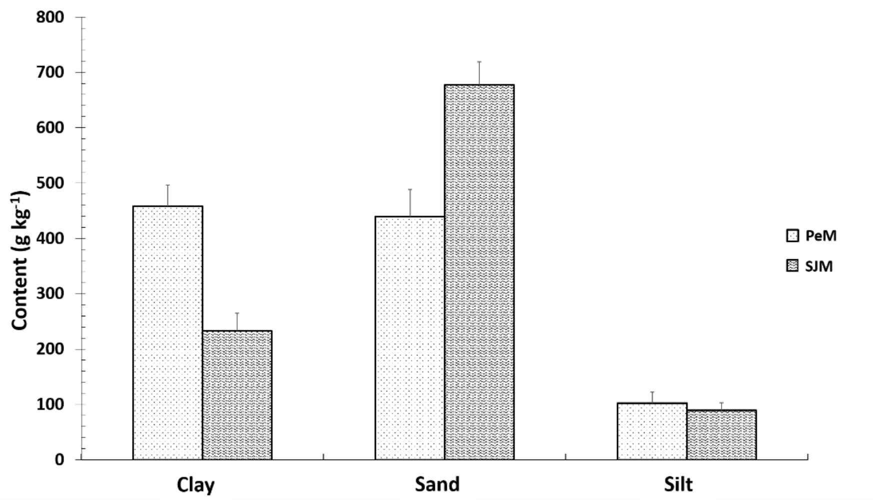


Figure 1.2. Clay, sand and silt content (g kg^{-1}) in the Pedra (PeM) and São João (SJM) experimental fields.

The maximum value of clay content for the PeM and SJM fields is 537 and 310 g kg^{-1}, respectively. The mean OM content in the two experimental areas decreased over time (Figure 1.3), and the average OM content was higher than 20 g dm^{-3} for PeM and less than 12 g dm^{-3} for SJM. Phosphorus levels increased over time for both fields. The SJM field has approximately a phosphorus content three times greater than that of the PeM field. Only the SJM field maintained an average critical level of 16 mg dm^{-3} of available P. Unlike P, K decreased over time in the PeM field, while that in the SJM field increased in the third ratoon. The PeM field was richer in potassium content and was the only field to maintain an average content above the critical level (critical level of K = 1.6 mmol$_c$ dm^{-3}). The Ca and Mg contents were always higher than the critical level for sugarcane crops established by Raij et al. (1997) for both fields, but the calcium contents decreased over time in the PeM field. The soil pH always remained on average within the acidity range of 5.1 to 5.5 for both areas. However, some places in both fields presented minimum levels of pH within the high acidity range (4.4 < pH < 5.0). The CEC increased in SJM but decreased in PeM, following the Ca and Mg attributes. The BS remained on average higher than 60% (critical level) in SJM and lower than this level in PeM over the years.

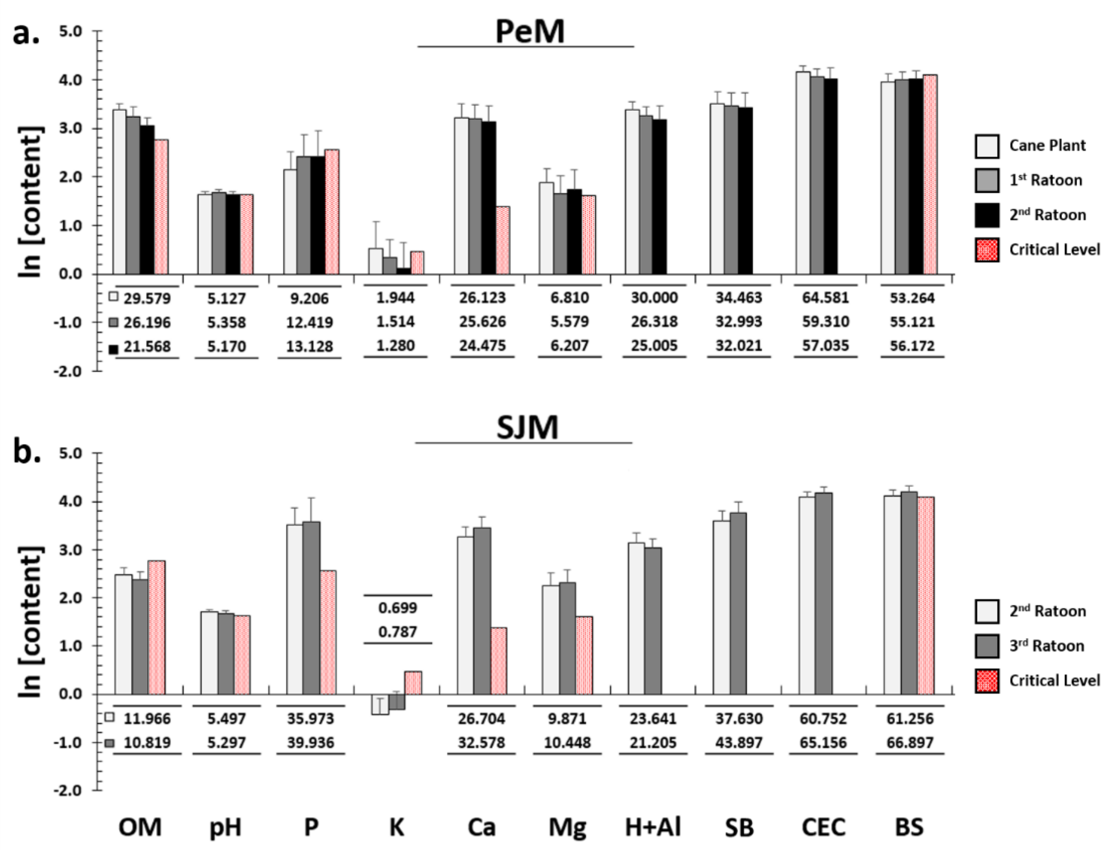


Figure 1.3. Natural logarithm (ln) of soil attributes content in Pedra (PeM - a) and São João (SJM - b) fields. Numbers represent the average content of soil attributes. Red columns represent the critical level according to Raij et al. (1997). [Units]: [OM] - [g dm^{-3}]; [pH] - [in $CaCl_2$]; [P] - [mg dm^{-3}]; [K, Ca, Mg, H+Al, SB and CEC] - [mmol$_c$ dm^{-3}]; [BS] - [%].

The average sugarcane yield decreased over the course of the sugarcane crop season, with the highest decrease registered from the first to the second ratoon in PeM (from 94 to 60 Mg ha^{-1}). The raw yield data distribution shows the absence of discrepant values for both areas (Figure 1.4), and the lowest data variability was recorded for the second ratoon in PeM (CV = 8%). The highest yields were recorded for PeM (~140 Mg ha^{-1} - cane plant), while the lowest were recorded for SJM (~37 Mg ha^{-1} - third ratoon). The maps of spatial variability in yield are shown in Figure 1.5. A PCA of the original contents of soil attributes and yield was conducted, and the first two principal components account for ~67% of the total data variability (Figure 1.6). The projection of variables onto the factor plane suggest that the sugarcane yield is related directly to K, OM and H+Al contents (Figure 1.6 - a). The projection of the instances on the factor plane divided the dataset into two main clusters (Figure 1.6 - b), clearly differentiating the experimental fields.

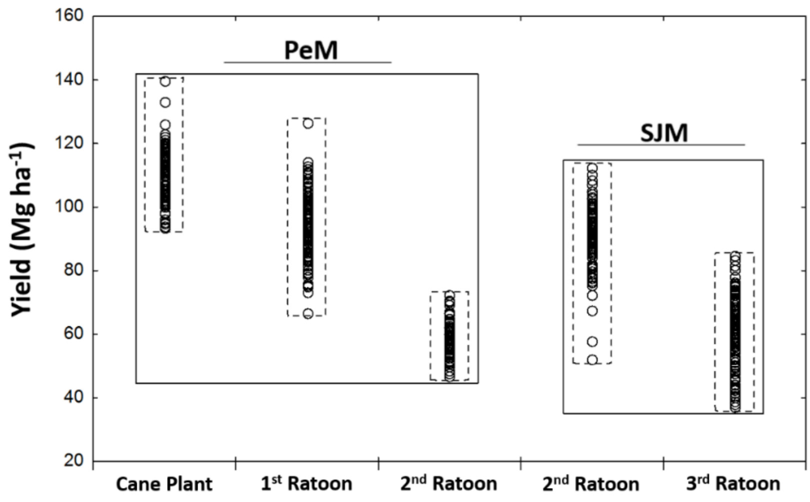


Figure 1.4. Yield (Mg ha^{-1}) data variability in the sampling grids for the Pedra (PeM) and São João (SJM) fields.

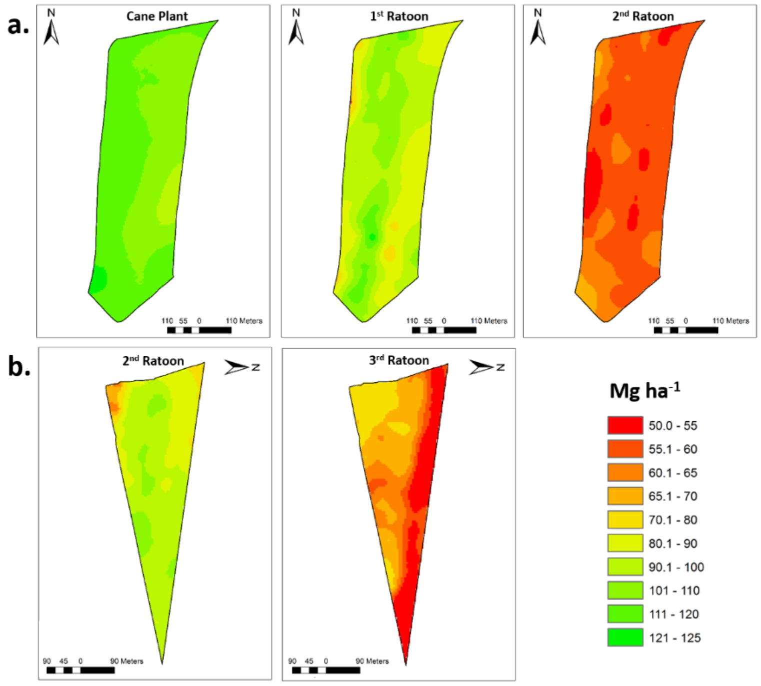


Figure 1.5. Spatial variability maps of sugarcane yield (Mg ha^{-1}) for the Pedra (PeM – a) and São João (SJM – b) fields.

The highest Pearson's correlation coefficient between yield and soil attributes (Table 1.1) were those between yield and OM, K and H+Al (r = 0.48, 0.32 and 0.39, respectively) for spatial variability, while pH showed a significant temporal correlation (r = 0.39). SB was directly related to the variations in Ca and Mg contents spatially (r = 0.97 and 0.81, respectively) and temporally (r = 0.99 and 0.77, respectively). The spatial variability of clay content is intrinsically related to the OM content (r = 0.82). Although the correlation is low, it is possible to observe a significant and positive trend in OM temporal variation related to SB, CEC, Ca, Mg, BS and P contents (r = 0.34, 0.34, 0.32, 0.31, 0.28 and 0.16, respectively).

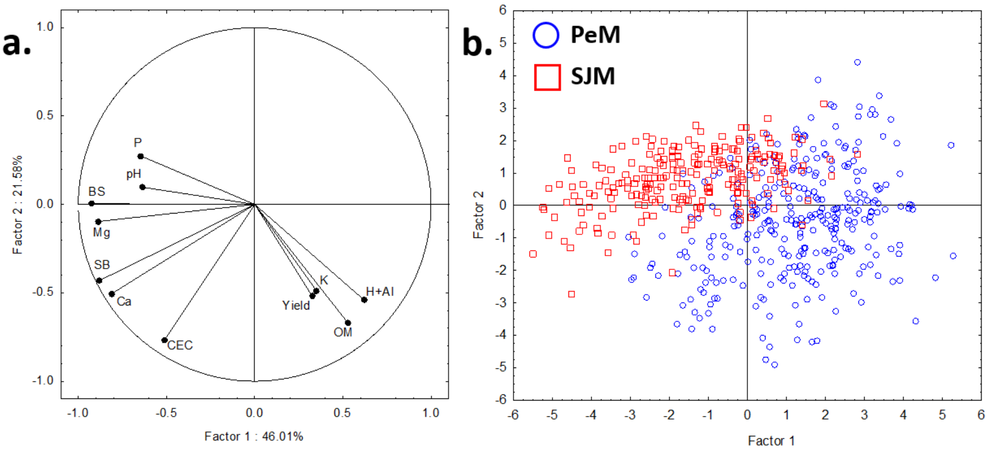


Figure 1.6. Principal component analysis (PCA) of soil attributes and sugarcane yield of the Pedra (PeM - blue) and São João (SJM - red) fields. Projection of the variables (a) and instances (b) on the first two principal components (PCs).

Table 1.1. Pearson correlation coefficient of soil attributes and yield for spatial (below of the main diagonal) and temporal (above of the main diagonal) variability.

	Clay	**OM**	**pH**	**P**	**K**	**Ca**	**Mg**	**H+Al**	**SB**	**CEC**	**BS**	**Yield**
OM	0.82*	-	0.02	0.16*	0.10	0.32*	0.31*	0.07	0.34*	0.34*	0.28*	0.00
pH	-0.30*	-0.27*	-	0.00	-0.09	0.10	0.03	-0.35*	0.09	-0.04	0.30*	0.39*
P	-0.71*	-0.65*	0.29*	-	0.05	0.09	0.12*	0.08	0.11	0.13*	0.04	0.06
K	0.54*	0.52*	-0.14*	-0.39*	-	0.15*	0.18*	0.09	0.23*	0.25*	0.19*	0.00
Ca	-0.26*	-0.09*	0.40*	0.37*	-0.11*	-	0.66*	0.03	0.99*	0.92*	0.77*	0.00
Mg	-0.58*	-0.44*	0.51*	0.59*	-0.26*	0.68*	-	-0.14*	0.77*	0.66*	0.70*	-0.13*
H+Al	0.43*	0.52*	-0.62*	-0.34*	0.25*	-0.23*	-0.46*	-	-0.01	0.37*	-0.52*	0.01
SB	-0.35*	-0.19*	0.46*	0.46*	-0.11*	0.97*	0.81*	-0.32*	-	0.93*	0.80*	-0.02
CEC	-0.09*	0.14*	0.10*	0.23*	0.04	0.84*	0.53*	0.28*	0.82*	-	0.55*	-0.02
BS	-0.48*	-0.39*	0.67*	0.47*	-0.19*	0.77*	0.80*	-0.76*	0.83*	0.38*	-	0.02
Yield	0.24*	0.48*	0.01	-0.28*	0.32*	-0.11*	-0.16*	0.39*	-0.13*	0.11*	-0.28*	-

*significant at 5%.

In dataset of the present paper, the highest yield class frequency is high, with an overall mean of 83.45 Mg ha^{-1}. In each experimental field, the highest yield class frequency was high as well, with averages of 88.61 and 76.36 Mg ha^{-1} for PeM and SJM, respectively. The RF algorithm analysis indicated that the most important attribute that directly impacts sugarcane yield was OM followed by CEC and clay content (Figure 1.7 – a). These factors may be the main soil attributes that limit yield. However, an RF regression indicated that the soil attribute that most influenced yield through time was pH followed by SB and P (Figure 1.7 – b). This finding is evidenced by the trend in the Pearson's correlation coefficient between yield and pH.

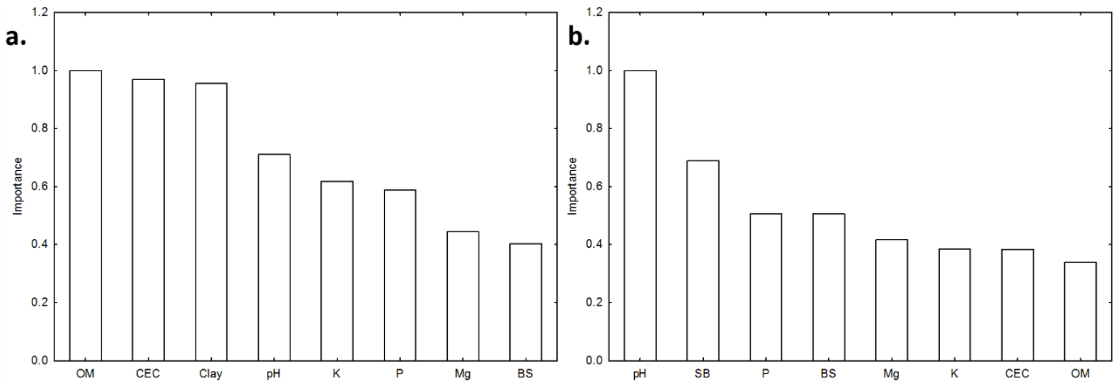


Figure 1.7. Ranking of the first eight soil attributes (plot importance) that explain the spatial (a) and temporal (b) variability of sugarcane yield (dependent variable).

Dividing the experimental fields at the first level of the CHAID decision tree algorithm, soil OM was the most significant variable explaining yield at the PeM field, a critical value equal to 23 g dm^{-3} (Figure 1.8). Contents above this value showed a higher frequency of high yields (M = 99.59 Mg ha^{-1}), while lower levels showed low yields (M = 69.81 Mg ha^{-1}). The attribute that most influenced the yield for SJM was soil pH, where low pH levels (pH < 5.0) were associated with an increased frequency of low yields (M = 73.96 Mg ha^{-1}), while high pH levels (pH > 5.6) were associated with high yields (M = 81.81 Mg ha^{-1}).

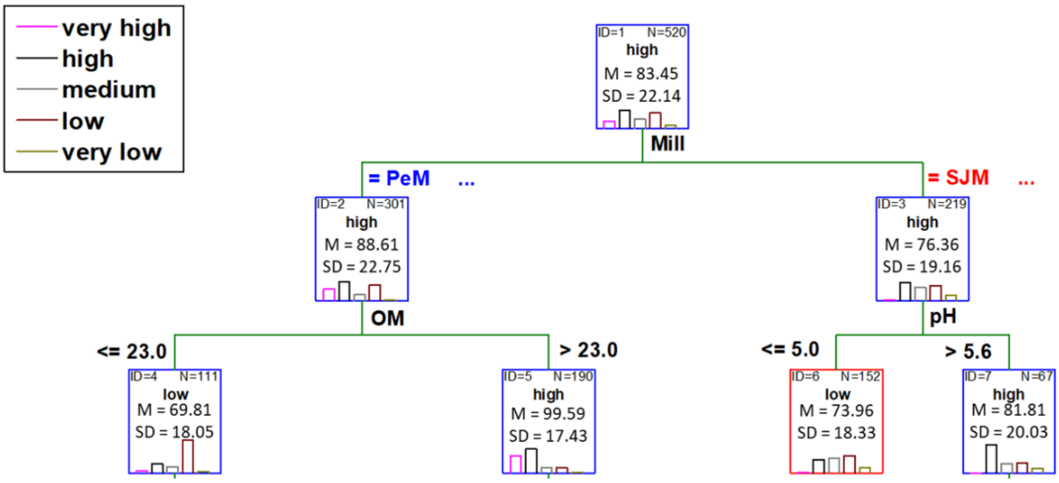


Figure 1.8. Decision tree results of the first two levels of a CHAID algorithm. M – average yield (Mg ha^{-1}); SD – standard deviation of yield (Mg ha^{-1}) and N – Number of instances in the nodes.

1.4. Discussion

Difference in the clay contents between experimental fields are clear. The soils in PeM and SJM fields can be classified as clay and sandy loam (EMBRAPA, 1999), respectively. The maximum clay contents in the soil show some clayey regions at PeM, while the SJM field present some regions ranging from sandy loam to medium soil texture. The average contents of soil OM decreased for both fields over the years, a pattern that has been commonly observed in the sugarcane fields in the central southern region of Brazil. As expected, the OM content followed the soil clay content (r = 0.84). The most clayey field (PeM) presented higher OM contents, while SJM presented OM levels lower than 12 g dm^{-3}. The OM contents are within the expected values according to Raij et al. (1997), with sandy soils presenting contents lower than 15 g dm^{-3} and clayey soils ranging between 16 and 30 g dm^{-3}. There is a trend of higher OM contents in clayey soils than in sandy soils due to the formation of soil aggregates, thereby allowing the clay particles to protect soil OM from microbiological attack (Razafimbelo et al., 2013).

The variability of the yield data in the sampling grid, which were adjusted according to the linear regression described in Driemeier et al. (2016), shows the robustness of the regression in removing noise and discrepancies in the sugarcane yield monitor dataset, as reported in Maldaner et al. (2015) and Rodrigues Jr. et al. (2012). The spatial variability maps of sugarcane yield (Figure 1.5) indicated that the noise from yield monitors was removed when the linearization filter was applied, as described in Driemeier et al. (2016), and showed a clear spatial pattern for the fields. Due to the different management approaches adopted in the field experiments, in the PeM field (where P and K fertilizers were applied), the average K content decreased over the years, which was not expected. In contrast, the average P content increased. In the SJM field (where fertilizers were not applied), contrary to expectations, there was an increase in the mean K and P levels in the crop seasons evaluated. One hypothesis for these changes in soil attributes can be derived from the Pearson's correlation for temporal variability (Table 1.1). Despite of the low correlation, there is evidence that where OM increased, the P and K increased as well, and the inverse is also true. Setting the P content as a dependent variable in the RF algorithm, this hypothesis is proven (Figure 1.9). For both fields, the soil attribute that better explains the P content through time is soil OM. This fact was addressed by Nogueirol et al. (2014) and shows the importance of soil OM for the availability of macro and micronutrients in the soil. The cycling of nutrients present in the straw from green cane harvesting can contribute significantly to increases in OM. According to Menandro et al. (2017), on average, sugarcane straw has the potential to recycle 48, 15 and 80 kg ha^{-1} of N, P_2O_5 and K_2O, respectively, annually into the soil or into soil OM. The PeM field, which had high OM content, presented higher yields, and there was a direct correlation between these attributes ($r = 0.60$, data not shown) that was also shown by the correlation with all soil data sets ($r = 0.48$). As one of the most important soil attributes for defining the sugarcane yield and the availability of nutrients such as phosphorus and nitrogen in the soil (Nogueirol et al., 2014), OM content exhibited higher concentrations in the soil, more nutrients could be provided, and consequently, greater yields could be achieved. Indeed, OM has an important effect on the physical properties of agricultural soils, mainly under rainfed conditions. This effect occurs because OM promotes soil aggregation, which also indirectly impacts other physical attributes of soil such as soil bulk, soil porosity, soil aeration, water capacity and water drainage, which are essential for soil-crop yield capacity (Bayer and Mielniczuk, 2008). Furthermore, soil conservation management can help to maintain adequate soil OM levels over time, as reported by Carvalho et al. (2016), and improve both the quality of soil and its function of sustaining adequate plant growth (Cherubin et al., 2018). In a recent major review, Carvalho et al. (2016) suggested that 7 Mg ha^{-1} of straw should be left on the soil after the harvest to ensure minimum soil quality parameters. As expected, the higher availability of Ca and Mg caused an increase in the SB for both areas because the soil sum of bases is strictly related to these elements (Raij et al., 1991).

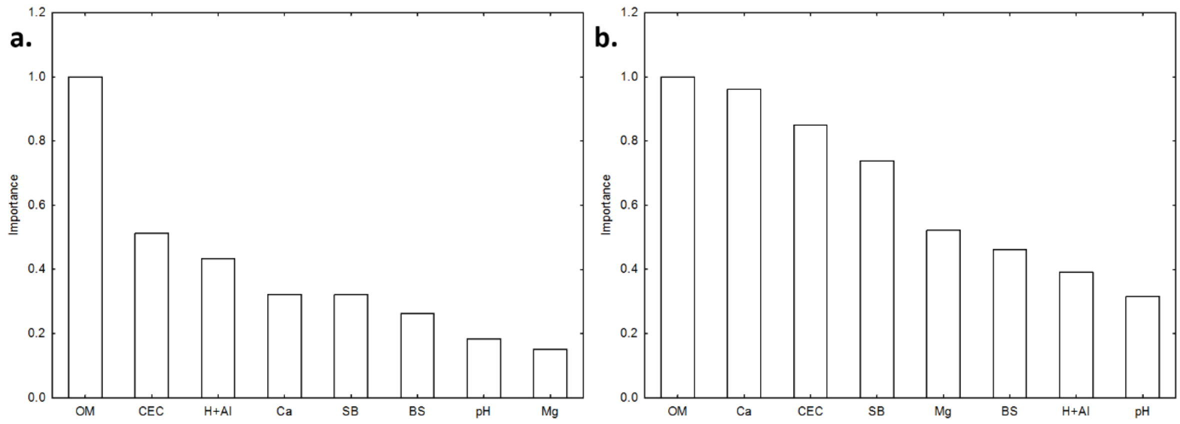


Figure 1.9. Ranking of the first eight soil attributes (plot importance) that explain the temporal P content variability for the PeM (a) and SJM (b) fields.

The RF algorithm results show a clear influence of soil OM on agricultural yield. OM followed by CEC and clay content are the three most relevant soil attributes that impact sugarcane yield with similar levels of impact (Figure 1.7 – a). Such relations are not as clear in a simple Pearson's correlation analysis, as reported by Cerri and Magalhães (2012), but the RF algorithm shows definitively that these soil attributes influence the spatial variations in yield. The classification of soils according OM and clay content shows the importance of these soil attributes for establishing yield potential zones (Landell et al., 2003). Clay soils present higher yield potentials compared to sandy soils, as evidenced in the present paper, and are intrinsically related to OM content. In the Brazilian sugarcane industry, fields are managed according to production environments (Landell et al., 2003), and soil texture is one of the most important factors for classifying these environments.

With the CHAID decision tree algorithm (Figure 1.8), the influence of available soil OM content in the soil clearly delimited different yield potentials. The critical level of 23.0 g dm^{-3} distinguished the yield potentials, with a difference of 30 Mg ha^{-1} between these areas for the PeM field. In the SJM field, the soil pH over the years was a determining soil factor that differentiated yield potentials. Although not a recent discovery, Malavolta (1979) shows that higher nutrient availability for crops occurs with lower soil acidity (pH > 5.6). With recent improvements in technology and data acquisition (Viscarra and Bouma, 2016), this knowledge can be applied at a site-specific level, and field-specific assessment can be implemented. Yield maps combined with other soil and landscape parameters are often used to define yield zones (Buttafuoco et al., 2010; Diker et al., 2004), but this approach has mainly been used for grain crops and not for sugarcane because yield monitors are not widely adopted in commercial sugarcane fields, where technological improvements are still necessary.

Within a critical range (pH between 5.1 and 5.5, according to Raij et al., 1997), pH can be considered the most important attribute influencing yield at the SJM field since fertilizer was not applied. As addressed above, other nutrients, such as P and K, may have been available at sites where the pH was above the critical level. Moreover, the OM may have helped with P availability as well, as shown in a previous analysis (Figure 1.9). The present paper provides evidence that the pH must be controlled annually to fall within a specific range in low-yield potential fields like SJM. This management approach is not typically applied in Brazilian sugarcane fields, where pH is managed at fixed rates and only at the time of planting or once every two years. The RF regression analysis showed the high importance of pH through time, which was directly related to yield variations (Figure 1.8). By way of support, the first level of one of the trees generated by RF (Figure 1.10) shows that increases in pH from one year to another (variation > 0.15) resulted in yield decreases of ~15 Mg ha^{-1}. However, where pH decreased between years (variation < 0.15), yield decreases of ~33 Mg ha^{-1} were found. The findings showed that pH is a key factor in sugarcane fields, where lower yield decreases were found in sites where pH increased.

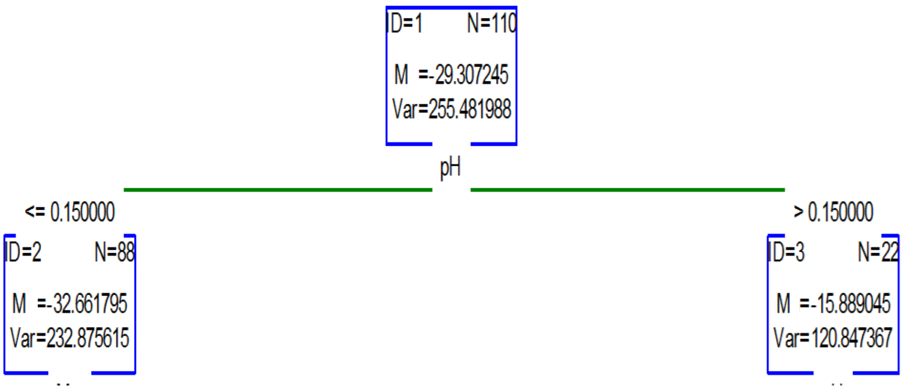


Figure 1.10. Decision tree of the random forest (RF) regression algorithm applied through time.

The use of proximal soil sensors to characterize the spatial variability of pH can be fundamental for the rational application of limestone; that is, such an approach used in the right place and right amount can increase production profitability (Sanches et al., 2018). The real-time proximal soil sensing of OM contents (Huang et al., 2017) can be an efficient alternative for delineating management zones in sugarcane fields. Finally, agronomic knowledge from big datasets of the spatial and temporal variability in soil and yield can help producers define management zones for their crop fields. Critical levels of some soil attributes should be managed on a site-specific basis to increase the profitability and sustainability of sugarcane production.

1.5.Conclusion

The present paper shows the importance of combining yield monitor data with data mining techniques to derive spatial and temporal patterns from soil and crop datasets. The findings show that OM and pH are the most important attributes that directly impact the yield potential through space and time, respectively. Mapping soil limiting factors can aid in the creation of management zones to improve the profitability of sugarcane fields. Finally, higher P availability may be directly associated with the amount of soil OM, indicating the importance of a conservationist management approach in attaining the minimum soil quality parameters.

Acknowledgements

The authors thank the São Paulo Research Foundation (grant process: 2015/01587-0, 2014/14965-0, 2013/50942-2 and 2008/09265-9) and the sugarcane mills for technical support and for making the experimental fields available. We also thank to Dr Francelino Augusto Rodrigues for provide data from fields.

1.6.References

Abdel-Rahman, E.M., Ahmed, F.B., 2008. The application of remote sensing techniques to sugarcane (Saccharum spp. hybrid) production: a review of the literature. *Int. J. Remote Sens.* 29, 3753-3767.

Arslan, S. and Colvin, T. 2002. An evaluation of the response of yield monitors and combines to varying yields. *Precision Agriculture* 3, 107-122.

Atkins, P., Paula, J. de, 2010. *Physical Chemestry*, 9th ed. Oxford University Press, Oxford.

Bayer, C., Mielniczuk, J. *Dinâmica e função da matéria orgânica*. 2008. In: Santos, G.A.; SILVA, L.S.; CANELLAS, L.P.; CAMARGO, F.A.O. Fundamentos da matéria orgânica do solo: Ecossistemas tropicais e subtropicais. Porto Alegre, ed. Metropole, 654p.

Bocca, F.F., Rodrigues, L.H.A., Arraes, N.A.M., 2015. When do I want to know and why? Different demands on sugarcane yield predictions. *Agricultural Systems* 135, 48-56.

Bocca, F.F., Rodrigues, L.H.A., 2016. The effect of tuning, feature engineering, and feature selection in data mining applied to rainfed sugarcane yield modelling. *Computers and Electronics in Agriculture* 128, 67-76.

Bordonal, R.O., Lal, R., Ronquim, C.C., Figueiredo, E.B., Carvalho, J.L.N., Maldonado Jr, W., Milori, D.M.B.P., Scala Jr, N.L., 2017. Changes in quantity and quality of soil carbon due to the land-use conversion to sugarcane (Saccharum officinarum) plantation in southern Brazil. *Agriculture, Ecosystems & Environment* 240, 54-65.

Bouma, J., Stoorvogel, J., van Alphen, B. J., Booltink, W. G., 1999. Pedology, Precision Agriculture, and the Changing Paradigm of Agricultural Research. *Soil Science Society of America* 63(6), 1763-1768.

Breiman, L., 2001. Random forests. *Machine Learning* 45, 5-32.

Buttafuoco, G., Castrignano, A., Colecchia, A. S., Ricca, N., 2010. Delineation of management zones using soil properties and a multivariate geostatistical approach. *Italian Journal of Agronomy* 5(4), 323-332.

Carvalho, J.L.N., Nogueirol, R.C., Menandro, L.M.S., Bordonal, R.O., Borges, C.D., Cantarella, H., Franco, H.C.J., 2016. Agronomic and environmental implications of sugarcane straw removal: a major review. *Global Change Biology Bioenergy* 1, 1-12.

Cerri, D.G.P., Magalhães, P.S.G., 2012. Correlation of physical and chemical attributes of soil with sugarcane yield. *Pesquisa Agropecuária Brasileira* 47, 613-620.

Cherubin, M.R., Oliveira, D.M. da S., Feigl, B.J., Pimentel, L.G., Lisboa, I.P., Gmach, M.R., Varanda, L.L., Morais, M.C., Satiro, L.S., Popin, G.V., Paiva, S.R. de, Santos, A.K.B. dos, Vasconcelos, A.L.S. de, Melo, P.L.A. de, Cerri, C.E.P., Cerri, C.C., 2018. Crop residue harvest for bioenergy production and its implications on soil functioning and plant growth: A review. *Scientia Agricola* 75, 255–272.

Confederação Nacional da Indústria (CNI). 2017. *O setor sucroenergético em 2030: dimensões, investimentos e uma agenda estratégica*. Brasília, CNI, 108 p.

Colaço, A.F., Molin, J.P., 2017. Variable rate fertilization in citrus: a long-term study. *Precision Agriculture* 18, 169-191.

Companhia Nacional do Abastecimento (CONAB). 2017. *Acompanhamento da safra Brasileira. Cana-de-açúcar, SAFRA 2017/18 Primeiro Levantamento Abril/2017*. Brasília, DF, 62p.

Dias, F.L.F., Mazza, J.A., Matsuoka, S., Perecin, D., Maule, R.F., 1999. Productivity of sugarcane in relation to climate and soils of the northwestern São Paulo state. *Revista Brasileira de Ciência do Solo* 23, 627-634.

Diker, K., Heermann, D. F., Brodahl, M. K., 2004. Frequency analysis of yield for delineating yield response zones. *Precision Agriculture* 5(5), 435–444.

Driemeier, C.E., Ling, L.Y., Sanches, G.M., Pontes, A.O., Magalhães, P.S.G., Ferreira, J.E., 2016. A computational environment to support research in sugarcane agriculture. *Computers and Electronics in Agriculture* 130, 13–19.

Empresa Brasileira de Pesquisa Agropecuária (EMBRAPA). 1999. *Sistema brasileiro de classificação dos solos*. Rio de Janeiro: Embrapa Solos, 412 p.

Everingham Y.L., Lowe, K.H., Donald, D.A., Coomans, D.H., Markley, J., 2007. Advanced satellite imagery to classify sugarcane crop characteristics. *Agronomy Sustainable Development* 27(2), 111-117.

Everingham, Y.L., Smyth, C.W., Inman-Bamber, N.G., 2009. Ensemble data mining approaches to forecast regional sugarcane crop production. *Agricultural and Forest Meteorology* 149 (3-4), 689-696.

Everingham, Y.L., Inman-Bamber, N.G., Sexton, J., Stokes, C., 2015a. A dual ensemble agroclimate modelling procedure to assess climate change impacts on sugarcane production in Australia. *Agricultural Sciences* 6, 870-888.

Everingham YL, Sexton J, Robson A (2015b) A statistical approach for identifying important climatic influences on sugarcane yields. In: *Proc* Aust Soc Sugar Cane Technol. Bundaberg, Australia, pp 8–15

Everingham Y.L., Sexton, J., Skocaj, D., Inman-Bamber, G., 2016. Accurate prediction of sugarcane yield using a random forest algorithm. *Agronomy Sustainable Development* (2016), 36:27.

Fukuda S., Spreer, W., Yasunaga, E., Yuge, K., Sardsud, V., Müller, J., 2013. Random Forests modelling for the estimation of mango (Mangifera indica L. cv. Chok Anan) fruit yields under different irrigation regimes. *Agricultural Water Management* 116, 142-150.

Jeong, J.H., Resop, J.P., Mueller, N.D., Fleisher, D.H., Yun, K., Butler, E.E., Timlin, D.J., Shim, K., Gerber, J.S., Reddy, V.R., Kim, S., 2016. Random Forests for Global and Regional Crop Yield Predictions. *PLoS ONE* 11(6): e0156571. doi:10.1371/journal.pone.0156571

Huang, J., Pedrera-Parrilla, A., Vanderlinden, K., Taguas, E.V., Gómez, J.A., Triantafilis, J., 2017. Potential to map depth-specific soil organic matter content across an olive grove using quasi-2d and quasi-3d inversion of DUALEM-21 data. *Catena* 152, 207-217.

Johnson, R.M., Richard Jr., E.P., 2005. Sugarcane Yield, Sugarcane Quality, and Soil Variability in Louisiana. *Agronomy Journal* 97(3), 760–771.

Johnson, R.A., Wichern, D.W., 2007. *Statistical Analysis,* sixth edit. ed. Pearson Pretice Hall, Upper Saddle River.

Kass, G., 1980. An exploratory technique for investigating large quantities of categorical data. *Applied Statistics* 29(2), 119-127.

Khoshgoftaar, T.M., Golawala, M., Hulse, J. Van, 2007. An Empirical Study of Learning from Imbalanced Data Using Random Forest. 19*th* IEEE Int. Conf. Tools with Artif. Intell. 310–317.

Landell, M.G.A., Prado, H., Vasconcelos, A.C.M., Perecin, D., Rossetto, R., Bidóia, M.A.P., Silva, M.A., Xavier, M.A., 2003. Oxisol subsurface chemical attributes related sugarcane productivity. *Scientia Agricola* 60, 741-745.

Lebourgeois, V., Dupuy, S., Vintrou, É., Ameline, M., Butler, S., Bégué, A., 2017. A Combined Random Forest and OBIA Classification Scheme for Mapping Smallholder Agriculture at Different Nomenclature Levels Using Multisource Data (Simulated Sentinel-2 Time Series, VHRS and DEM). *Remote Sensing* 9, 259.

Magalhães, P.S.G., Cerri, D.G.P., 2007. Yield Monitoring of Sugar Cane. *Biosystems Engineering* 96, 1–6.

Magalhães, P.S.G., Sanches, G.M., Franco, H.C.J., Driemeier, C.E., Kolln, O.T., Braunbeck, O.A., 2014. Precision Agriculture in Sugarcane Production. A Key Tool to Understand Its Variability. *In:* 12 International Conference on Precision Agriculture, 2014, Sacramento, CA. 12th ICPA Abstracts Book.

Malavolta, E. 1979. *ABC da Adubação*. 4th edição. São Paulo SP, Editora Agronomia Ceres, 255 p.

Maldaner, L.F., Spekken, M., Eitelwein, M.T., Molin, J. P., 2015. Removal of errors on maps of productivity of sugarcane. *In*: X SBIAGRO – Congresso Brasileiro de Agroinformárica. Piracicaba-SP, 11 p.

McBratney, A., Whelan, B., Ancev, T., 2006. Future directions of precision agriculture. *Precision Agriculture* 6, 7-23.

Menandro, L.M.S., Cantarella, H., Franco, H.C.J., Pimenta, M.T.B., Rabelo, S.C., Sanches, G.M., Carvalho, J.L.N., 2017. Comprehensive assessment of sugarcane straw: implications for biomass and bioenergy production. *Biofuels Bioproducts & Biorefining-Biofpr* 11(3), 488-504.

Newlands, N.K., Zamar, D.S., Kouadio, L.A., Zhang, Y., Chipanshi, A., Potgieter, A., Toure, S., Hill, H.S.J., 2014. An integrated, probabilistic model for improved seasonal forecasting of agricultural crop yield under environmental uncertainty. Frontiers in Environmental Science. doi:10.3389/fenvs.2014.00017

Nogueirol, R.C., Cerri, C.E.P., Silva, W.T.L., Alleoni, L.R.F., 2014. Effect of no-tillage and amendments on carbon lability in tropical soils. *Soil & Tillage Research* 143, 67-76.

Parente, L., Ferreira, L., Faria, A., Nogueira, S., Araújo, F., Teixeira, L., Hagen, S., 2017. Monitoring the brazilian pasturelands: A new mapping approach based on the landsat 8 spectral and temporal domains. *International Journal of Applied Earth Observation and Geoinformation* 62, 135–143.

Park, S.J., Hwang, C.S., Vlek, P.L.G., 2005. Comparison of adaptive techniques to predict crop yield response under varying soil and land management conditions. *Agricultural Systems* 85(1), 59–81.

Raij, B. van., 1991. *Fertilidade do solo e adubação*. Piracicaba, Ceres/Potafos, 343p.

Raij, B. van., Cantarella, H., Quaggio, J.A., Furlani, A.M.C., 1997. *Recomendações de adubação e calagem para o Estado de São Paulo*. Campinas. Instituto Agronômico; Fundação IAC., Campinas.

Razafimbelo, T., Chevallier, T., Albrecht, A., Chapuis-Lardy, L., Rakotondrasolo, F.N., Michellon, R., Rabeharisoa, L., Bernoux, M., 2003. Texture and organic carbon contents do not impact amount of carbon protected in Malagasy soils. *Scientia Agricola* 70(3), 204-208.

Rodrigues Jr., F.A., Magalhães, P.S.G., Franco, H.C.J., 2012. Soil attributes and leaf nitrogen estimating sugar cane quality parameters: Brix, pol and fibre. *Precision Agriculture* 14, 270–289.

Rodrigues Jr., F.A., Magalhães, P.S.G., Franco, H.C.J., Beauclair, E.G.F., Cerri, D.G.P., 2013. Correlation Between Chemical Soil Attributes and Sugarcane Quality Parameters According to Soil Texture Zones. *Soil Science* 178, 147-156.

Rossi Neto, J., de Souza, Z.M., de Medeiros Oliveira, S.R., Kölln, O.T., Ferreira, D.A., Carvalho, J.L.N., Braunbeck, O.A., Franco, H.C.J., 2017. Use of the Decision Tree Technique to Estimate Sugarcane Productivity Under Edaphoclimatic Conditions. *Sugar Tech* 19(6), 662-668.

Sanches, G.M., Magalhães, P.S.G., Remacre, A.Z., Franco, H.C.J., 2018. Potential of apparent soil electrical conductivity to describe the soil pH and improve lime application in a clayey soil. *Soil & Tillage Research* 175, 217-225.

Silva, C.B., Moraes, M.A.F.D., Molin, J.P., 2011. Adoption and use of precision agriculture technologies in the sugarcane industry of São Paulo state, Brazil. *Precision Agriculture* 12(1), 67–81.

Souza, Z.M., Cerri, D.G.P., Colet, M.J., Rodrigues, L.H.A., Magalhães, P.S.G., Mandoni, R.J.A., 2010. Análise dos atributos do solo e produtividade da cultura de cana-de-açúcar com o uso da geoestatística e árvore de decisão. *Ciência Rural* 40, 840-847.

Tulbure, M.G., Wimberly, M.C., Boe, A., Owens, V.N., 2012. Climatic and genetic controls of yields of switchgrass, a model bioenergy species. *Agriculture, Ecosystems & Environment* 146(1), 121-129.

Viscarra Rossel, R.A., Bouma, J., 2016. Soil sensing: a new paradigm for agriculture. *Agricultural Systems* 148, 71–74.

Waclawovsky, A.J., Sato, P.M., Lembke, C.G., Moore, P.H., Souza, G.M., 2010. Sugarcane for bioenergy production: an assessment of yield and regulation of sucrose content. *Plant Biotechnology Journal* 8, 263-276.

Wolfert, S., Ge, L., Verdouwa, C., Bogaardt, MJ., 2017. Big Data in Smart Farming – A review. *Agricultural Systems* 153, 69-80.

Yan-e, D., 2011. Design of Intelligent Agriculture Management Information System Based on IoT. In: Intelligent *Computation Technology and Automation* (ICICTA),.Guangdong, Shenzhen. 1:1045-1049.

Yost, M.A., Kitchen, N.R., Sudduth, K.A., Sadler, E.J., Drummond, S.T., Volkmann, M.R., 2016. Long-term impact of a precision agriculture system on grain crop production. *Precision Agriculture* 18(5), 823-842.

Chapter 2: Comprehensive assessment of soil spatial variability related to topographic parameters in sugarcane fields (Geoderma)

Guilherme M. Sanches[1*], Paulo S. Graziano Magalhães[1], Ana C. dos Santos Luciano[2] and Henrique C. J. Franco[1]

[1] University of Campinas – UNICAMP - Ph.D. Program in Bioenergy – Interdisciplinary Center for Energy Planning, 13083-896, Campinas, São Paulo, Brazil

[2] Brazilian Bioethanol Science and Technology Laboratory (CTBE), Brazilian Center for Research in Energy and Materials (CNPEM)

[*]Corresponding author – guilherme.sanches@cropman.com.br/+55 14 99164 8711

Abstract: Landscape are intrinsically related to soil spatial variability. Understanding soil fertility based on topographic parameters is essential to ensure sustainable agronomic management through the rational use of inputs. The aim of the paper was to perform a comprehensive assessment of soil organic matter (OM), pH, sum of bases (SB) and cation exchange capacity (CEC) according to topographic parameters, with the goal of identifying spatial patterns and know the relationship between them to capture the soil variability in sugarcane fields. A soil dataset from nine sugarcane experimental fields was evaluated. Approximately 3,000 soil samples, collected between 2008 and 2017, were evaluated. The topographic parameters of vertical and horizontal curvatures were related to the variability of the soil attributes. The results showed that the horizontal morphometric classes (H_{Conv}, H_{Plan} and H_{Div}), associated with vertical concave areas (V_{Conc}), presented higher levels of OM, SB and CEC, which indicated that these areas have higher soil fertility, where $V_{Conc}H_{Div}$ showed the highest soil fertility. For all vertical morphometric classes (V_{Conc}, V_{Ret} and V_{Conv}), soil pH levels were higher when associated with horizontal divergent areas (H_{Div}) and lower when associated with convergent areas (H_{Conv}), suggesting that stricter soil acidity management was needed in the H_{Conv} areas. The $V_{Conv}H_{Conv}$ areas, where the lower soil fertility was observed, should be sampled with greater accuracy for adequate soil spatial characterization due to the high CV observed when compared to other morphometric classes assessed. The results showed that the detected spatial patterns were temporally stable. With high spatial and temporal stability, topographic parameters could be excellent (economically feasible and easily assessed) sources of information to support soil sampling processes and to map fertility zones within fields, helping farmers in site-specific management of their crops to increase yields and

profitability of production. **Keywords:** precision agriculture; soil sampling; site-specific management; fertility zones; landscape parameters

2.1.Introduction

Sugarcane production, the main source of Brazilian biomass for ethanol production, will experience significant changes in the coming years. To increase sugarcane production, it will be necessary to advance technologies that can increase crop yields to exceed the current yield average of 73 Mg ha^{-1} (CONAB, 2017). The increase in production should be accompanied by sustainable crop management, improving the application of inputs to reduce environmental impacts. Understanding soil spatial variability is essential to managing inputs in a sustainable way. Thus, characterizing soil spatial variability is a process that must be carried out with accuracy.

Precision agriculture (PA) encompasses a package of tools and technologies that allow characterization of the spatial and temporal variabilities of soils with accuracy, utilizing the information on variability to optimize the inputs. PA is considered the most feasible approach to achieving sustainable agriculture (Bullock et al., 2007). Although several technologies are available, soil sampling to characterize the spatial variability of soil attributes still interests many in the scientific community. Furthermore, mapping the spatial variability of soil nutrients is the way that PA enables efficient agronomic decisions. However, one of the limiting factors to mapping soil with high accuracy is the number of samples required, which often results in the sampling process being physically and economically impractical (Peets et al., 2012). In addition, estimates of models based on single variables are expensive and time consuming, especially when laboratory analyses are involved (Simbahan and Dobermann, 2006). To overcome this challenge, some studies have been carried out on soil sampling procedures in the past few decades (Webster and Oliver, 1992; Nanni et al., 2011; Montanari et al., 2012; Stepien et al., 2013; Cherubin et al., 2014; Fortes et al., 2015; Sanches et al., 2018). Although several procedures have been recommended, the most common sampling procedures used for soil mapping are regularly spaced grids. Although this method has benefits, its high cost and low efficiency are issues that still need to be addressed. The use of previous information on soil spatial variability and topographic parameters may represent an intelligent solution to overcome this bottleneck, improving soil sampling processes and spatial characterizations (Sanches et al., 2018), especially in sugarcane fields where the adoption of PA is low (Silva et al., 2011).

Soil spatial variability may be due to natural or anthropogenic influences that result from five main factors: climate, microorganisms, landscape, parent material and time (Jenny, 1941). Anthropogenic influences promote a soil disturbance mainly due to the management applied, generating variations in nutrient content. However, attention should be given to influences caused by topography. The relationship between soils and topographic parameters is intrinsic (Moore et al., 1993). The variability of physical and chemical soil attributes is related to the topographic position affecting pedogenetic processes, transport and storage of water in the soil profile (Sanchez et al., 2009). Topographic parameters, referred to as geomorphometric variables, are extremely important parameters that influence chemical-physical soil attribute variability (Muños et al., 2011; Brubaker et al., 1993; Fulton et al., 1996; Chung et al., 2001; Gaston et al., 2001; Wilson and Gallant, 2000). Despite the intrinsic relationship between topographic and soil attributes, sampling procedures addressing the physic-chemical characterization do not consider topographical parameters, such as those proposed by Valeriano and Rosseti (2008), and few studies have examined the relationship between them in sugarcane fields, that are manage with high amount of inputs.

To ensure sustainable site-specific management of sugarcane fields, understanding soil spatial variability related to topographic parameters is extremely important. The aim of the present study is to carry out a comprehensive assessment of soil spatial variability in terms of organic matter (OM), pH, sum of bases (SB) and cation exchange capacity (CEC) in sugarcane fields as a function of topographic parameters, with the goal of assessing the patterns and divergences among them to improve soil management by farmers. Understanding soil variability patterns through space and time may help sustainable management of sugarcane fields. In addition, topographic parameters derived easily from broadly available digital elevation models are a source of information (economically feasible and easily assessed) with a great potential to aid in site-specific management and to improve fertilizer application.

2.2. Materials and Methods

2.2.1. Soil chemical characterization

The dataset used in this study is from sugarcane experimental fields where PA research is carried out. All data are stored in the Agronomic Database (BDAgro) reported in Driemeier et al. (2016). Data from nine sugarcane experimental fields were evaluated in this study (Figure 2.1). All experimental fields [labeled as Field A (21°16'35.65"S 47°32'15.65"W), Field B (21°16'56.77"S 47°32'00.39"W), Field C (21°49'11.69"S 48°35'44.21"W), Field D

(21°46'28.12"S 48°37'34.05"W), Field E (22°23'37.90"S 47°18'31.40"W), Field F (22°26'30.33"S 52°36'04.15"W), Field G (21°38'12.18"S 48°39'05.49"W), Field H (21°49'04.10"S 48°25'35.97"W) and Field I (21°49'04.10"S 47°44'11.29"W)] are located in São Paulo State, Brazil. The experimental fields are in the cities of Serrana (Fields A and B), Nova Europa (Fields C, D and G), Araras (Field E), Euclides da Cunha Paulista (Field F), Descalvado (Field I) and Bebedouro (Field H). Only soil surface layer data (0.00 to 0.20 m), where the most sugarcane active root are present, were evaluated. For all fields, the soil was sampled by grids with different densities (Table 2.1). The experimental fields A, B, E and G were sampled for more than 1 year. Approximately 3,000 soil samples, collected between 2008 and 2017, were evaluated. The attributes OM, pH, SB and CEC, which are soil attributes that directly impact the spatial and temporal variability of sugarcane yields, were assessed.

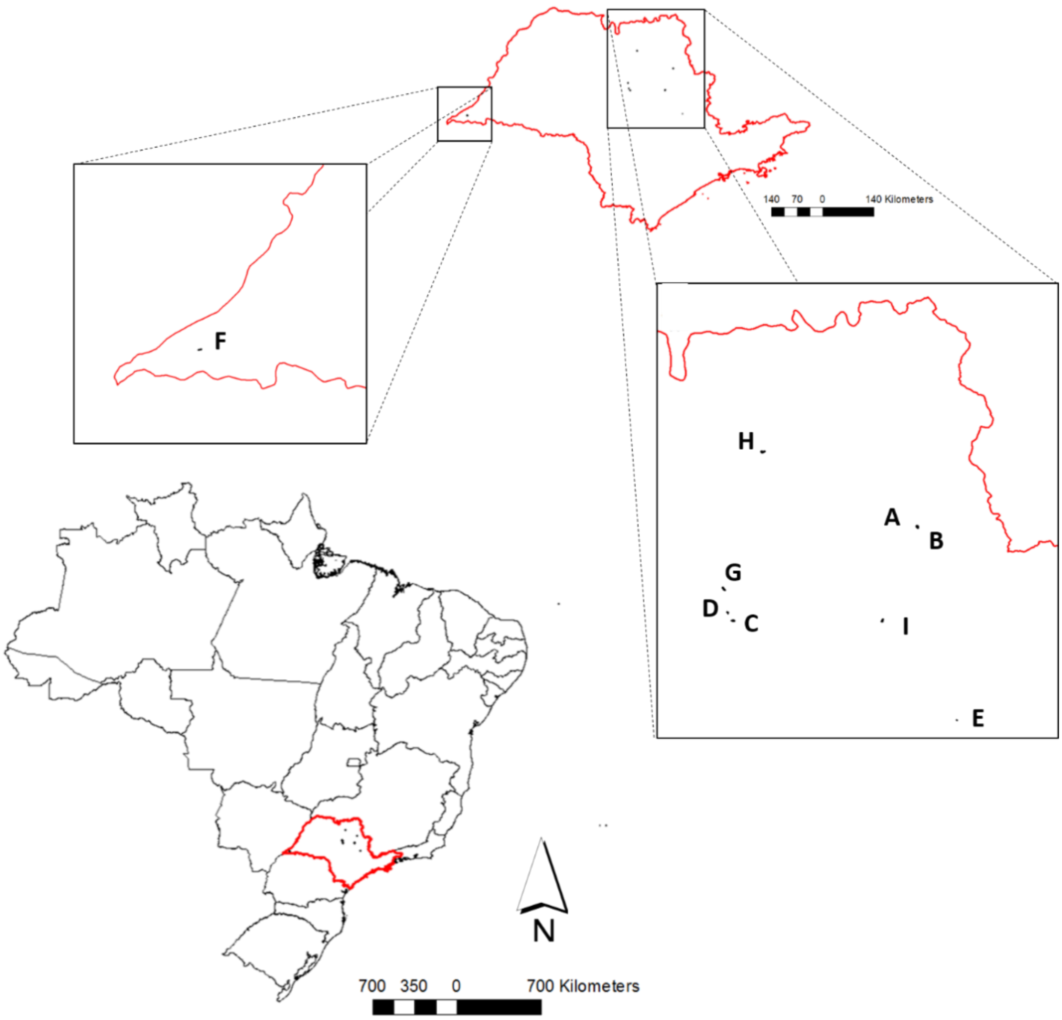


Figure 2.1. Geographic location of the sugarcane experimental fields in São Paulo State, Brazil.

Table 2.1. Soil sampling characteristics of the sugarcane experimental fields.

Field	Area [ha]	Years	Grid [m]	Samples	Density [samples ha^{-1}]
A	52.57	2011, 2012, 2013 and 2014	50 x 50	204	3.88
B	58.07	2011, 2012 and 2013	50 x 50	24	0.41
C	95.88	2014	50 x 50	303	3.16
D	34.81	2014	50 x 50	128	3.68
E	10.08	2008, 2009, 2011 and 2012	30 x 30	117	11.61
F	97.65	2014	100 x 100	197	2.02
G	102.06	2016 and 2017*	50 x 50	424	4.15
H	108.09	2017	75 x 75	183	1.69
I	90.04	2017	100 x 100	119	1.32

* 100 x 100 m grid with 214 samples collected.

2.2.2. Topographic dataset

The topographic parameters used in this study were obtained from the Topodata database (Brasil, 2008). These data were generated by Valeriano and Rosseti (2008) and Valeriano and Albuquerque (2010), where the Shuttle Radar Topography Mission (SRTM) data were refined to a 30-m resolution (Valeriano and Rossetti, 2012; Rabus et al., 2003). Geomorphometric variables of terrain formations, resulted from vertical (V) and horizontal (H) curvatures, were assessed. Terrain formation is divided into 9 classes, produced by three vertical curvature (concave, rectilinear and convex areas, labeled as 'V_{Conc}', 'V_{Ret}' and 'V_{Conv}', respectively) and three horizontal curvature (convergent, planar and divergent areas, labeled as 'H_{Conv}', 'H_{Plan}' and 'H_{Div}', respectively), both according to classifications proposed by Valeriano and Rosseti (2008). The 9 classes are: '$V_{Conc}H_{Conv}$', '$V_{Conc}H_{Plan}$', '$V_{Conc}H_{Div}$', '$V_{Ret}H_{Conv}$', '$V_{Ret}H_{Plan}$', '$V_{Ret}H_{Div}$', '$V_{Conv}H_{Conv}$', $V_{Conv}H_{Plan}$' and '$V_{Conv}H_{Div}$'. The soil sampling points were associated with the morphometric classes that were located in.

2.2.3. Data analysis

Data analysis was performed by different steps (Figure 2.2). First, all data were analyzed to remove discrepant values according to the methodology described in Driemeier et al. (2016). Any data that deviated by more than 3 standard deviations (SD) was treated as outliers. Second, all soil attributes were normalized to an interval of 0 to 1 (Equation 1), within the respective experimental field, and evaluated year. This step placed the data, regardless of the site and year, in the same range of variation to allow future comparisons.

$$X_p = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (1)$$

where X_p is the normalized attribute value, x_i is the original attribute value; x_{min} and x_{max} are respectively the minimum and maximum values of the attribute assessed within the respective experimental field and evaluated year.

A random sampling by each morphometric class was performed to balance the classes and avoid bias in the analysis. Three-hundred samples per class were adopted for each z_j iteration of the random sampling. At each iteration, the mean (M) and coefficient of variation (CV), by morphometric class, of the soil attribute were calculated. We performed 10 iterations to allow a statistical evaluation and ensure an adequate comparison. We assessed the level of significance (α = 0.05) regarding the difference between the mean values of classes and apply LSD test to distinguish classes into homogeneous groups. Therefore, a box-plot was used to visualize the data variability of all the iterations by morphometric classes, using the mean as the second quartile. Finally, a principal component analysis (PCA) was also applied to simplify the evaluated soil dataset and assess the variability of the principal components (PCs) within the evaluated areas. To verify the spatial patterns at a temporal level, we evaluated the first two main components in field A, where sampling was performed for 4 years.

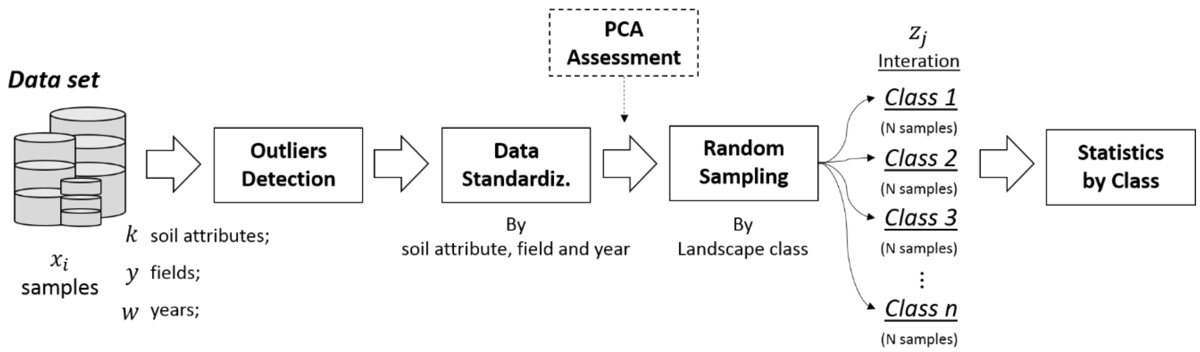


Figure 2.2. Data analysis process applied to dataset.

2.3.Results

Field E was the flattest, while field A presented a greater slope (Figure 2.3 - b), with averages equal to 2.5% and 9.5%, respectively. Fields G, A and I had the largest variability in slope, showing a high variability of terrain elevations.

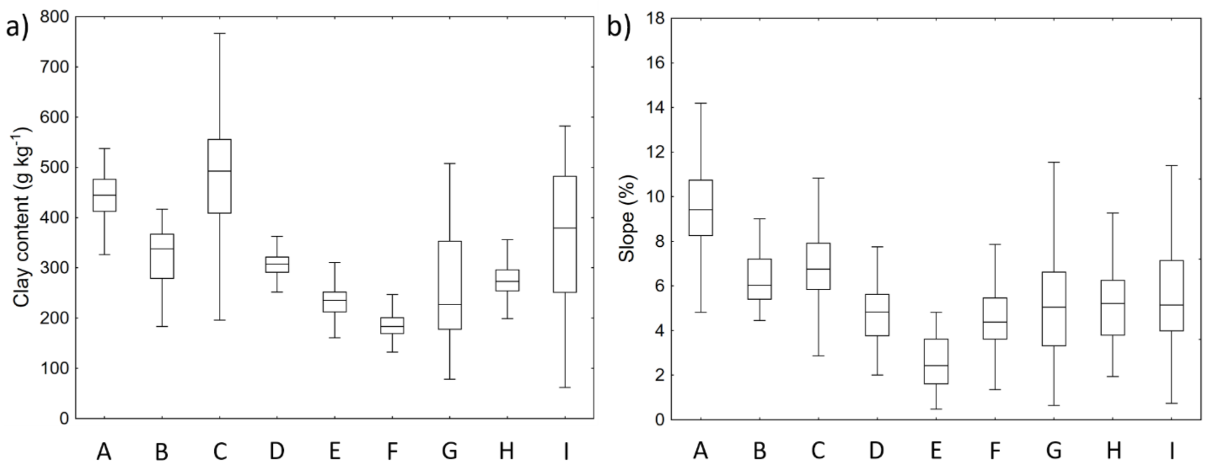


Figure 2.3. Clay content (a) and slope (b) variability of the experimental fields.

Experimental Fields A, C and I showed the highest averages of clay content, with averages of 452, 492 and 379 g kg^{-1}, respectively (Figure 2.3 – a). The experimental Field F, which had the lowest average clay content, showed the lowest levels for all the soil attributes (Figure 2.4). In addition, Field F showed the highest variability of pH (Figure 2.4 – b) and the lowest variability of SB (Figure 2.4 – c) and CEC (Figure 2.4 – d). The average OM and variability of OM in Fields F and H were similar, with averages of approximately 13.5 g dm^{-3}. Fields G and I showed the highest variability of OM content, followed by clay content variability. On average, the pH levels of all the experimental fields were within a range of 5.0 to 5.6 (Figure 2.4 – b). The SB and CEC had the highest variability in Fields C and I (Figure 2.4 – c and d). The highest average values of the attributes, except for CEC, were in Field I (OM = 30.1 g dm^{-3}, pH = 5.6 and SB = 60.1 $mmol_c$ dm^{-3}). The highest average CEC was in Field C (CEC = 76.8 $mmol_c$ dm^{-3}).

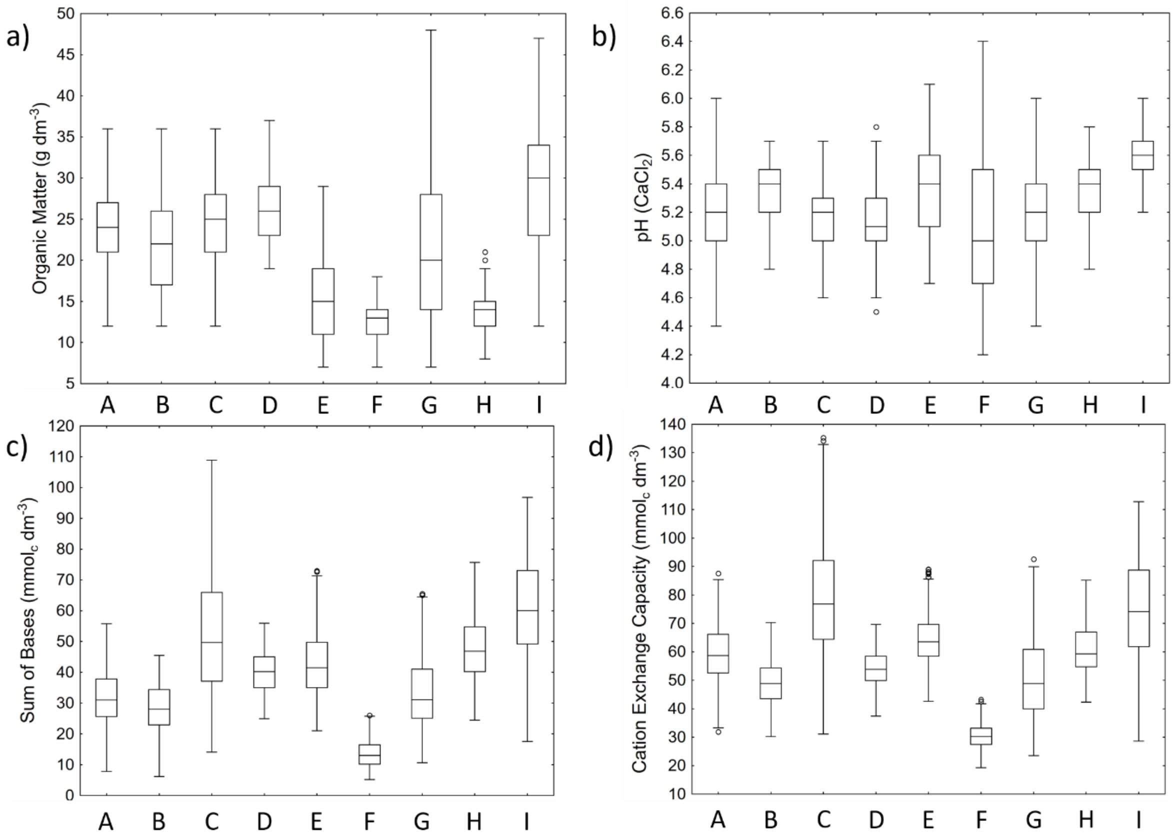


Figure 2.4. Organic matter (a), pH (b), sum of bases (c) and cation exchange capacity (d) variability of the experimental fields.

The horizontal morphometric classes associated with V_{Conc} areas showed the highest average levels for all soil attributes, except for pH (Figure 2.5). The pH (Figure 2.5 – b) showed lower average levels in the H_{Conv} areas associated with all vertical morphometric classes. For pH, at each vertical morphometric class, the level increases from H_{Conv} to H_{Div} ($H_{Conv} < H_{Plan} < H_{Div}$). For OM (Figure 2.5 – a), SB (Figure 2.5 – c) and CEC (Figure 2.5 – d), the content trend to decrease from H_{Conv} to H_{Div} in the V_{Ret} areas; the opposite behavior observed for pH levels. For these same soil attributes, in the V_{Conv} areas, the highest content is associated with H_{Plan} areas, followed by H_{Div} and H_{Conv}. The $V_{Conv}H_{Conv}$ areas showed the lowest average levels for all attributes assessed. Except for pH, there was a decreasing trend in the content of the soil attributes assessed from $V_{conc}H_{Conv}$ until $V_{Conv}H_{Conv}$.

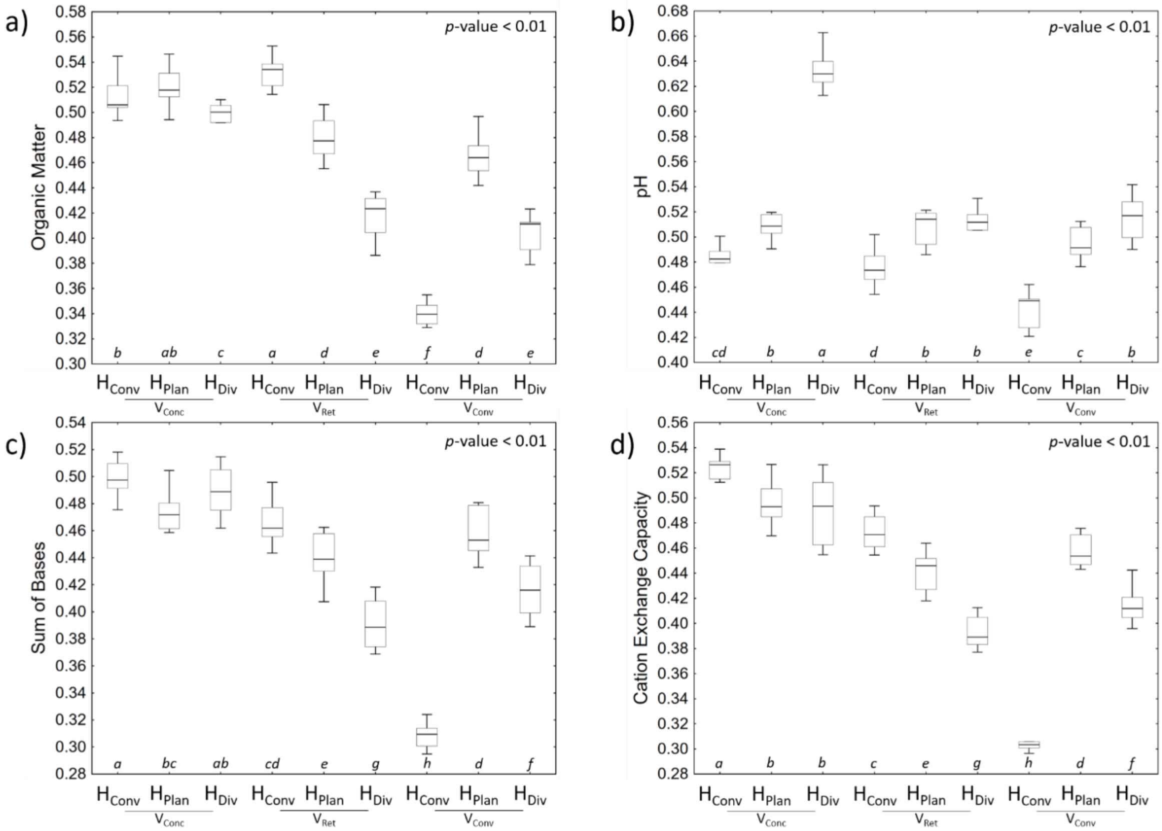


Figure 2.5. Variability of the normalized content of the iterations for organic matter (a), pH (b), sum of bases (c) and cation exchange capacity (d) according morphometric classes. Lowercase letters - LSD test of mean comparisons.

The $H_{Conv}V_{Conv}$ area showed the highest CV for all soil attributes assessed, demonstrating greater spatial variability of these soil attributes within these areas and differing statistically from all morphometric areas assessed (Figure 2.6). On the other hand, except for CEC, the $V_{Conc}H_{Div}$ areas showed the lowest CV for all attributes assessed, indicating a lower spatial variability. For OM (Figure 2.6 – a) and SB (Figure 2.6 – c), the lowest CV was observed in all horizontal morphometric classes associated with V_{Conc} areas. For CEC (Figure 2.6 – d), the $V_{Conc}H_{Conv}$ and $V_{Conc}H_{Plan}$ showed the lowest CV. In absolute terms, in average, the pH showed lower CVs in the most areas assessed.

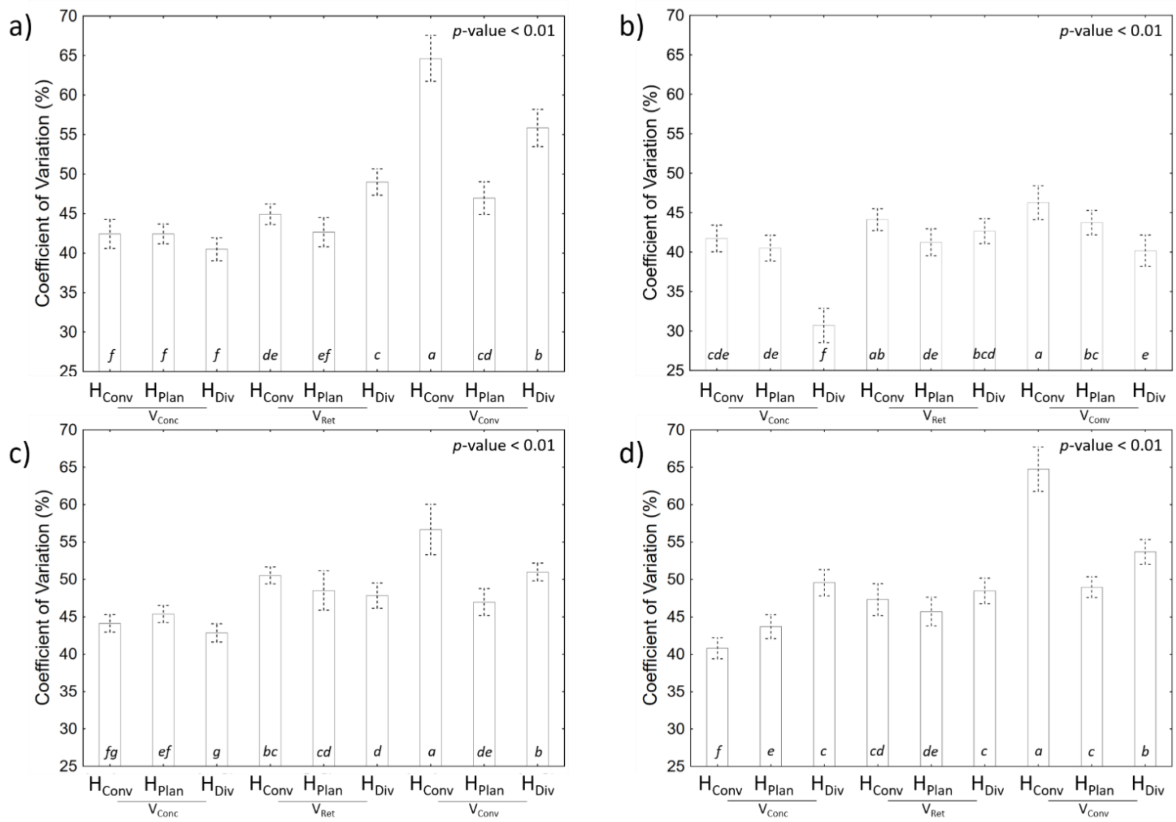


Figure 2.6. Coefficient of variation (CV) of the iterations for organic matter (a), pH (b), sum of bases (c) and cation exchange capacity (d) according morphometric classes. Lowercase letters - LSD test of mean comparisons.

The first two PCs explained approximately 82% of the total variance of the data evaluated (Table 2.2). PC 1 is directly related to the SB and CEC attributes (ρ = 0.93 and 0.88, respectively). The pH correlated positively with PC 1 (ρ = 0.49) and negatively with PC 2 (ρ = -0.79), while OM correlated positively with both components (Figure 2.7 – a). Following the same trend observed previously, the highest contents of PC1 was observed in V_{Conc} areas ($V_{Conc}H_{Div}$ > $V_{Conc}H_{Conv}$ > $V_{Conc}H_{Plan}$). On the other hand, $V_{Conv}H_{Conv}$ showed the lowest level for PC1. The PC2, represented mostly by pH (negatively) and OM (positively), showed the same trend, with higher and lower levels in $V_{Conc}H_{Div}$ and $V_{Conv}H_{Conv}$, respectively.

Table 2.2. Factor coordinates of the soil attributes related to principal components. Eigenvalues and total variance explained by the components.

Attribute	PC 1	PC 2	PC 3	PC 4
OM	0.6168	0.5705	-0.5421	-0.0151
pH	0.4972	-0.7892	-0.3479	0.0940
SB	0.9263	-0.1340	0.2182	-0.2763
CEC	0.8868	0.1857	0.3442	0.2464
Eigenvalue	2.27	1.00	0.58	0.15
Variance (%)	56.80	25.02	14.52	3.65

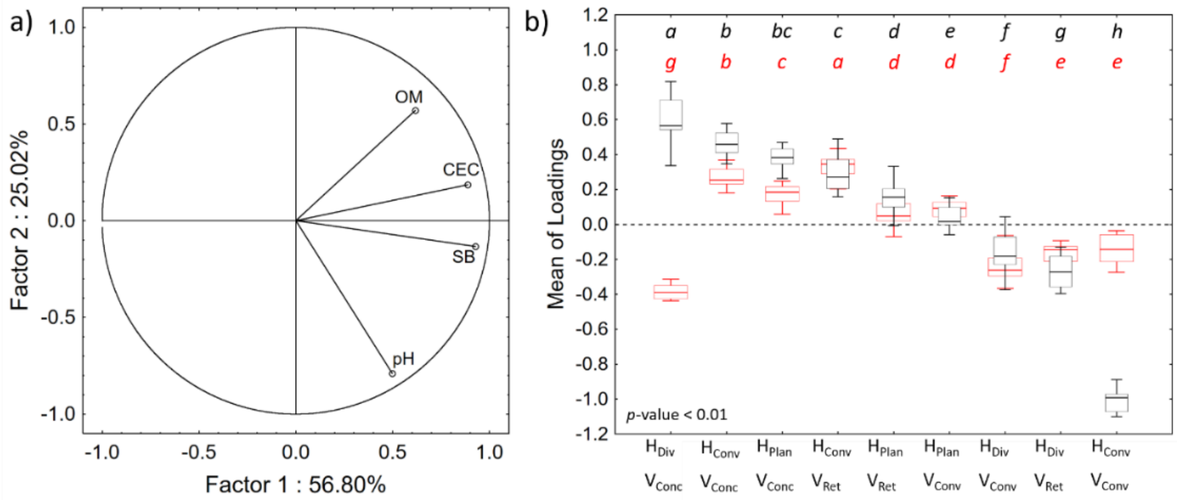


Figure 2.7. Projection of the soil attributes in the unitary plane of the first two main components (a) and variability of the loadings of the iterations for PC 1 (black) and PC 2 (red) according morphometric classes (descending order of PC1 levels). Lowercase letters - LSD test of mean comparisons (b).

At a temporal scale, in the experimental field A (where samples were taken for four successive years) there was a decreasing trend from H_{Conv} to H_{Div} associated with V_{Conc} and V_{Ret} areas for both PC1 (Figure 2.8 – a) and PC2 (Figure 2.8 – b). The same trend was not observed for PC1 in 2013. In this way, excepted for 2013, it's possible observe that there was a spatial trend that remains at temporal level, mainly in V_{Conc} and V_{Ret} areas. The V_{Conv} areas showed a behavior that not remains temporally, showing a greater variability in these areas.

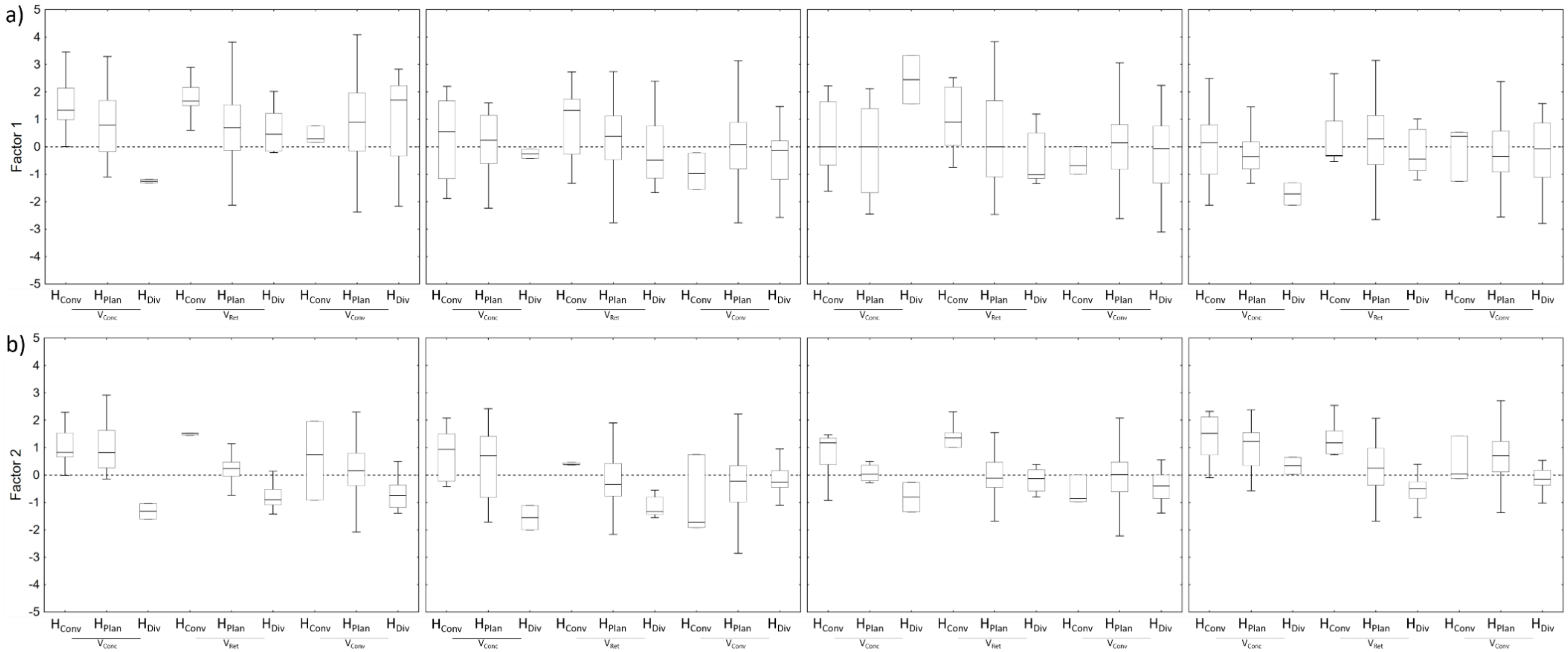


Figure 2.8. Variability of the average content for PC1 (a) and PC2 (b) in the experimental field A throughout the soil sampling periods 2011 to 2014 (left to right) in the morphometric classes assessed.

2.4.Discussion

The investigated fields contained very sandy/silt (clay < 150 g kg^{-1}) and very clayey (clay > 600 g kg^{-1}) sites. Thus, different soil fertility classes were included, since soil textural class is directly related to the availability of water and nutrients (Raij et al., 2001). This relationship is exemplified by the highest sand content field, Field F, that had lower average levels of OM, SB and CEC (Figure 4). Fields G and I, which had high slope variability, also showed significant changes in clay content, indicating a correlation between these attributes, as reported by Brubaker et al. (1993). Soil acidity values, defined by pH values, were similar for all the fields, with values between 5.0 and 5.6. However, soil pH should be maintained between 5.5 and 6.0, which is ideal for the nutrient absorption by crops (Malavolta, 1979). Field F, the sandiest, presented very low (pH > 6.0) and very high (pH < 4.3) acidity sites, where the greatest spatial variability was observed for this attribute.

Regardless of the site and soil fertility class, the OM, SB and CEC attributes showed the highest average levels in V_{Conc} areas (Figure 2.5 – a, – c and – d, respectively). The findings indicated that these areas always tend to contain higher levels of these attributes, thus showing higher soil fertility in the sugarcane fields. Thus, the fertilizer applications in these sites can be managed in a different way from the other sites, where the V_{Conc} areas are more fertile, in average, than the V_{Conv} areas. Due to their geomorphological shape, the concave areas present different elevation values, where generally higher elevations occur at the edges of these areas, and lower elevations occur in the central regions. Thus, sediments and other soil components, influenced by gravity and erosive agents, tend to move to the lower elevations of these areas. Our findings were consistent with this finding and explained the higher soil fertility shown in these areas. The PCA (Figure 2.7) also corroborated the presented results, where the V_{Conc}, associated with all horizontal morphometric classes, present greater soil fertility, as expressed by PC 1.

On the other hand, for all vertical morphometric classes associated with H_{Conv} areas showed the lowest soil pH levels, i.e., sites with relative higher acidity. The character convergent, associated with horizontal terrain formation, showed that these lands tend to be more acidity than divergent areas. So, H_{Conv} areas in the fields could be manage in a different way to adequate the soil pH values. One reason for soil acidification is due to nutrient absorption by crops. Potassium and magnesium absorption by crops promote the release of H^+ ions into the soil (Epstein and Bloom, 2005), changing the soil pH, being a possible explanation of the higher soil acidity in areas with convergent horizontal character. The H_{Div} areas had sites with higher pH values, where the $V_{Conc}H_{Div}$ area showed the highest values. A differentiated limestone application will be necessary in these areas to balance the soil pH and make nutrients available for plants, contributing to an increase in the yield potential of these sites.

In terms of the spatial variability presented by morphometric classes, a common behavior was observed among the investigated sugarcane fields. The soil attributes assessed had higher CVs within $V_{Conv}H_{Conv}$ (Figure 2.6). This morphometric class showed the lower values of PC1 (Figure 2.7 – b), demonstrating that higher CV can be associated with low fertility zones. Excepted for CEC, the lowest CV was observed in the $V_{Conc}H_{Div}$ areas, indicating a lower spatial variability. In this way, the results demonstrated that a lower soil sampling density will be necessary in the $V_{Conc}H_{Div}$ areas for an adequate soil spatial characterization. This approach does not apply in $V_{Conv}H_{Conv}$ areas, where the inverse is true, i.e., a larger amount of soil samples is required to characterize the soil.

As the most important soil attributes for defining the sugarcane yield (Nogueirol et al., 2014), soil OM, pH, SB and CEC, represented by PC1 (Figure 2.7 – a), showed the same spatial variability behavior at the temporal level (Figure 2.8). Excepted for 2013, PC1 was a decreasing trend from H_{Conv} to H_{Div} associated with V_{Conc} and V_{Ret} areas (Figure 2.8 – a). The results indicate that a more rigorous management to adequate de soil fertility may be required in H_{Div} areas due to the lower levels of soil attributes assessed in field A.

Regardless of soil fertility and slope class, the patterns of spatial variability were constant in the experimental fields, showing a temporal trend for field A. This knowledge can help farmers who wish to carry out site-specific management of their crops by applying the right amount of fertilizers. According to our findings, the $V_{Conc}H_{Div}$ areas could receive a relatively smaller amount of fertilizers in comparison to $V_{Conv}H_{Conv}$ areas (Figure 2.7 – b). Topographic parameters, which have high temporal stability, could be a great alternative (economically feasible and easily accessible) type of information that could be used for management zone delineation. Some studies have assessed landscape parameters in terms of management zone delineation (Brubaker et al., 1994; Yang et al., 1998; Siqueira et al., 2010) that is intrinsically related to yield variations in the fields. Combining the topographical attributes of vertical and horizontal curvatures, specifically the V_{Conc} character of the landscape (whose soil fertility is always relatively greater) with V_{Conv} areas (with lower soil fertility), it is possible to develop fertility zone maps for site-specific management of the fields. So, the landscape attributes and their derivations can be an excellent alternative for managing sugarcane fields in a sustainable way.

Although the present study focuses only on the soil conditions in sugarcane fields, the patterns of spatial variability shown here can be applied to other crops, which is a great way for farmers to apply localized management of their fields. More accurate digital elevation models (DEMs) and their derivatives using different technologies, such as drones, can be used in the future to evaluate the content and variability of soil attributes as presented here. The relationship between soil fertility zones and crop yield could be investigated to provide greater indicators of the topographic attributes available in the Topodata database (Brasil, 2008) that are an excellent alternative for localized and efficient management of sugarcane fields.

2.5.Conclusion

As a great source of information (economically feasible and easily accessible) about spatial and temporal variability of soil attributes in the field, topographic parameters showed that can be used to manage sugarcane fields in a site-specific way. The findings of present comprehensive assessment of sugarcane fields showed that some morphometric classes present greater soil fertility and lower CV, like $V_{Conc}H_{Div}$ and $V_{Conv}H_{Conv}$, respectively. So, while $V_{Conv}H_{Conv}$ areas would require higher soil sampling densities to characterize soil spatial variability due to their high CVs, in the $V_{Conc}H_{Div}$ areas the fertilizer applications may be relatively lower due these areas are characterized by zones with higher contents of OM, pH, SB and CEC. Soil acidity management should be more rigorous in horizontal convergent (H_{Conv}) areas due to their lower levels of pH. The patterns of spatial variability were verified at a temporal level for field A, indicating that topographic parameters can be used to define fertility zones within fields. Finally, topographic attributes proved to be an excellent alternative for farmers to use to establish fertility zones in their fields to manage accordingly.

Acknowledgments

The authors thank the São Paulo Research Foundation (grant process: 2015/01587-0, 2014/14965-0, 2013/50942-2 and 2008/09265-9) and the sugarcane mills for technical support and the use of the experimental fields. We also thank to Professor Dr. Lucas Rios do Amaral for provide data from fields.

2.6.References

Brasil. Instituto Nacional de Pesquisas Espaciais (INPE). Topodata: banco de dados geomorfométricos do Brasil. Variáveis geomorfométricas locais. São José dos Campos, 2008. <http://www.dsr.inpe.br/topodata/>.

Brubaker, S.C., Jones, A.J., Lewis, D.T., Frank, K. 1993. Soil properties associated with landscape position. *Soil Science Society of America Journal* 57, 235-239.

Brubaker, S.C., Jones, A.J., Frank, K., Lewis, D.T. 1994. Regression Models for Estimating Soil Properties by Landscape Position. *Soil Science Society of America Journal 58*(6), 1763–1767.

Bullock, D.S., Kitchen, N., Bullock, D.G. 2007. Multidisciplinary Teams: A Necessity for Research in Precision Agriculture Systems. *Crop Science* 47(5), 1765.

Cherubin, M.R., Santi, A.L., Eitelwein, M.T., Da Ros, C.O., Bisognin, M.B. 2014. Sampling grids used to characterise the spatial variability of pH, Ca, Mg and V% in Oxisols. *Revista Ciência Agronômica* 45:659-672.

Chung, S.O., Sung, J.H., Sudduth, K.A., Drummond, S.T., Hyun, B.K. 2001. Spatial variability of yield, chlorophyll content, and soil properties in a Korean rice paddy field. In P.C. Robert et al (ed.) *Proc.* 5th International Conf. on precision agriculture. [CD-rom] ASA, CSSA, Madison, WI.

Companhia Nacional do Abastecimento (CONAB). 2017. *Acompanhamento da safra Brasileira. Cana-de-açúcar, SAFRA 2017/18 Primeiro Levantamento Abril/2017*. Brasília, DF, 62p.

Driemeier, C., Ling, L.Y., Sanches, G.M., Pontes, A.O., Magalhães, P.S.G., Ferreira, J.E. 2016. A computational environment to support research in sugarcane agriculture. *Computers and Electronics in Agriculture* 130, 13–19.

Epstein, E; Bloom, AJ. 2005. *Mineral nutrition of plants: principles and perspectives*. 2. ed. Sunderland: Sinauer Associates. 380 p.

Fortes, R., Millán, S, Prieto, M.H., Campillo, C. 2015. A methodology based on apparent electrical conductivity and guided soil samples to improve irrigation zoning. *Precision Agriculture* 16:441–454.

Fulton, J.P., Wells, L.G., Shearer, S.A., Barnhisel, R.I. 1996. Spatial variation of soil physical properties: Aprecursor to precision tillage. *ASAE* Paper No. 961002. International Meeting, Phoenix, Arizona. 14–18 July 1996. ASAE, St. Joseph, MI.

Gaston, L.A., Locke, M.A., Zablotowicz, R.M., Reddy, K.N. 2001. Spatial variability of soil properties and weed populations in the Mississippi delta. *Soil Science Society America Journal* 65, 449–459.

Jenny, H. 1941. *Factors of soil formation*. McGraw-Hill. New York.

Johnson, R. A.; Wichern, D. W. 2007. *Applied Multivariate Statistical Analysis. Sixth Edition.* Prentice Hall. p. 800.

Malavolta, E. 1979. *ABC da Adubação*. 4a edição. São Paulo SP, Editora Agronomia Ceres.

Montanari, R., Souza, G.S.A., Pereira, G.T., Marques Jr., J., Siqueira, D.S., Siqueira, G.M. 2012. The use of scaled semivariograms to plan soil sampling in sugarcane fields. *Precision Agriculture* 13(5):542-552.

Moore, I. D., Gessler, P. E., Nielsen, G.A., Peterson, G.A. 1993. Soil attribute prediction using terrain analysis. *Soil Science Society of America Journal* 57 (2), 443-452.

Muñoz, V.A, Valeriano, M.M., Weill, M.A.M. 2011. Estudo das relações solo-relevo pela análise geomorfométrica de dados SRTM e TOPODATA e a técnica de recuperação de conhecimento a partir de mapas. In: XV Simpósio Brasileiro de Sensoriamento Remoto – SBSR. Curitiba, PR, Brasil. *Anais* INPE p.9261.

Nanni, M. R., Povh, F.P., Demattê, J.A.M., Oliveira, R.B., Chicati, M.L., Cezar, E. 2011. Optimum size in grid soil sampling for variable rate application in site-specific management. *Scientia Agrícola* 68(3):386-392.

Nogueirol, R.C., Cerri, C.E.P., Silva, W.T.L., Alleoni, L.R.F., 2014. Effect of no-tillage and amendments on carbon lability in tropical soils. *Soil & Tillage Research* 143, 67-76.

Peets, S., Mouazen, A.M., Blackburn, K., Boyan, K., Wiebensohn, J. 2012. Methods and procedures for automatic collection and management of data acquired from on-the-go sensors with application to on-the-go soil sensors. *Computers and Electronics in Agriculture* 81, 104 – 112.

Rabus, B., Eineder, M., Roth, R., Bamler, R. 2003. The Shuttle Radar Topography Mission—a new class of digital elevation models acquired by spaceborne radar. *ISPRS Journal of Photogrammetry & Remote Sensing* 57, 241-262.

Raij, B., Andrade, J.C., Cantarella H., Quaggio, J.A. 2001 Análise química para avaliação da fertilidade de solos tropicais. ,Campinas, Instituto Agronômico

Sanches, G.M., Magalhães, P.S.G., Remacre, A.Z., Franco, H.C.J., 2018. Potential of apparent soil electrical conductivity to describe the soil pH and improve lime application in a clayey soil. *Soil & Tillage Research* 175, 217-225.

Sanchez, R.B., Marques Júnior, J., de Souza, Z.M., Pereira, G.T., Martins Filho, M.V. 2009. Spatial variability of soil attributes and of erosion factors in different landforms. *Bragantia* 68 (4), 1095-1103.

Silva, C.B., Moraes, M.A.F.D., Molin, J.P., 2011. Adoption and use of precision agriculture technologies in the sugarcane industry of São Paulo state, Brazil. *Precision Agriculture* 12(1), 67–81.

Simbahan, G.C., Dobermann, A., Goovaerts, P., Ping, J., Haddix, L. 2006. Fine-resolution mapping of soil organic carbon based on multivariate secondary data. *Geoderma* 132, 471-489.

Siqueira, D. S., Marques, J., Pereira, G. T. 2010. The use of landforms to predict the variability of soil and orange attributes. *Geoderma 155*(1–2), 55–66.

Stepien, M., Gozdowski, D., Samborski, S.A. 2013. A case study on the estimation accuracy of soil properties and fertilizer rates for different soil-sampling grids. *Journal of Plant Nutrition and Soil Science* 176(1):57-68.

Valeriano, M.M., Rosseti, D.F. 2008. TOPODATA: seleção de coeficientes geoestatísticos para o refinamento unificado de dados SRTM. São José dos Campos: *INPE*, 50p.

Valeriano, M.M., Albuquerque, P.C.G. 2010. *Topodata: processamento dos dados SRTM.* São José dos Campos, SP: INPE: Coordenação de Ensino, Documentação e Programas Especiais (INPE-16702-RPQ/854). 79p.

Valeriano, M.M., Rossetti, D.F. 2012. Topodata: Brazilian full coverage refinement of SRTM data. *Applied Geography* 32, 300-309.

Webster, R., Oliver, M. A. 1992. Sample adequately to estimate variograms of soil properties. *Soil Science* 43(1), 117-192.

Wilson, J.P., Gallant, J.C. 2000. *Terrain analysis: principles and applications.* 1st Ed. New York: John Wiley & Sons, Inc. 478p.

Yang, C., Peterson, C. L., Shropshire, G. J., Otawa, T. 1998. Spatial Variability of Field Topography and Wheat Yield in the Palouse Region of the Pacific Northwest. *Transactions of the ASAE*, *41*(1), 17–27.

Chapter 3: Wide-range assessment of spatial and temporal variability of soil attributes by an electromagnetic induction (EMI) sensor in Brazilian sugarcane fields (Catena)

Guilherme M. Sanches[1*] and Paulo S. Graziano Magalhães[1]

[1]University of Campinas – UNICAMP - Ph.D. Program in Bioenergy – Interdisciplinary Center for Energy Planning

[*]Corresponding author – guilherme.sanches@cropman.com.br/+55 14 99164 8711

Abstract: The soil apparent electrical conductivity (ECa) has been highlighted as a valuable information with high potential to map the soil fertility and yield potential of fields. However, sugarcane fields still have few results that shows the applicability of this information to define the soil spatial variability and its fertility conditions. The objective of this paper was to provide a comprehensive assessment of the relationship among ECa, evaluated by an electromagnetic induction (EMI) sensor, and the spatial variability of clay content, organic matter (OM) and cation exchange capacity (CEC) in sugarcane fields. Six experimental sugarcane fields were evaluated, totaling 412 hectares mapped and 2,000 soil samples collected between 2011 and 2017. The results showed that ECa was able to map sites with higher clay content, OM and CEC, corresponding to classes of greater soil electrical conductivity. Low ECa classes presented greater spatial variability of the evaluated soil attributes, i.e., places that should be sampled with greater accuracy and higher sample density for a suitable soil spatial characterization. The ECa variability was directly proportional to clay content (R^2 = 0.97), OM (R^2 = 0.65) and CEC (R^2 = 0.76) variabilities. In general, the patterns founded at spatial variability level were temporarily remained. The EMI sensor is an excellent tool to define the spatial variability of soil fertility and could be used for a guided soil sampling to manage the sugarcane fields in an adequate sustainable way. **Keywords:** apparent electrical conductivity, proximal sensing, precision farming, site-specific management.

3.1. Introduction

The high-quality soil fertility mapping is one of the main procedures to ensure more sustainable production. Intrinsically related to Precision Agriculture (PA), this mapping consists in a detailed soil sampling using modern equipment and techniques (Bullock et al., 2007). Map the soil spatial variability is the way where PA can make decisions and efficient agronomic practices to increase profitability of production. However, to ensure a precise mapping of this variability, a dense soil sampling has been adopted; turn the activity unfeasible and unable to perform a differential management of crops. On the other hand, with the increase advent of information technology (IT) in agriculture, many soil sensing techniques (Rossel and Bouma, 2016) are available to map the spatial variability of fields.

Within the historical context of affordable technologies to acquire high-quality information to manage the crop spatial variability, the apparent electrical conductivity (ECa) of soil it has been highlighted as an effective method to evaluate quickly, with high resolution and low cost, the general soil fertility conditions (Sudduth et al., 2005) and soil yield potential (Corwin and Lesch, 2005 and 2003). ECa measurement has several advantages, such as high-speed data acquisition, easy to use, portable for field applications, and is a non-invasive method (Reedy and Scanlon, 2003). As a tool first applied to geology, ECa has been highlighted as a powerful information for agriculture in the last decades, showed great correlation with soil salinity, clay content, cation exchange capacity (CEC), clay minerals, pore size and distribution, organic matter and temperature (Molin and Faulin, 2013; Ekwue and Bartholomew, 2011; Corwin and Lesch, 2005; McBratney et al., 2005; Tarr et al., 2005; Domsch e Giebel 2004; Triantafilis et al., 2000; Sudduth et al., 2001; Kitchen et al., 1999; Rhoades et al., 1999). How ECa reflects the cumulative effect of soil matrix properties (mainly soil texture, cation exchange capacity, SOM and solute content), since these soil matrix properties are correlated with the yield, the ECa can also be highly correlated to crop yield (Godwin et al. 2003; Kitchen et al., 2005). Even more, recently, Serrano et al. (2017) addressed the ECa data and it's great spatial and temporal stability, turn it a valuable information for site-specific management of crops.

For instance, Heil and Schmidhalter (2017) showed a broad review of the ECa potential by an electromagnetic induction (EMI) sensor. However, within the crops assessed by Heil and Schmidhalter where the technology has been applied, neither of them were in sugarcane fields. In Brazilian fields, ECa has been used mainly to define the soil productive potential (Siqueira et al., 2015), soil fertility mapping (Medeiros et al., 2018), moisture differences (Costa et al., 2014; Molin and Faulin, 2013) and management zones (Molin and Castro, 2008). Moreover, the studies mostly applied sensors that measure ECa by direct contact principle (Sanches et al., 2018; Medeiros et al., 2018; Sana et al., 2014; Molin and Faulin, 2013; Salton et al., 2011; Valente et al., 2012; Molin and Castro, 2008), with few studies that use IEM (Sanches et al., 2019b; Siqueira et al., 2015). Within this context, the objective of this paper was provided a wide-ranging assessment of the relationship among soil attributes (clay content, organic matter and cation exchange capacity), that directly impact the sugarcane yield (Sanches et al., 2019a), and ECa at spatial and temporal level in Brazilian sugarcane fields by an EMI sensor. We intended to provide a comprehensive knowledge if ECa information, provided by an EMI sensor, can reflect the soil attributes variability and how it can help the producers to ensure an adequate site-specific management of their fields.

3.2. Material and Methods

3.2.1. Experimental fields

All experimental fields (Figure 3.1), were labeled as: field A (21°16'35.65"S 47°32'15.65"W), field B (21°49'11.69"S 48°35'44.21"W), field C (21°46'28.12"S 48°37'34.05"W), field D (21°38'12.18"S 48°39'05.49"W), field E (21°49'04.10"S 48°25'35.97"W) and field F (21°49'04.10"S 47°44'11.29"W), and are located in São Paulo state, Brazil. The experimental fields are in the cities of Serrana (Fields A), Nova Europa (Fields B, C and D), Bebedouro (Field E) and Descalvado (Field F). The fields slope ranged from 3.3% to 9.4% (Figure 3.2).

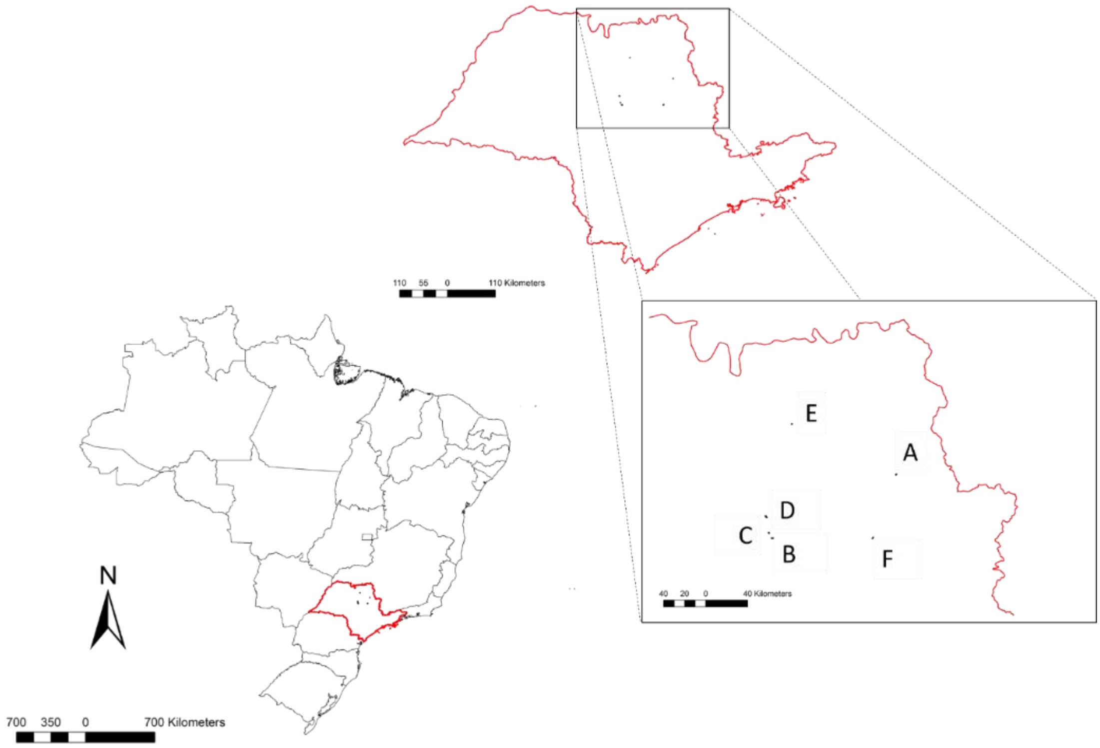


Figure 3.1. Geographic location of the sugarcane experimental fields in São Paulo state, Brazil.

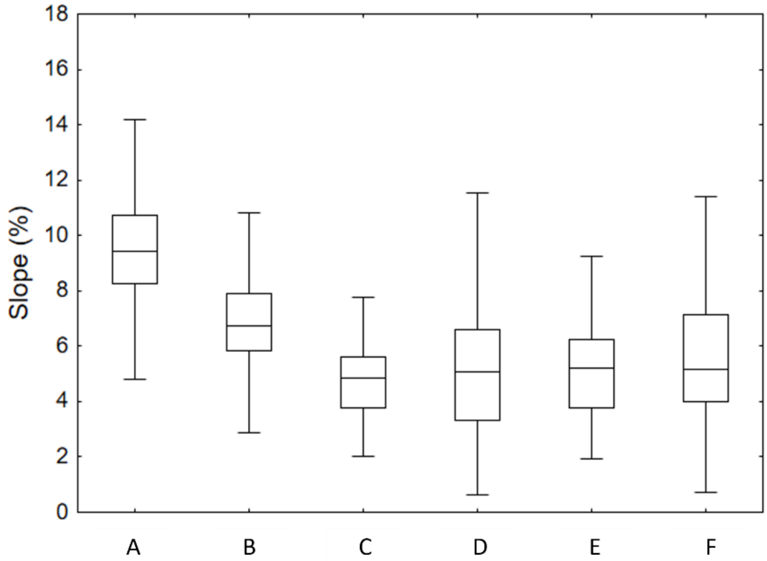


Figure 3.2. Slope (%) variability of the sugarcane experimental fields in São Paulo state, Brazil.

3.2.2. Soil dataset

The soil dataset used are from six sugarcane experimental fields (Figure 3.3) where PA researches are carried out by the University of Campinas (UNICAMP). All data are stored in the Agronomic Database (BDAgro) of CTBE/CNPEM, reported in Driemeier et al. (2016). Only the soil surface layer data (0.00 to 0.20 m) were evaluated. For all fields, the soil was sampled by regular grids with different densities (Table 3.1). The experimental fields A and D were sampled for more than 1 year. About 2000 soil samples were collected between 2011 and 2017 and analyzed for clay content, OM and CEC, which are directly impacting in the spatial and temporal variability of sugarcane yield.

Table 3.1. Soil sampling characteristics of the sugarcane experimental fields.

Field	**Area** [ha]	**Years**	**Grid** [m]	**Samples**	**Dens.** [samples ha^{-1}]
A	52.57	2011, 2012, 2013 and 2014	50 x 50	204	3.88
B	95.88	2014	50 x 50	303	3.16
C	34.81	2014	50 x 50	128	3.68
D	102.06	2016 and 2017*	50 x 50	424	4.15
E	37.50	2017	75 x 75	66	1.76
F	90.04	2017	100 x 100	119	1.32

* 100 x 100 m grid with 214 samples was collected.

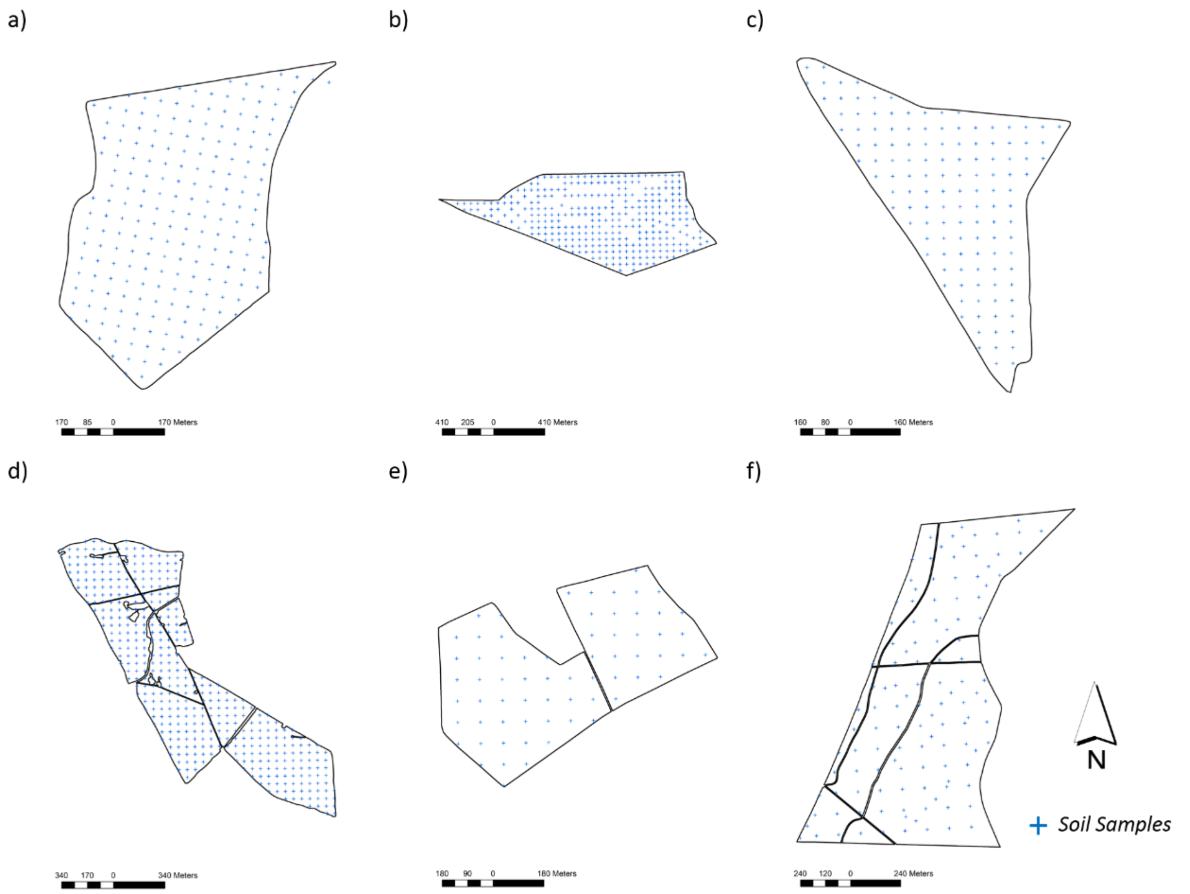


Figure 3.3. Soil sampling grids of experimental fields A (a), B (b), C (c), D (d), E (e) and F (f).

3.2.3. Apparent Electrical Conductivity (ECa) data set

The soil ECa was measured using the electromagnetic induction (EMI) sensor EM38-MK2® (Geonics, Ontario, Canada), the most widely used EMI sensor in agriculture (Doolittle and Brevick, 2014). The measures were obtained between May and July, the lowest rainfall season in all fields assessed. Each field were mapped within a short period (maximum of 2 days per field). We used the 0.5 m coil separation readings in the horizontal dipole mode, that reaches a maximum sensitivity directly below to the instrument. Technical data, construction and tool specification of EM38-MK2® are described in Heil and Schmidhalter (2017). The ECa was measured in parallel rows with intervals of 5-10 m pulled by a field vehicle. The data logger frequency was 1 Hz (Table 3.2). No rainfall was occurred on the ECa measurement days that could change the soil moisture and, consequently, influence the ECa measurements. Finally, the ECa maps was obtained by applying ordinary kriging (OK).

Table 3.2. Apparent electrical conductivity (ECa) data of the sugarcane experimental fields.

Field	Valid N	Area [ha]	Dens. [readings ha^{-1}]	Mean	Median	Min.	Max.	Range	SD	CV
				[mS m^{-1}]						
A	18438	52.57	350.74	122.838	117.403	15.352	225.117	209.765	45.693	37.198
B	25657	95.88	267.59	30.851	29.844	-55.430	227.500	282.93	43.517	141.052
C	13312	34.81	382.45	5.055	4.727	-4.766	78.008	82.774	3.737	73.931
D	79304	102.06	777.04	-51.846	-70.958	-124.727	137.190	261.9173	34.394	-66.338
E	10102	37.50	269.40	-57.095	-57.695	-77.695	38.789	116.484	7.626	-13.357
F	24499	90.04	272.09	-4.228	-15.508	-109.414	242.695	352.109	68.343	-1616.474

3.2.4. Data analysis

To assess the relationship between ECa and soil attributes, the data analysis process was performed according Figure 3.4. First, the ECa and soil data were analyzed to remove discrepant values from field readings or laboratory errors. Any input value that deviated from the mean by more than three standard deviations was treated as an outlier. The ECa data were reduced to the soil sample grid by linear polynomial surface regression (*fittype fuction*) using Matlab software (MathWorks, Natick, Massachusetts) in a buffer zone according to the linearization method described by Driemeier et al. (2016). After the removal of discrepant values, the correlation between soil attributes and ECa was calculated by Pearson's correlation coefficient (*r*). Second, all soil attributes were normalized to the interval 0 to 1 (Equation 1), within the respective experimental field and evaluated year. This step put the data, regardless of the site and year, in the same range of variation to allow future comparisons.

$$X_p = \frac{x_i - x_{min}}{x_{max} - x_{min}} \qquad (1)$$

where X_p is the normalized attribute value, x_i is the original attribute value; x_{min} and x_{max} is, respectively, the minimum and maximum values of the attribute assessed within the respective experimental field and evaluated year.

We performed a K-means cluster analysis to verify the best number of clusters (classes) for ECa at experimental fields. V-fold cross validation was performed to define the number of clusters, varying from 2 to 25. After that, ECa data of each experimental field was divided into classes by three types of classification methods. We tested the Quantil (Q), Natural Breaks (NB) and Geometrical Intervals (GI) classification methods. One hundred samples, per ECa class, were adopted for each z_j iteration of the random sampling. We performed 10 iterations.

At each iteration was calculated the mean (M) and coefficient of variation (CV), by ECa class, of the soil attribute assessed. At first time, we evaluated the clay content within ECa classes divided by the three types of classification methods tested. The objective was to decide what classification method show better difference between classes. The best classification method was selected, and the steps was performed again for OM and CEC. The box-plot was used to visualize the data variability of all iterations by ECa classes. Linear adjustment between ECa and soil attributes (by ranges of measurement) was performed to verify the robustness of ECa data to measure the soil spatial variability of fields. Finally, to verify the spatial patterns at temporal level, we evaluated the OM and CEC content at fields A and D, where soil sampling was performed for more than 1 year.

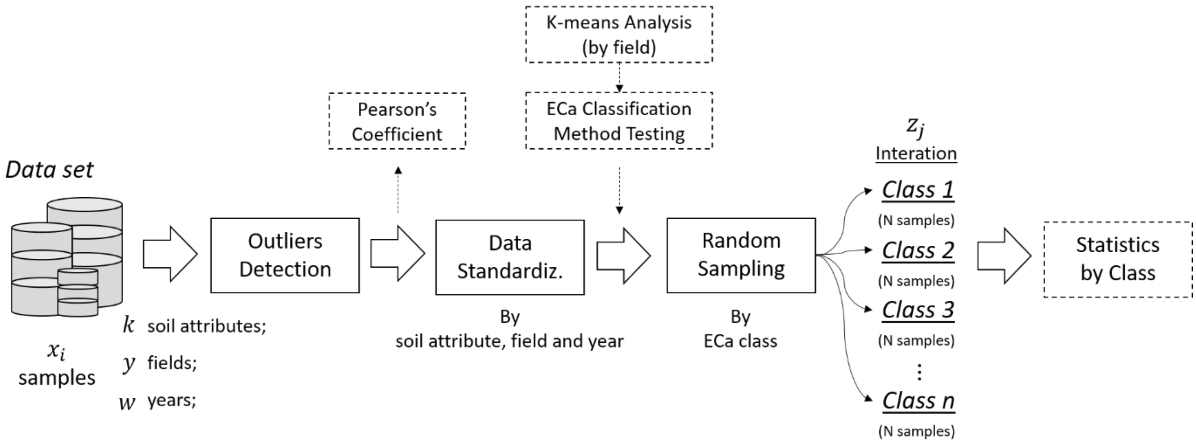


Figure 3.4. Data analysis process applied to dataset.

3.3. Results

The study comprised experimental fields with wide range of clay content variability (Figure 3.5 - a). Fields assessed were from high sandy (clay < 150 g kg^{-1}) until high clayey (clay > 600 g kg^{-1}). Fields B and F showed the greatest clay content variability, while fields C and E the smallest. Fields B and F showed measurement ranges equal to 648 g kg^{-1} and 520 g kg^{-1} respectively. Fields C and E, which presented lower clay content variability, also presented lower variability of OM and CEC (Figure 3.5 - b and c, respectively). While field B showed the highest average levels for clay and CEC, field F had the highest OM content on average.

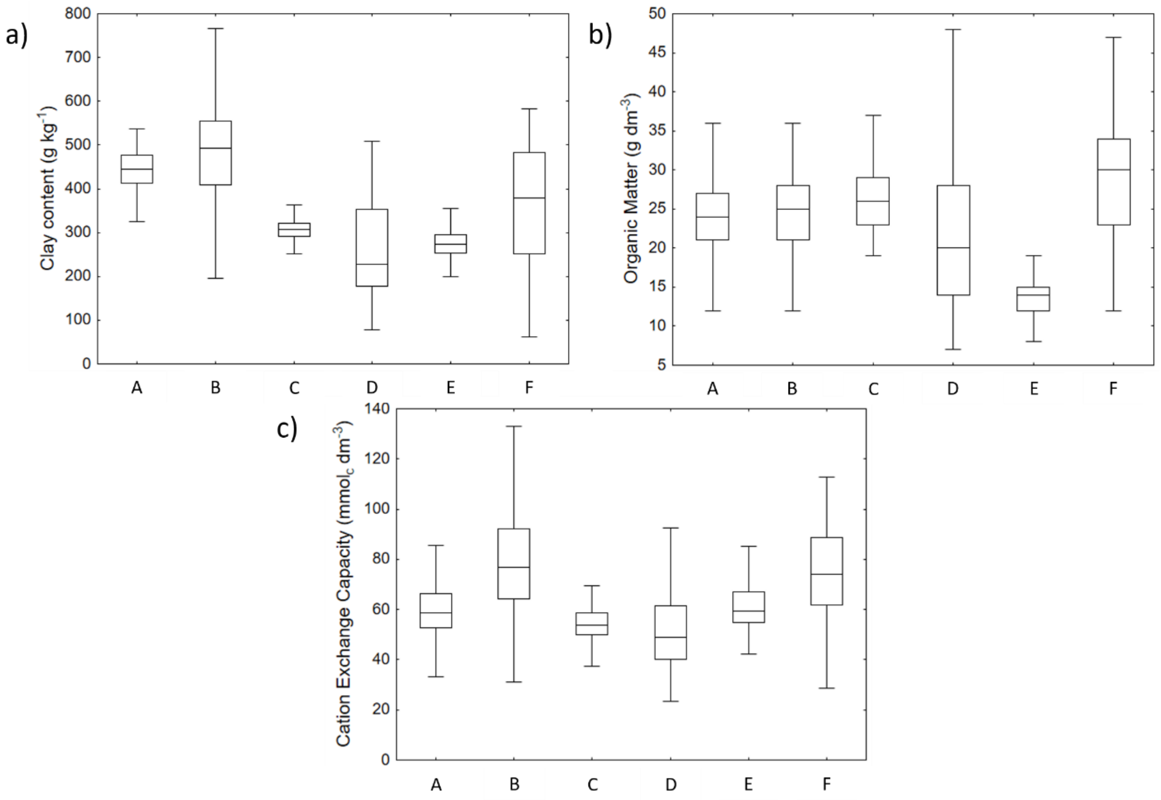


Figure 3.5. Clay content (a), organic matter (b) and cation exchange capacity (c) variability among experimental fields.

Like clay content variability, fields B and F showed the greatest variability in soil ECa (Figure 3.6). Except for field A (Figure 3.6 - a), the other fields presented negative values in the ECa readings, justified by the principle of measurement and equipment calibration as reported in Heil and Schmidhalter (2017). The highest ECa variability was observed in field F (Figure 3.6 - f), with a measurement range equal to 352 mS m^{-1} (Table 3.2). Fields C and E showed the lowest ECa measurement ranges, following clay content, OM and CEC variability trends.

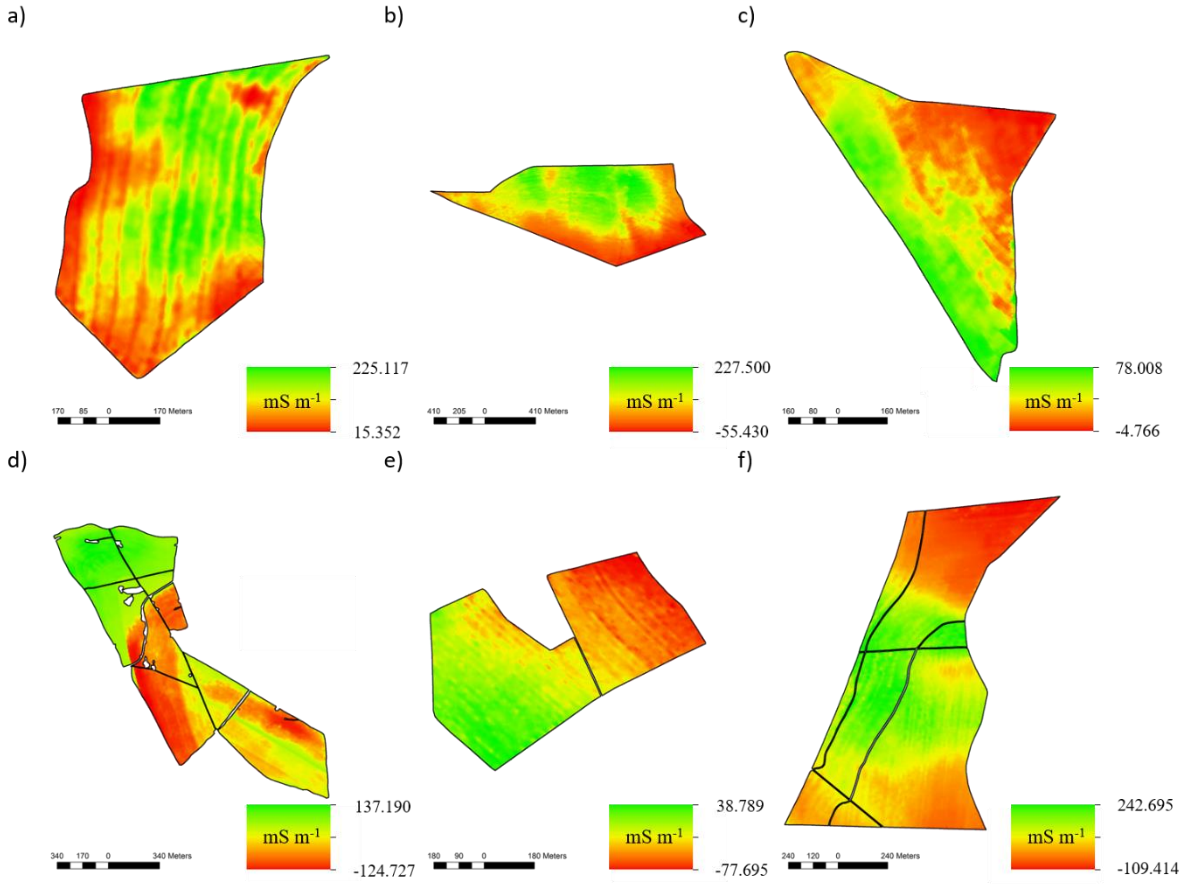


Figure 3.6. Spatial variability maps of apparent electrical conductivity (ECa) of experimental fields A (a), B (b), C (c), D (d), E (e) and F (f).

A direct and significant correlation was founded between ECa and clay content (Table 3.3) for fields A, B, D and F (r = 0.48, 0.71, 0.81 and 0.78 respectively), corresponding to the fields with high clay content variability. In the fields C and E, where low clay content variability was observed, the correlation with ECa was not significant (r = 0.08 and -0.12, respectively). Excepted for OM content at field E, OM and CEC correlated positively with ECa for all fields and years assessed, where the highest correlation of these attributes was for field D (r = 0.70 in 2017 and r = 0.59 in 2016, respectively, for OM and CEC).

Table 3.3. Pearson's correlation coefficient between ECa and soil attributes assessed.

Field	Year	Clay	OM	CEC
A	2011	0.48*	0.16*	0.06
	2012		0.12	0.15*
	2013		0.25*	0.04
	2014		0.09	0.07
B	2014	0.71*	0.30*	0.37*
C	2014	0.08	0.13	0.14
D	2016	0.81*	0.62*	0.59*
	2017		0.70*	0.56*
E	2017	-0.12	-0.28*	0.07
F	2017	0.78*	0.59*	0.28*

*Significant at 5%.

The assessment of clustering cost curves by K-means algorithm showed that the best number of classes for experimental fields A, B and C were 6, while for fields D, E and F were 5 (Figure 3.7). So, like differences in fields assessed were low, we adopted five classes to perform further analysis and aiming to simplify the results.

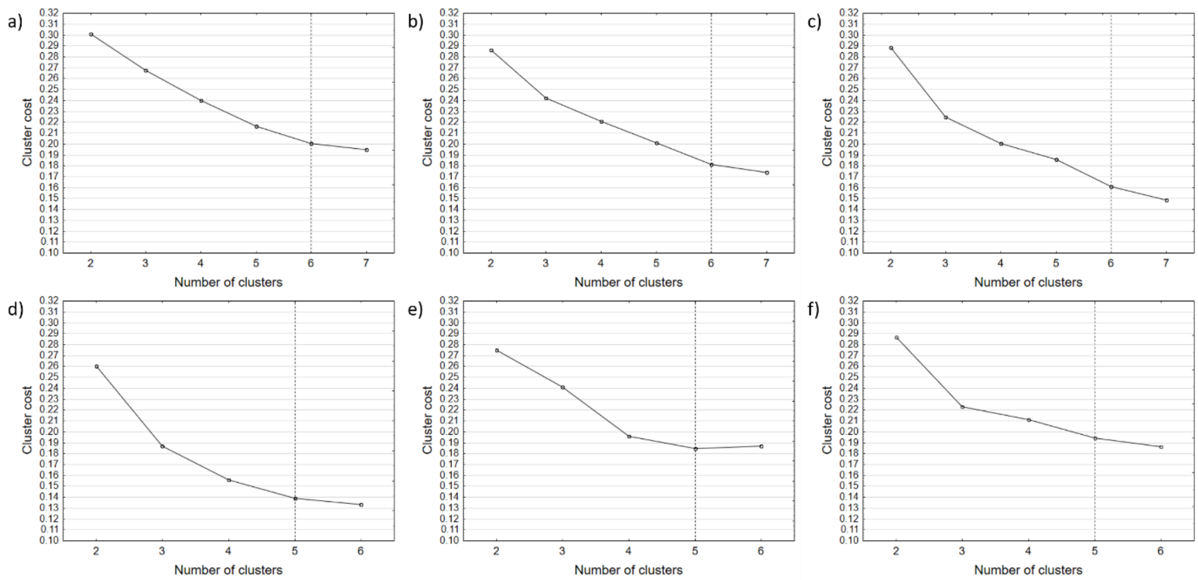


Figure 3.7. Clustering cost curves of experimental fields A (a), B (b), C (c), D (d), E (e) and F (f). Optimal number of clusters (dashed line).

Dividing into five classes, quantil classification method showed the best division of clay content for ECa classes (Figure 3.8). All iterations produced, for NB and GI methods, overlap of classes 3 and 4. Thus, we assumed that the Q method was the most suitable for separation and classification of ECa data into classes. For subsequent analyzes were adopted five classes divided by quantil method.

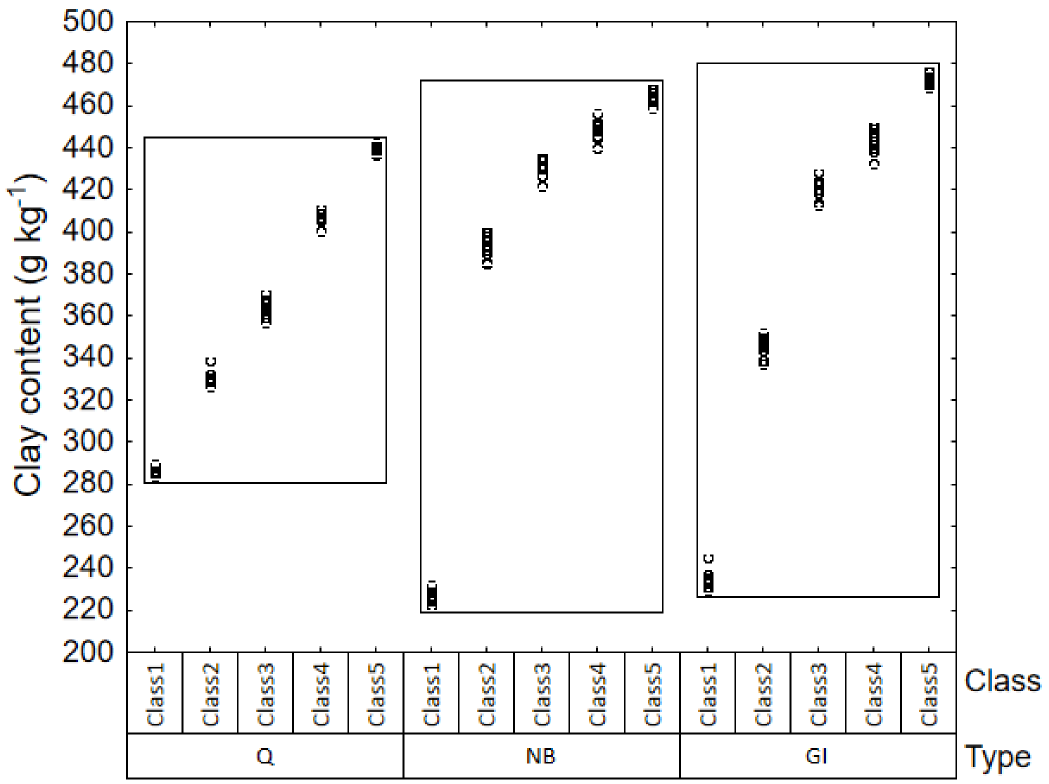


Figure 3.8. Clay content variability (g kg^{-1}) by five classes defined according quantil (Q), natural breaks (NB) and geometrical intervals (GI) classification methods.

How class 1 has the lowest and class 5 the highest values of ECa, clay content (Figure 3.9 - a), OM (Figure 3.9 - b) and CEC (Figure 3.9 - c) showed a clear trend of growth from class 1 to 5 according to box-plot performed by random sampling assessment. In this way, as expected, the classes with low ECa evidenced sandy areas with lower contents of OM and CEC. The CV from 10 iterations performed, showed that the less conductive classes also present greater variability in the contents, with a decrease trend from class 1 to 5. Clay content and CEC showed a significant decreasement starting from class 3, while OM (Figure 3.9 – b) showed a linear decrease.

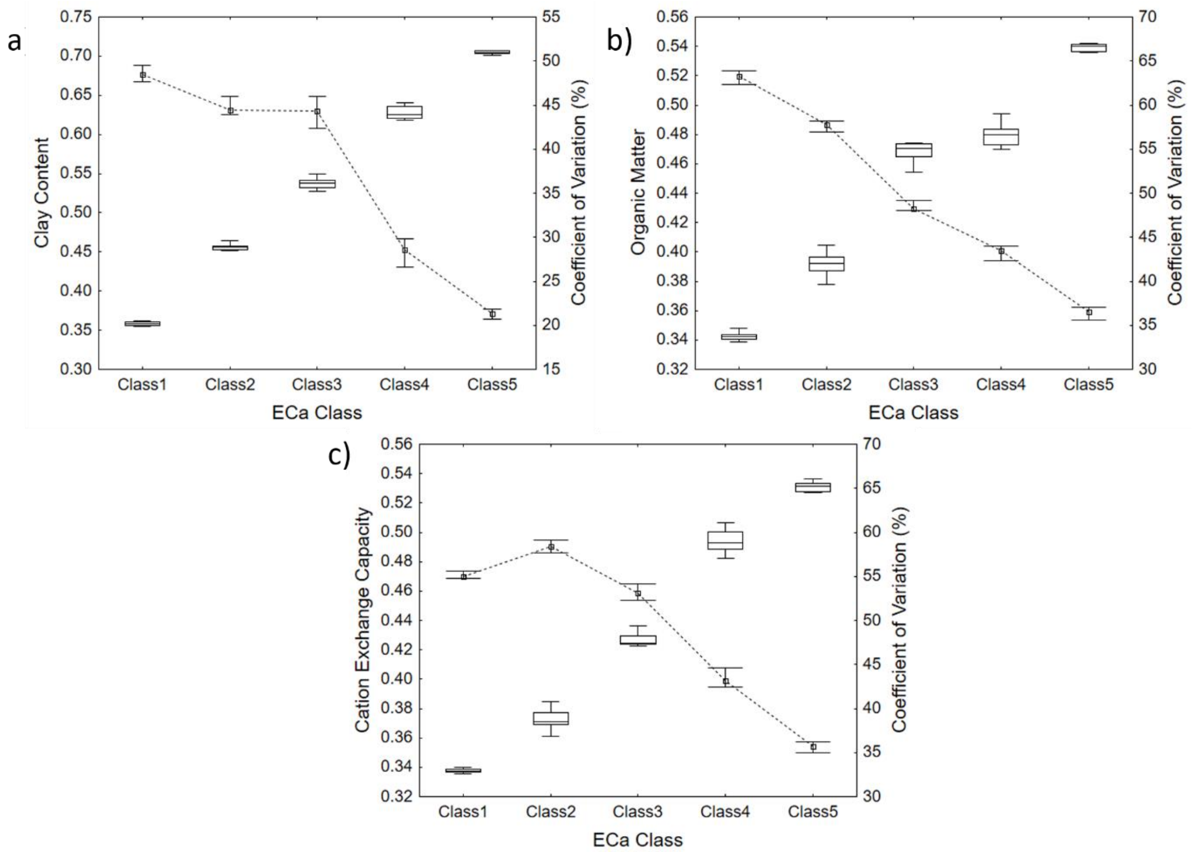


Figure 3.9. Standard content (y-axis left) and coefficient of variation (y-axis right – dashed line) of the iterations, per ECa class, of clay content (a), organic matter (b) and cation exchange capacity (c).

By linear adjustment of ECa measurement range with clay content, OM and CEC ranges of all the experimental fields assessed, it is possible to visualize that, excluding field B, a good correlation between attributes ranges. The line adjusted means that a variation of 1.0 mS m^{-1} meant a variation of 1.5 g kg^{-1}, 0.11 g dm^{-3} and 0.24 $mmol_c$ dm^{-3} in clay content, OM and CEC, respectively (Figure 3.10 – a, b and c, respectively). The results showed that ECa, measured by an EMI sensor, shows a high correlation with soil texture variability of fields assessed (R^2 = 0.97), showing great correlations with OM (R^2 = 0.65) and CEC (R^2 = 0.76).

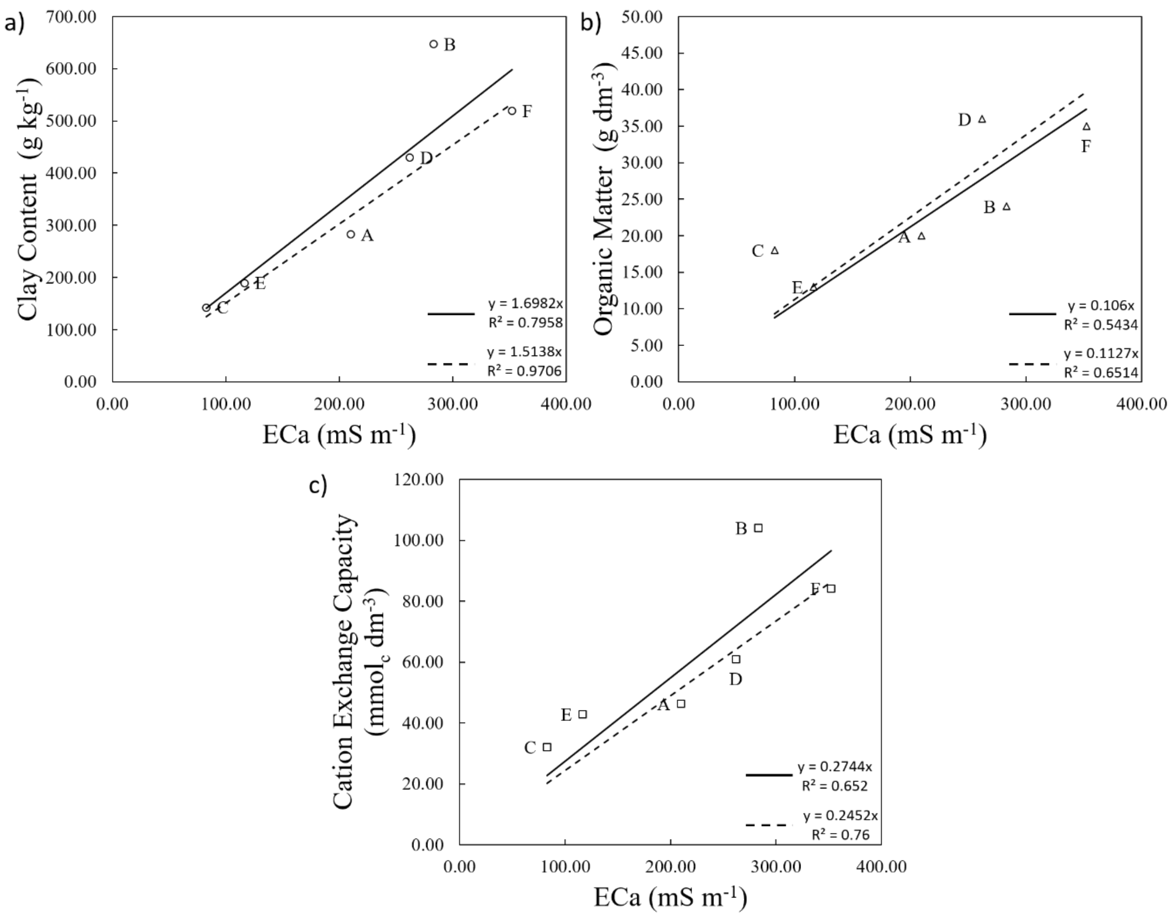


Figure 3.10. Linear adjustment of clay content (a), organic matter (b) and cation exchange capacity (c) with apparent electrical conductivity (ECa) variability of experimental fields assessed. Adjustment including (solid line) and excluding (dashed line) field B.

At time level, OM and CEC showed the same growth trend from class 1 to 3, as previously observed (Figure 3.9), for the first two year of assessment for field A (Figure 3.11). The trend is clear evidenced in field D (Figure 3.12) for both soil attributes assessed, while in field A this trend is not as clear in 2013 and 2014. In field A, from 2011 to 2013, the average level of OM showed a declining trend, as can also be clearly seen from 2016 to 2017 in field D (Figure 3.12 - a). Excepted in 2013 for field A, the variability of OM and CEC is lower for class 5 compared to class 1, evidencing the higher CV found in the lower ECa classes, as showed previously (Figure 3.9). For field D, classes 4 and 5 always showed greater contents than classes, 1, 2 and 3 for both OM and CEC. In general, the patterns founded at spatial variability level, were temporarily remained, where class 1 showed smaller average contents than class 5.

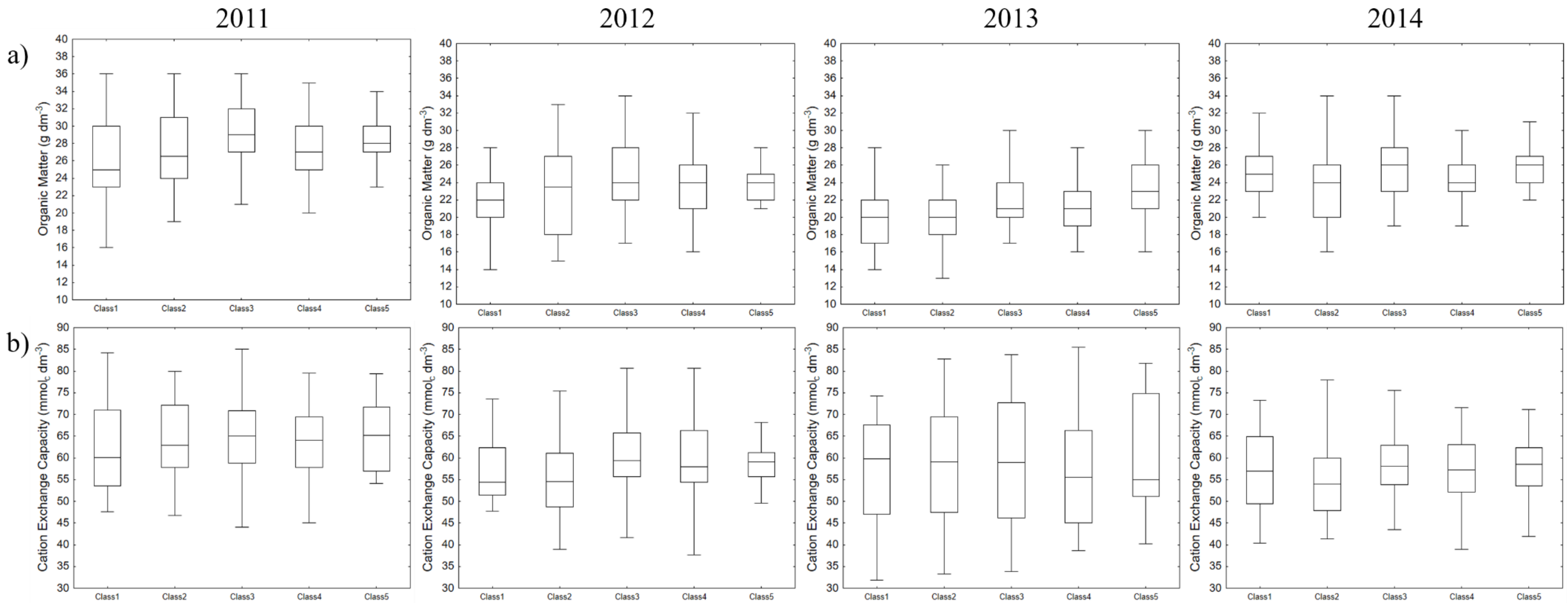


Figure 3.11. Organic matter (a) and cation exchange capacity (b) variability by ECa classes for the evaluated years in experimental field A.

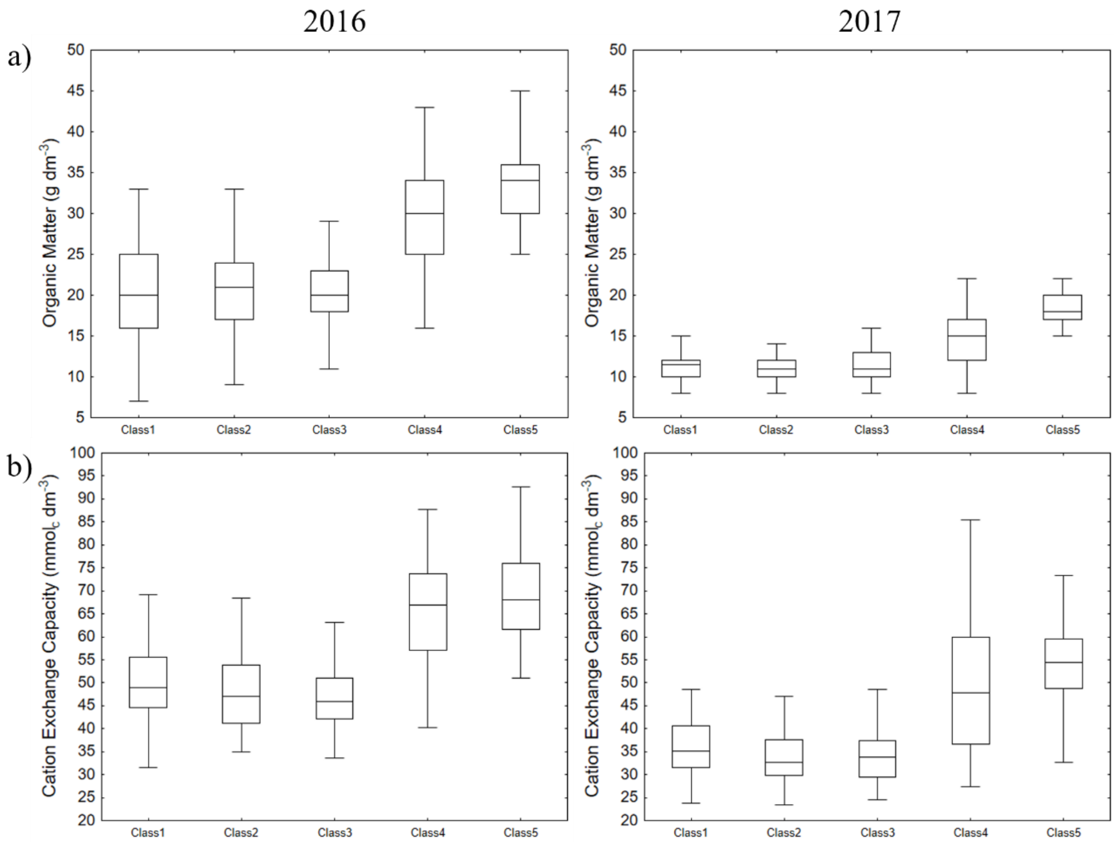


Figure 3.12. Organic matter (a) and cation exchange capacity (b) variability by ECa classes for the evaluated years in experimental field D.

3.4. Discussion

By clay content observed in the experimental fields, the present study covered different soil types and slope classes. Even more, different soil fertility classes were included, since soil textural class is directly related to the availability of water and nutrients (Raij et al., 2001), addressing the wide-range assessment proposed here for sugarcane fields. Soil ECa, measured by EMI sensors, proved to be a high-quality information from fields to map the soil fertility in sugarcane fields, showing high potential to map yield potential zones (Sanches et al., 2019b; Siqueira et al., 2015). The ECa division into five classes, by quantil method, showed be the most suitable to distinguish the differences between soil texture zones, where areas with high ECa showed higher clay content and, thus, higher OM and CEC, soil attributes that driven sugarcane yield (Sanches et al., 2019a). So, a good option for farmers to divided fields into management zones can be done dividing ECa measurements into quantil classes.

Related to soil spatial variability mapping, an issue that still arouses interest of the scientific community is related to an efficient (economically and physically feasible) soil spatial characterization of its variability, as reported by Peets et al. (2012). The results founded in the present study can addressed this bottleneck, as evidenced by the ECa division into classes by quantil method. CV can be an excellent indicative to assist the sampling and soil mapping process. While ECa lower classes must be sampled more rigorously, that is, with a higher sample density, the more conductive classes can be sampled with fewer samples for an adequate soil characterization. Among the different types of sensing technologies for soil nutrient mapping, as addressed by Adamchuk et al. (2004), ECa sensors are an excellent and complementary alternative to map the spatial variability of soil fertility. Furthermore, ECa can also aid the interpolation methods as an auxiliary variable to map the soil spatial variability (Sanches et al., 2018). Moreover, conductive classes could receive, in general, lower amounts of fertilizers in comparison to the lower conductivity classes, mainly because higher ECa classes have more fertility and yield potential, helping in a sustainable site-specific management of sugarcane fields. Although results reported here not established quantitative indicators of soil sampling and fertilizer recommendations by ECa zones, further studies can be carried out to address these questions according qualitative information reported.

Clay content and CEC are important soil attributes which are related to both nutrient supply and water availability, with several studies indicating their prediction with EMI (De Benedetto et al., 2012; Mahmood et al., 2012; Piikki et al., 2013; Huang et al., 2014). The present study showed that, despite the low correlation between ECa and soil attributes (Table 3.3), the measurement range of these attributes were highly correlated (R^2 = 0.97, 0.65 and 0.76 for clay content, OM and CEC, respectively). Sanches et al. (2019b) showed a review of Pearson's correlation variability between ECa and soil attributes, where highest correlations were observed for clay content (r = 0.89) and CEC (r = 0.82) too. Despite the low correlations observed here, as reported by Sanches et al. (2019b), a low correlation does not mean that these attributes were not physically related. The extreme behavior of field B, treated as an outlier, may be related to the soil salinity of the field. One of the hypotheses is that the field, located near to the mill production unit, received fertilization through vinasse application (residue generated in the manufacture of sugar and ethanol and rich in potassium). Vinasse application can lead to soil acidification, thus influencing ECa and justifying the behavior founded.

Temporally stable (Serrano et al., 2017), ECa can be extremely valuable information for a site-specific management of sugarcane fields. Fields A and D, assessed, respectively, for 4 and 2 successive years, showed that the ECa classes are good indicative to differentiate sites with higher and lower OM and CEC contents. This fact is clearly observed for the first year of evaluation for both fields, exactly when the crop was planted. In another years of cultivation, the trend does not seem to be so clear. A possible explanation can be the management used in the fields, justifying the results founded. The management of the sugarcane in Brazil, characterized by the low adoption of precision agriculture technologies (Silva et al., 2011) and high mechanization of agricultural operations (Franco et al., 2018), has been causing serious problems on soil fertility and, consequently, on crop yield. This fact can be observed by OM decreasement content in the fields, especially in field D, where we can see a significant decrease from 2016 to 2017. OM is one of the most important soil attributes to define sugarcane yield (Sanches et al., 2019a) and the availability of nutrients such as phosphorus and nitrogen in the soil (Nogueirol et al., 2014). This decreasing trend in soil OM is common in Brazilian sugarcane fields, especially if soil tillage operations are used. In this way, especially in field A, the sugarcane management can be promoted a disturbance in soil fertility and quality conditions, where the ECa higher classes not showed the expected higher soil OM and CEC contents than ECa lower classes. Despite the disturbance observed, in general, patterns at spatial variability level were temporarily remained, where class 1 always showed smaller average contents than class 5. As reported by Carvalho et al. (2016), soil conservation management can help to maintain adequate soil OM levels over time and, consequently, maintain the adequate soil quality and fertility conditions. Even more, the low adoption of PA and the inadequate management of sugarcane fields justify the crop yield stagnation in the last decade, not exceeding the average yield of 80 Mg ha^{-1} (CONAB, 2017).

Finally, the ECa mapping of sugarcane fields can be an excellent alternative for a site-specific management as showed here. Despite the low Pearson's correlation founded between ECa and soil attributes, the ECa quantil classes are a good option for farmers establish zones in their fields to manage the soil fertility, allow the establishment of precision production environments (Sanches et al., 2019b) and the yield potential zones.

3.5. Conclusion

Despite the high variability presented in soil, ECa classes, defined by quantil method, showed that the low electrical conductivity sites tend to present lower OM and CEC contents. The higher ECa classes showed smaller CV for all soil attributes assessed, i.e., sites that can be characterized with smaller amounts of samples to an adequate soil mapping than lower ECa classes. The clay content variability was directly proportional to the ECa variability ($R^2 = 0.97$), where line adjusted means that 1.0 mS m^{-1} of ECa corresponded to 1.5 g kg^{-1} of clay. OM (R^2

= 0.65) and CEC (R^2 = 0.76) showed great correlation with ECa variability too. Regular grids to soil sampling, where previous soil spatial variability is not used, could be overcome to an optimized soil sampling by a cheap and fastest soil spatial variability information like ECa. The EMI sensor is an excellent tool to define the spatial variability of soil fertility, that can be used for growers in site-specific management of their fields.

Acknowledgments

The authors thank the São Paulo Research Foundation (grant process: 2015/01587-0, 2014/14965-0, 2013/50942-2 and 2008/09265-9) and the sugarcane mills for technical support and the availability of the experimental fields.

3.6. References

Adamchuk, V.I., Hummel, J.W., Morgan, M.T., and Upadhyaya, S.K. 2004. On-the-go soil sensors for precision agriculture. *Computers and Electronics in Agriculture* 44(1), 71-91.

Bullock, D.S., Kitchen, N., Bullock, D.G. 2007. Multidisciplinary Teams: A Necessity for Research in Precision Agriculture Systems. *Crop Science* 47(5), 1765. 2007.

Carvalho, J.L.N., Nogueirol, R.C., Menandro, L.M.S., Bordonal, R.O., Borges, C.D., Cantarella, H., Franco, H.C.J. 2016. Agronomic and environmental implications of sugarcane straw removal: a major review. *Global Change Biology Bioenergy* 1, 1-12.

Companhia Nacional do Abastecimento (CONAB). 2017. *Acompanhamento da safra Brasileira. Cana-de-açúcar, SAFRA 2017/18 Primeiro Levantamento Abril/2017*. Brasília, DF, 62p.

Corwin, D.L., Lesch, S.M. 2003. Application of soil electrical conductivity to precision agriculture. *Agronomy Journal*. 95, 455–471.

Corwin, D.L., Lesch, S.M. 2005. Apparent soil electrical conductivity measurements in agriculture. *Computers and Electronics in Agriculture*, *46*(1–3 SPEC. ISS.), 11–43.

Costa, M.M., Queiroz, D.M., Pinto, F.A.C., Reis, E.F., Santos, N.T. 2014. Moisture content effect in the relationship between apparent electrical conductivity and soil attributes. *Acta Scientiarum* 36:395-401.

De Benedetto, D., Castrignanò, A., Sollitto, D., Modugno, F., Buttafuoco, G. 2012. Integrating geophysical and geostatistical techniques to map the spatial variation of clay. *Geoderma* 171-172:53–63.

Domsch, H., Giebel, A. 2004. Estimation of soil textural features from soil electrical conductivity recorded using the EM38. *Precision Agriculture*, *5*(4), 389–409.

Doolittle, J.A., Brevik, E.C. 2014. The use of electromagnetic induction techniques in soils studies. *Geoderma* 223-225, 33–45.

Driemeier, C., Ling, L.Y., Sanches, G.M., Pontes, A.O., Magalhães, P.S.G., Ferreira, J.E. 2016. A computational environment to support research in sugarcane agriculture. *Computers and Electronics in Agriculture* 130, 13–19.

Ekwue, E.; Bartholomew, J. 2011. Electrical conductivity of some soils in Trinidad as affected by density, water and peat content. *Biosystems Engineering* 108: 95-103.

Franco, H.C.J., Castro, S.G.Q., Sanches, G.M., Kölln, O.T., Bordonal, R.O., Borges, B.M.M.N., Borges, C.D. 2018. *Alternatives to Increase the Sustainability of Sugarcane Production in Brazil under High Intensive Mechanization*. In. Singh, P., Tiwari, A.K. Sustainable Sugarcane Production. Apple Academic Press – 426 p.

Godwin, R.J., Wood, G.A., Taylor, J.C., Knight, S.M., Welsh, J.P. 2003. Precision farming of cereal crops: A review of a six year experiment to develop management guidelines. *Biosystems Engineering*, *84*(4), 375–391.

Heil, K., Schmidhalter, U. 2017. The application of EM38: Determination of soil parameters, selection of soil sampling points and use in agriculture and archaeology. *Sensors (Switzerland)*, *17*(11), 44.

Huang, J., Lark, R.M., Robinson, D.A., Lebron, I., Keith, A.M., Rawlins, B., Tye, A., Kuras, O., Raines, M., Triantafilis, J. 2014. Scope to predict soil properties at within-field scale from small samples using proximally sensed γ-ray spectrometer and EM induction data. *Geoderma* 232–234, 69–80.

Kitchen, N.R., Sudduth, K.A., Myers, D.B., Drummond, S.T., Hong, S.Y. 2005. Delineating productivity zones on claypan soil fields using apparent soil electrical conductivity. *Computers and Electronics in Agriculture*, *46*(1–3 SPEC. ISS.), 285–308.

Kitchen, N.R., Sudduth, K.A., Drummond, S.T. 1999. Soil electrical conductivity as a crop productivity measure for claypan soils. *Journal of Production Agriculture* 12: 607-617.

Mahmood, H.S., Hoogmoed, W.B., van Henten, E.J. 2012. Sensor data fusion to predict multiple soil properties. *Precision Agriculture* 13, 628–645.

McBratney, A.B., Minasny, B., Whelan, B.M. 2005. Obtaining 'useful' high-resolution soil data from proximally-sensed electrical conductivity/resistivity (PSEC/R) surveys. In: Stafford, J.V. (Ed.), *Proceedings* of the 5th European Conference on Precision Agriculture. Wageningen

Academic Publishers, The Netherlands, pp. 503–510.

Medeiros, W.N., Valente, D.S.M., Queiroz, D.M., Pinto, F.A.C., Assis, I.R. 2018. Apparent soil electrical conductivity in two different soil types. *Revista Ciência Agronômica* 49 (1):43-52.

Molin, J. P., Castro, C. N. 2008. Establishing management zones using soil electrical conductivity and other soil properties by the fuzzy clustering technique. *Scientia Agricola* 65(6):567-573.

Molin, J.P., Faulin, G.C. 2013. Spatial and temporal variability of soil electrical conductivity related to soil moisture. *Scientia Agricola* 70(1):1-5.

Nogueirol, R.C., Cerri, C.E.P., Silva, W.T.L., Alleoni, L.R.F. 2014. Effect of no-tillage and amendments on carbon lability in tropical soils. *Soil & Tillage Research* 143, 67-76.

Peets, S., Mouazen, A.M., Blackburn, K., Kuang, B.,Wiebensohn, J. 2012. Methods and procedures for automatic collection and management of data acquired from on-the-go sensors with application to on-the-go soil sensors. *Computers and Electronics in Agriculture*, *81*, 104–112.

Piikki, K., Söderström, M., Stenberg, B. 2013. Sensor data fusion for topsoil clay mapping. *Geoderma* 199, 106–116.

Raij, B.V., Andrade, J.C., Cantarella, H., Quaggio, J.A. 2001. *Análise química para avaliação da fertilidade de solos tropicais.* Campinas, Instituto Agronômico.

Reedy, R.C., Scanlon, B.R. 2003. Soil water content monitoring using electromagnetic induction. *Journal of Geotechnical and Geoenvironmental Engineering* 129:1028-1039.

Rhoades, D.A., Dowrick, D.J. 1999. Variability of damage ratios for property in earthquakes. *Earthquake Spectra* 15:297-316.

Rossel, R.A.V., Bouma, J. 2016. Soil sensing: a new paradigma for agriculture. *Agricultural Systems* 148, 71–74.

Salton, J.C., Tomazi, M., Comunello, E., Zanatta, J.A., Rabello, L.M. 2011. Electrical conductivity and physical and chemical attributes of an Oxisol after 15 years in management systems in Mato Grosso do Sul state. p. 254-260. *In:* Inamasu, R.Y., Naime, J.M., Resende, A.V., Bassoi, L.H., Bernardi, A.C.C., eds. Precision Agriculture: a new look. Embrapa Instrumentação, SP, Brazil (in Portuguese, with abstract in English).

Sana, R.S., Anghinoni, I., Brandão, Z.N., Holzschuh, M.J. 2014. Spatial variability of physical-chemical attributes of soil and its effects on cotton yield. *Revista Brasileira de Engenharia Agrícola e Ambiental* 18: 994-1002 (in Portuguese, with abstract in English).

Sanches, G.M., Magalhães, P.S.G., Franco, H.C.J. 2019a. Site-specific assessment of spatial and temporal variability of sugarcane yield related to soil attributes. *Geoderma* 334:90-98.

Sanches, G.M., Paula, M.T.N., Magalhães, P.S.G., Duft, D.G., Vitti, A.C., Kolln, O.T., Borges, B.M.M.N., Franco, H.C.J. 2019b. Precision production environments for sugarcane fields. *Scientia Agricola 7*6(1):10-17.

Sanches, G.M., Magalhães, P.S.G., Remacre, A.Z., Franco, H.C.J. 2018. Potential of apparent soil electrical conductivity to describe the soil pH and improve lime application in a clayey soil. Soil & Tillage Research 175, 217-225.

Serrano, J.M., Shahidian, S., Marques da Silva, J. 2017. Spatial variability and temporal stability of apparent soil electrical conductivity in a Mediterranean pasture. *Precision Agriculture* 18(2):245-263.

Silva, C.B., Moraes, M.A.F.D., Molin, J.P. 2011. Adoption and use of precision agriculture technologies in the sugarcane industry of São Paulo state, Brazil. *Precision Agriculture* 12(1), 67–81.

Siqueira, G.M., Silva, E.F.F., da Fonte, D.J. 2015. Spatial distribution of soil apparent electrical conductivity measured by electromagnetic induction and sugarcane yield. *Bragantia* 74:215-223.

Sudduth, K.A., Drummond, S.T., Kitchen, N.R. 2001. Accuracy issues in electromagnetic induction sensing of soil electrical conductivity for precision agriculture. *Computers and Electronics in Agriculture* 31: 239-264.

Sudduth, K A., Kitchen, N.R., Wiebold, W.J., Batchelor, W.D., Bollero, G.A., Bullock, D.G., et al. 2005. Relating apparent electrical conductivity to soil properties across the north-central USA. *Computers and Electronics in Agriculture*, *46*(1–3 SPEC. ISS.), 263–283.

Tarr, A.B., Moore, K.J., Burras, C.L., Bullock, D.G., Dixon, P.M. 2005. Improving map accuracy of soil variables using soil electrical conductivity as a covariate. *Precision Agriculture*, *6*(3), 255–270.

Triantafilis, J., Laslett, G.M., McBratney, A.B. 2000. Calibrating an Electromagnetic Induction Instrument to Measure Salinity in Soil under Irrigated Cotton. Soil Science Society of America Journal, 64(3), 1009.

Valente, D.S.M.; Queiroz, D.M.; Pinto, F.A.C.; Santos, N.T.; Santos, F.L. 2012. The relationship between apparent soil electrical conductivity and soil properties. *Revista Ciência Agronômica* 43: 683-690.

III. General Discussion

In the current Brazilian agricultural scenario, the adoption of PA increases every year for all Brazilian agribusiness segments. Although several crops are investigated by researches in PA context, wheat and maize are the most addressed crops when compared with sugarcane. The technology adoption by wheat and maize fields may evidence the reasons for the advancement of these crops when compared to sugarcane. In the last decades, it was possible to observe the expressive growth of yield in maize and wheat when compared with sugarcane (Figure 2). While maize and wheat crops showed yield increases about 30% and 19% from 2000 (4.76 to 6.20 Mg ha^{-1} and 3.00 to 3.60 Mg ha^{-1}, respectively, for maize and wheat), sugarcane showed a growth of 8% (71.23 to 76.82 Mg ha^{-1}) in the same period. The genetic improvement of these crops can be one of the main reasons (Tian et al., 2011), unlike in sugarcane where little genetic improvements was made in the last years. In addition, a sugarcane yield decline can be observed since 2008, when the mechanization of the sugarcane harvest was intensified in Brazil (Franco et al., 2018). The lack of PA technologies adoption in the Brazilian sugarcane sector, reported by Silva et al. (2011), may have contribute to the yield stagnation in the last decade, not exceeding 80 Mg ha^{-1} of average yield.

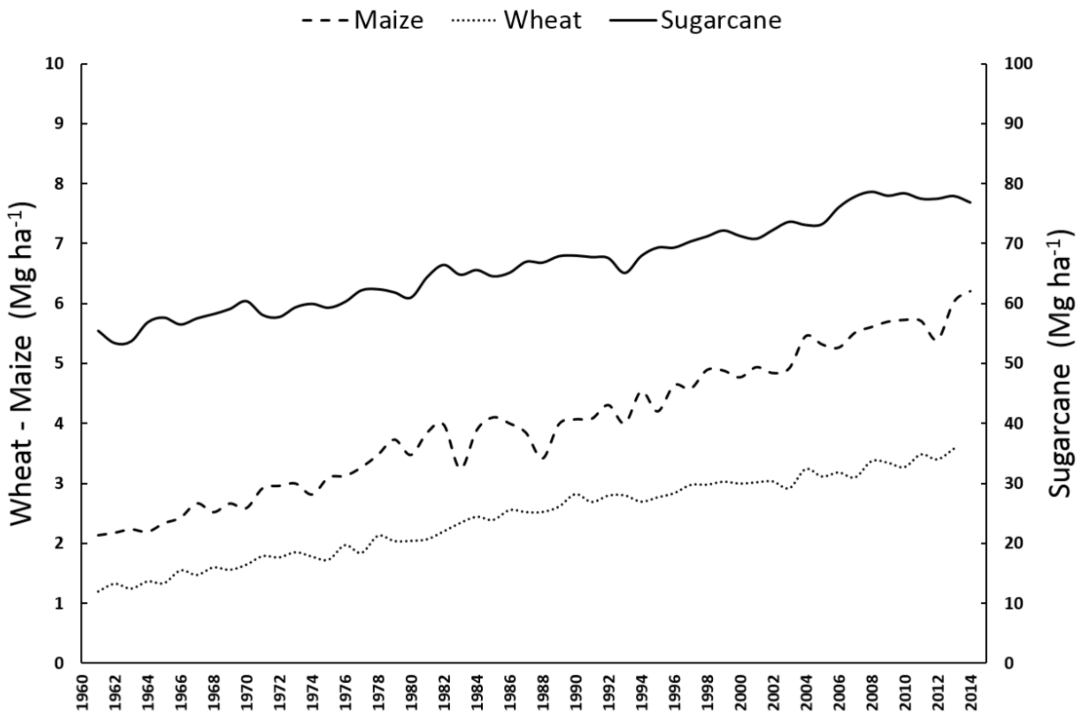


Figure 2. Yield (Mg ha^{-1}) of wheat, maize and sugarcane crops from 1961 to 2014. Source: FAOSTAT, 2016.

To meet the COP-21 goals, National Confederation of Industry (CNI), in partnership with the University of São Paulo (FEA/USP), estimated that it will be necessary that Brazil produced 942 million tons of sugarcane per season in 2030 (CNI, 2017). The best economic and environmental option is to increase the yield. However, Brazil will need to move forward to reach new levels and exceed the current Brazilian average of 73 Mg ha^{-1} (CONAB, 2017). The genetic potential of the crop is about 300 Mg ha^{-1} (Waclawovsky et al., 2010). The major limitations are related to hydrous deficit, an inadequate crop management and the availability amounts of nutrients for plants. In terms of crop management, one issue that may assist sugarcane fields to achieve the goals and ensure greater production sustainability is the Precision Agriculture (PA). PA is an approach that includes several technologies and tools that can contribute significantly to overcome these challenges and improve the production profitability.

Among technologies available to assist site-specific management of sugarcane fields, yield monitor, topographic parameters and apparent electrical conductivity demonstrated to be promising to help farmers in soil spatial characterization, as demonstrated here. Although these technologies are commercially available, they are still little adopted in the last years, mainly because few studies at long-term were showed in the literature. Thus, the adoption of yield monitors in sugarcane fields could allow to identify which soil attributes are directly impacting the crop yield. Perhaps, at others sugarcane fields the main soil attributes that impact yield are not the same as those founded here, such as MO and pH. However, the constant yield mapping and soil attributes allow to identify the limiting nutrients for the plant by applying the appropriate statistical tools and techniques, such as Random Forest algorithm.

How one of the limiting factors to map the soil with high accuracy is the amount of samples required, which often turn the sampling process physically and economically impractical (Peets et al., 2012), the findings showed that this bottleneck can be overcome. The landscape formations and ECa have proved to be excellent sources of information that could be allow an efficient soil sampling process. The different classes of landscape and ECa allow to divide the field into zones with different fertility levels, enabling farmers to create zones with different yield potentials. These sources of information can also be used as auxiliary variables in multivariate interpolation methods, as demonstrated in Sanches et al. (2018), helping to characterize the soil spatial variability. The combination of these data can be evaluated in future studies to increase the accuracy of soil spatial characterization of the fields. Furthermore, with high temporal stability, the topographical and ECa attributes can not only aid sugarcane fields, but also other crops that use a large amount of inputs and needed to rationalize the fertilizer applications.

Finally, the current world scenario, where resources are increasingly scarce and environmental pollution increasing, the PA adoption will be fundamental. The area and/or yield expansion to reach the COP-21 goals without considering the sustainable management alternatives, like PA technologies, are not sufficient to promote a sustainable production. The sugarcane yield stagnation in the last five years must be addressed, where the PA and other technologies improvements should guide the agenda of government and producers.

IV. General Conclusion

The present work proved that yield monitors, topographic and ECa parameters are an excellent source of information to manage sugarcane fields in a site-specific way. The results showed that the spatial and temporal characterization of soil attributes is essential to ensure a sustainable site-specific management of sugarcane fields. Soil organic matter (OM), clay content and cation exchange capacity (CEC) are important soil factors that directly impact sugarcane yield, that can be spatial characterized by topographic and ECa parameters. Furthermore, it was observed that the temporal variability in the yield is caused mainly by the variability in the pH. ECa and topographic parameters, that are temporally stable, showed that pH should be manage differently in H_{Conv} topographic formations. ECa spatial variability maps showed a greater correlation with variability of clay conten (R^2 = 0.97), OM (R^2 = 0.65) and CEC (R^2 = 0.76). Regular grids to soil sampling, where previous soil spatial variability is not used, could be overcome to an optimized soil sampling by a cheap and fastest soil spatial variability information like ECa and topographic parameters. The EMI sensor and SRTM topographic data are excellent tools to define the spatial variability of soil fertility, that can be used for growers to describe the soil spatial variability in a precise and sustainable way. We expected that the present study can help the Brazilian sugarcane industry to increase the adoption of PA technologies, reducing production costs and the environmental impacts through the rational use of inputs and help the Brazil to reach the targets established by 2030.

V. References

Abdel-Rahman, E.M., Ahmed, F.B., 2008. The application of remote sensing techniques to sugarcane (Saccharum spp. hybrid) production: a review of the literature. *Int. J. Remote Sens.* 29, 3753-3767.

Adamchuk, V.I., Hummel, J.W., Morgan, M.T., and Upadhyaya, S.K. 2004. On-the-go soil sensors for precision agriculture. Computers and Electronics in Agriculture 44(1), 71-91.

Arslan, S. and Colvin, T. 2002. An evaluation of the response of yield monitors and combines to varying yields. *Precision Agriculture* 3, 107-122.

Atkins, P., Paula, J. de, 2010. *Physical Chemestry*, 9th ed. Oxford University Press, Oxford.

Balanço Energético Nacional. Empresa de Pesquisa Energética. Ano base 2015. 2016. Available at: https://ben.epe.gov.br/downloads/Relatorio_Final_BEN_2016.pdf. Access: 10/05/2017.

Bayer, C., Mielniczuk, J. *Dinâmica e função da matéria orgânica*. 2008. In: Santos, G.A.; SILVA, L.S.; CANELLAS, L.P.; CAMARGO, F.A.O. Fundamentos da matéria orgânica do solo: Ecossistemas tropicais e subtropicais. Porto Alegre, ed. Metropole, 654p.

Bocca, F.F., Rodrigues, L.H.A., 2016. The effect of tuning, feature engineering, and feature selection in data mining applied to rainfed sugarcane yield modelling. *Computers and Electronics in Agriculture* 128, 67-76.

Bocca, F.F., Rodrigues, L.H.A., Arraes, N.A.M., 2015. When do I want to know and why? Different demands on sugarcane yield predictions. *Agricultural Systems* 135, 48-56.

Bordonal, R.O., Lal, R., Ronquim, C.C., Figueiredo, E.B., Carvalho, J.L.N., Maldonado Jr, W., Milori, D.M.B.P., Scala Jr, N.L., 2017. Changes in quantity and quality of soil carbon due to the land-use conversion to sugarcane (Saccharum officinarum) plantation in southern Brazil. *Agriculture, Ecosystems & Environment* 240, 54-65.

Bouma, J., Stoorvogel, J., van Alphen, B. J., Booltink, W. G., 1999. Pedology, Precision Agriculture, and the Changing Paradigm of Agricultural Research. *Soil Science Society of America* 63(6), 1763-1768.

Brasil. Instituto Nacional de Pesquisas Espaciais (INPE). Topodata: banco de dados geomorfométricos do Brasil. Variáveis geomorfométricas locais. São José dos Campos, 2008. <http://www.dsr.inpe.br/topodata/>.

Breiman, L., 2001. Random forests. *Machine Learning* 45, 5-32.

Brubaker, S.C., Jones, A.J., Frank, K., Lewis, D.T. 1994. Regression Models for Estimating Soil Properties by Landscape Position. *Soil Science Society of America Journal 58*(6), 1763–1767.

Brubaker, S.C., Jones, A.J., Lewis, D.T., Frank, K. 1993. Soil properties associated with landscape position. *Soil Science Society of America Journal* 57, 235-239.

Bullock, D.S., Kitchen, N., Bullock, D.G. 2007. Multidisciplinary Teams: A Necessity for Research in Precision Agriculture Systems. *Crop Science* 47(5), 1765.

Buttafuoco, G., Castrignano, A., Colecchia, A. S., Ricca, N., 2010. Delineation of management zones using soil properties and a multivariate geostatistical approach. *Italian Journal of Agronomy* 5(4), 323-332.

Carvalho, J.L.N., Nogueirol, R.C., Menandro, L.M.S., Bordonal, R.O., Borges, C.D., Cantarella, H., Franco, H.C.J., 2016. Agronomic and environmental implications of sugarcane straw removal: a major review. *Global Change Biology Bioenergy* 1, 1-12.

Cerri, D.G.P., Magalhães, P.S.G., 2012. Correlation of physical and chemical attributes of soil with sugarcane yield. *Pesquisa Agropecuária Brasileira* 47, 613-620.

Cherubin, M.R., Oliveira, D.M. da S., Feigl, B.J., Pimentel, L.G., Lisboa, I.P., Gmach, M.R., Varanda, L.L., Morais, M.C., Satiro, L.S., Popin, G.V., Paiva, S.R. de, Santos, A.K.B. dos, Vasconcelos, A.L.S. de, Melo, P.L.A. de, Cerri, C.E.P., Cerri, C.C., 2018. Crop residue harvest for bioenergy production and its implications on soil functioning and plant growth: A review. *Scientia Agricola* 75, 255–272.

Cherubin, M.R., Santi, A.L., Eitelwein, M.T., Da Ros, C.O., Bisognin, M.B. 2014. Sampling grids used to characterise the spatial variability of pH, Ca, Mg and V% in Oxisols. *Revista Ciência Agronômica* 45:659-672.

Chung, S.O., Sung, J.H., Sudduth, K.A., Drummond, S.T., Hyun, B.K. 2001. Spatial variability of yield, chlorophyll content, and soil properties in a Korean rice paddy field. In P.C. Robert et al (ed.) *Proc.* 5th International Conf. on precision agriculture. [CD-rom] ASA, CSSA, Madison, WI.

Colaço, A.F., Molin, J.P., 2017. Variable rate fertilization in citrus: a long-term study. *Precision Agriculture* 18, 169-191.

Companhia Nacional do Abastecimento (CONAB). 2017. *Acompanhamento da safra Brasileira. Cana-de-açúcar, SAFRA 2017/18 Primeiro Levantamento Abril/2017*. Brasília, DF, 62p.

Confederação Nacional da Indústria (CNI). 2017. *O setor sucroenergético em 2030: dimensões, investimentos e uma agenda estratégica*. Brasília, CNI, 108 p.

Corwin, D. L., & Lesch, S. M. 2005. Apparent soil electrical conductivity measurements in agriculture. *Computers and Electronics in Agriculture*, *46*(1–3 SPEC. ISS.), 11–43.

Corwin, D.L., Lesch, S.M. 2003. Application of soil electrical conductivity to precision agriculture: Theory, principles, and guidelines. *Agronomy Journal* 95, 455–471.

Costa, M.M.; Queiroz, D.M.; Pinto, F.A.C.; Reis, E.F.; Santos, N.T. (2014). Moisture content effect in the relationship between apparent electrical conductivity and soil attributes. *Acta Scientiarum* 36:395-401.

De Benedetto D, Castrignanò A, Sollitto D, Modugno F, Buttafuoco G (2012) Integrating geophysical and geostatistical techniques to map the spatial variation of clay. *Geoderma* 171-172:53–63.

Dias, F.L.F., Mazza, J.A., Matsuoka, S., Perecin, D., Maule, R.F., 1999. Productivity of sugarcane in relation to climate and soils of the northwestern São Paulo state. *Revista Brasileira de Ciência do Solo* 23, 627-634.

Diker, K., Heermann, D. F., Brodahl, M. K., 2004. Frequency analysis of yield for delineating yield response zones. *Precision Agriculture* 5(5), 435–444.

Domsch, H., Giebel, A. (2004). Estimation of soil textural features from soil electrical conductivity recorded using the EM38. *Precision Agriculture*, *5*(4), 389–409.

Doolittle, J.A., Brevik, E.C., (2014). The use of electromagnetic induction techniques in soils studies. *Geoderma* 223-225, 33–45.

Driemeier, C., Ling, L.Y., Sanches, G.M., Pontes, A.O., Magalhães, P.S.G., Ferreira, J.E. 2016. A computational environment to support research in sugarcane agriculture. *Computers and Electronics in Agriculture* 130, 13–19.

Ekwue, E.; Bartholomew, J. (2011). Electrical conductivity of some soils in Trinidad as affected by density, water and peat content. *Biosystems Engineering* 108: 95-103.

Empresa Brasileira de Pesquisa Agropecuária (EMBRAPA). 1999. *Sistema brasileiro de classificação dos solos*. Rio de Janeiro: Embrapa Solos, 412 p.

Epstein, E; Bloom, AJ. 2005. *Mineral nutrition of plants: principles and perspectives*. 2. ed. Sunderland: Sinauer Associates. 380 p.

Everingham Y.L., Lowe, K.H., Donald, D.A., Coomans, D.H., Markley, J., 2007. Advanced satellite imagery to classify sugarcane crop characteristics. *Agronomy Sustainable Development* 27(2), 111-117.

Everingham Y.L., Sexton, J., Skocaj, D., Inman-Bamber, G., 2016. Accurate prediction of sugarcane yield using a random forest algorithm. *Agronomy Sustainable Development* (2016), 36:27.

Everingham YL, Sexton J, Robson A 2015b A statistical approach for identifying important climatic influences on sugarcane yields. In: *Proc* Aust Soc Sugar Cane Technol. Bundaberg, Australia, pp 8–15

Everingham, Y.L., Inman-Bamber, N.G., Sexton, J., Stokes, C., 2015a. A dual ensemble agroclimate modelling procedure to assess climate change impacts on sugarcane production in Australia. *Agricultural Sciences* 6, 870-888.

Everingham, Y.L., Smyth, C.W., Inman-Bamber, N.G., 2009. Ensemble data mining approaches to forecast regional sugarcane crop production. *Agricultural and Forest Meteorology* 149 (3-4), 689-696.

Food and Agriculture Organization**.** OECD-FAO**.** Agricultural Outlook 2015-2024. 11 July 2014. Pg. 148. Available at: http://www.fao.org/3/a-i4738e.pdf. Access: 14/02/2016.

Fortes, R., Millán, S, Prieto, M.H., Campillo, C. 2015. A methodology based on apparent electrical conductivity and guided soil samples to improve irrigation zoning. *Precision Agriculture* 16:441–454.

Franco, H.C.J., Castro, S.G.Q., Sanches, G.M., Kölln, O.T., Bordonal, R.O., Borges, B.M.M.N., Borges, C.D. (2018). *Alternatives to Increase the Sustainability of Sugarcane*

Production in Brazil under High Intensive Mechanization. In. Singh, P., Tiwari, A.K. Sustainable Sugarcane Production. Apple Academic Press – 426 p.

Fukuda S., Spreer, W., Yasunaga, E., Yuge, K., Sardsud, V., Müller, J., 2013. Random Forests modelling for the estimation of mango (Mangifera indica L. cv. Chok Anan) fruit yields under different irrigation regimes. *Agricultural Water Management* 116, 142-150.

Fulton, J.P., Wells, L.G., Shearer, S.A., Barnhisel, R.I. 1996. Spatial variation of soil physical properties: Aprecursor to precision tillage. *ASAE* Paper No. 961002. International Meeting, Phoenix, Arizona. 14–18 July 1996. ASAE, St. Joseph, MI.

Gaston, L.A., Locke, M.A., Zablotowicz, R.M., Reddy, K.N. 2001. Spatial variability of soil properties and weed populations in the Mississippi delta. *Soil Science Society America Journal* 65, 449–459.

Godwin, R. J., Wood, G. A., Taylor, J. C., Knight, S. M., Welsh, J. P. (2003). Precision farming of cereal crops: A review of a six year experiment to develop management guidelines. *Biosystems Engineering*, *84*(4), 375–391.

Heil, K., Schmidhalter, U. (2017). The application of EM38: Determination of soil parameters, selection of soil sampling points and use in agriculture and archaeology. *Sensors (Switzerland)*, *17*(11), 44.

Huang, J., Lark, R.M., Robinson, D.A., Lebron, I., Keith, A.M., Rawlins, B., Tye, A., Kuras, O., Raines, M., Triantafilis, J., 2014. Scope to predict soil properties at within-field scale from small samples using proximally sensed γ-ray spectrometer and EM induction data. Geoderma 232–234, 69–80.

Huang, J., Pedrera-Parrilla, A., Vanderlinden, K., Taguas, E.V., Gómez, J.A., Triantafilis, J., 2017. Potential to map depth-specific soil organic matter content across an olive grove using quasi-2d and quasi-3d inversion of DUALEM-21 data. *Catena* 152, 207-217.

Jenny, H. 1941. *Factors of soil formation*. McGraw-Hill. New York.

Jeong, J.H., Resop, J.P., Mueller, N.D., Fleisher, D.H., Yun, K., Butler, E.E., Timlin, D.J., Shim, K., Gerber, J.S., Reddy, V.R., Kim, S., 2016. Random Forests for Global and Regional Crop Yield Predictions. *PLoS ONE* 11(6): e0156571. doi:10.1371/journal.pone.0156571

Johnson, R.A., Wichern, D.W., 2007. *Statistical Analysis*, sixth edit. ed. Pearson Pretice Hall, Upper Saddle River.

Johnson, R.M., Richard Jr., E.P., 2005. Sugarcane Yield, Sugarcane Quality, and Soil Variability in Louisiana. *Agronomy Journal* 97(3), 760–771.

Kass, G., 1980. An exploratory technique for investigating large quantities of categorical data. *Applied Statistics* 29(2), 119-127.

Khoshgoftaar, T.M., Golawala, M., Hulse, J. Van, 2007. An Empirical Study of Learning from Imbalanced Data Using Random Forest. 19*th* IEEE Int. Conf. Tools with Artif. Intell. 310–317.

Kitchen, N. R., Sudduth, K. A., Myers, D. B., Drummond, S. T., Hong, S. Y. 2005. Delineating productivity zones on claypan soil fields using apparent soil electrical conductivity. *Computers and Electronics in Agriculture*, *46*(1–3 SPEC. ISS.), 285–308.

Kitchen, N.R.; Sudduth, K.A.; Drummond, S.T. 1999. Soil electrical conductivity as a crop productivity measure for claypan soils. *Journal of Production Agriculture* 12: 607-617.

Landell, M.G.A., Prado, H., Vasconcelos, A.C.M., Perecin, D., Rossetto, R., Bidóia, M.A.P., Silva, M.A., Xavier, M.A., 2003. Oxisol subsurface chemical attributes related sugarcane productivity. *Scientia Agricola* 60, 741-745.

Lebourgeois, V., Dupuy, S., Vintrou, É., Ameline, M., Butler, S., Bégué, A., 2017. A Combined Random Forest and OBIA Classification Scheme for Mapping Smallholder Agriculture at Different Nomenclature Levels Using Multisource Data (Simulated Sentinel-2 Time Series, VHRS and DEM). *Remote Sensing* 9, 259.

Loarie, S.R., Lobell, D.B., Asner, G.P., Mu, Q., Field, C.B. 2011. Direct impacts on local climate of sugarcane expansion in Brazil. *Nature Climate Change* 1, 105-109.

Magalhães, P.S.G., Cerri, D.G.P., 2007. Yield Monitoring of Sugar Cane. *Biosystems Engineering* 96, 1–6.

Magalhães, P.S.G., Sanches, G.M., Franco, H.C.J., Driemeier, C.E., Kolln, O.T., Braunbeck, O.A., 2014. Precision Agriculture in Sugarcane Production. A Key Tool to Understand Its Variability. *In:* 12 International Conference on Precision Agriculture, 2014, Sacramento, CA. 12^{th} ICPA Abstracts Book.

Mahmood, H.S., Hoogmoed, W.B., van Henten, E.J., 2012. Sensor data fusion to predict multiple soil properties. *Precision Agriculture* 13, 628–645.

Malavolta, E. 1979. *ABC da Adubação*. 4th edição. São Paulo SP, Editora Agronomia Ceres, 255 p.

Maldaner, L.F., Spekken, M., Eitelwein, M.T., Molin, J. P., 2015. Removal of errors on maps of productivity of sugarcane. *In*: X SBIAGRO – Congresso Brasileiro de Agroinformárica. Piracicaba-SP, 11 p.

McBratney, A., Whelan, B., Ancev, T., 2006. Future directions of precision agriculture. *Precision Agriculture* 6, 7-23.

McBratney, A.B., Minasny, B., Whelan, B.M., 2005. Obtaining 'useful' high-resolution soil data from proximally-sensed electrical conductivity/resistivity (PSEC/R) surveys. In: Stafford, J.V. (Ed.), Proceedings of the 5th European Conference on Precision Agriculture. Wageningen Academic Publishers, The Netherlands, pp. 503–510.

Medeiros, W.N.; Valente, D.S.M.; Queiroz, D.M.; Pinto, F.A.C.; Assis, I.R. 2018. Apparent soil electrical conductivity in two different soil types. *Revista Ciência Agronômica* 49 (1):43-52.

Menandro, L.M.S., Cantarella, H., Franco, H.C.J., Pimenta, M.T.B., Rabelo, S.C., Sanches, G.M., Carvalho, J.L.N., 2017. Comprehensive assessment of sugarcane straw: implications for biomass and bioenergy production. *Biofuels Bioproducts & Biorefining-Biofpr* 11(3), 488-504.

Molin, J. P.; Castro, C. N. 2008. Establishing management zones using soil electrical conductivity and other soil properties by the fuzzy clustering technique. *Scientia Agricola* 65(6):567-573.

Molin, J.P., Faulin, G.C. 2013. Spatial and temporal variability of soil electrical conductivity related to soil moisture. *Scientia Agricola* 70(1):1-5.

Montanari, R., Souza, G.S.A., Pereira, G.T., Marques Jr., J., Siqueira, D.S., Siqueira, G.M. 2012. The use of scaled semivariograms to plan soil sampling in sugarcane fields. *Precision Agriculture* 13(5):542-552.

Moore, I. D., Gessler, P. E., Nielsen, G.A., Peterson, G.A. 1993. Soil attribute prediction using terrain analysis. *Soil Science Society of America Journal* 57 (2), 443-452.

Muñoz, V.A, Valeriano, M.M., Weill, M.A.M. 2011. Estudo das relações solo-relevo pela análise geomorfométrica de dados SRTM e TOPODATA e a técnica de recuperação de conhecimento a partir de mapas. In: XV Simpósio Brasileiro de Sensoriamento Remoto – SBSR. Curitiba, PR, Brasil. *Anais* INPE p.9261.

Nanni, M. R., Povh, F.P., Demattê, J.A.M., Oliveira, R.B., Chicati, M.L., Cezar, E. 2011. Optimum size in grid soil sampling for variable rate application in site-specific management. *Scientia Agrícola* 68(3):386-392.

Newlands, N.K., Zamar, D.S., Kouadio, L.A., Zhang, Y., Chipanshi, A., Potgieter, A., Toure, S., Hill, H.S.J., 2014. An integrated, probabilistic model for improved seasonal forecasting of agricultural crop yield under environmental uncertainty. Frontiers in Environmental Science. doi:10.3389/fenvs.2014.00017

Nogueirol, R.C., Cerri, C.E.P., Silva, W.T.L., Alleoni, L.R.F., 2014. Effect of no-tillage and amendments on carbon lability in tropical soils. *Soil & Tillage Research* 143, 67-76.

Parente, L., Ferreira, L., Faria, A., Nogueira, S., Araújo, F., Teixeira, L., Hagen, S., 2017. Monitoring the brazilian pasturelands: A new mapping approach based on the landsat 8 spectral and temporal domains. *International Journal of Applied Earth Observation and Geoinformation* 62, 135–143.

Park, S.J., Hwang, C.S., Vlek, P.L.G., 2005. Comparison of adaptive techniques to predict crop yield response under varying soil and land management conditions. *Agricultural Systems* 85(1), 59–81.

Peets, S., Mouazen, A.M., Blackburn, K., Boyan, K., Wiebensohn, J. 2012. Methods and procedures for automatic collection and management of data acquired from on-the-go sensors with application to on-the-go soil sensors. *Computers and Electronics in Agriculture* 81, 104 – 112.

Piikki, K., Söderström, M., Stenberg, B., (2013). Sensor data fusion for topsoil clay mapping. *Geoderma* 199, 106–116.

Popp, J., Lakner, Z., Harangi-Rákos, M., Fári, M. 2014. The effect of bioenergy expansion: food, energy, and environment. *Renewable and Sustainable Energy Reviews* 32, 559-578.

Rabus, B., Eineder, M., Roth, R., Bamler, R. 2003. The Shuttle Radar Topography Mission—a new class of digital elevation models acquired by spaceborne radar. *ISPRS Journal of Photogrammetry & Remote Sensing* 57, 241-262.

Raij, B. van., 1991. *Fertilidade do solo e adubação*. Piracicaba, Ceres/Potafos, 343p.

Raij, B. van., Cantarella, H., Quaggio, J.A., Furlani, A.M.C., 1997. *Recomendações de adubação e calagem para o Estado de São Paulo*. Campinas. Instituto Agronômico; Fundação IAC., Campinas.

Raij, B.V.; Andrade, J.C.; Cantarella, H.; Quaggio, J.A. (2001) *Análise química para avaliação da fertilidade de solos tropicais.* Campinas, Instituto Agronômico.

Reedy, R.C.; Scanlon, B.R. (2003). Soil water content monitoring using electromagnetic induction. *Journal of Geotechnical and Geoenvironmental Engineering* 129:1028-1039.

Rhoades, D.A.; Dowrick, D.J. (1999). Variability of damage ratios for property in earthquakes. *Earthquake Spectra* 15:297-316.

Rodrigues Jr., F.A., Magalhães, P.S.G., Franco, H.C.J., 2012. Soil attributes and leaf nitrogen estimating sugar cane quality parameters: Brix, pol and fibre. *Precision Agriculture* 14, 270–289.

Rodrigues Jr., F.A., Magalhães, P.S.G., Franco, H.C.J., Beauclair, E.G.F., Cerri, D.G.P., 2013. Correlation Between Chemical Soil Attributes and Sugarcane Quality Parameters According to Soil Texture Zones. *Soil Science* 178, 147-156.

Rossel, R.A.V., Bouma, J., (2016). Soil sensing: a new paradigma for agriculture. *Agricultural Systems* 148, 71–74.

Rossi Neto, J., de Souza, Z.M., de Medeiros Oliveira, S.R., Kölln, O.T., Ferreira, D.A., Carvalho, J.L.N., Braunbeck, O.A., Franco, H.C.J., 2017. Use of the Decision Tree Technique to Estimate Sugarcane Productivity Under Edaphoclimatic Conditions. *Sugar Tech* 19(6), 662-668.

Salton, J.C.; Tomazi, M.; Comunello, E.; Zanatta, J.A.; Rabello, L.M. (2011). Electrical conductivity and physical and chemical attributes of an Oxisol after 15 years in management systems in Mato Grosso do Sul state. p. 254-260. *In:* Inamasu, R.Y.; Naime, J.M.; Resende, A.V.; Bassoi, L.H.; Bernardi, A.C.C., eds. Precision Agriculture: a new look. Embrapa Instrumentação, SP, Brazil (in Portuguese, with abstract in English).

Sana, R.S.; Anghinoni, I.; Brandão, Z.N.; Holzschuh, M.J. (2014). Spatial variability of physical-chemical attributes of soil and its effects on cotton yield. *Revista Brasileira de Engenharia Agrícola e Ambiental* 18: 994-1002 (in Portuguese, with abstract in English).

Sanches, G.M., Magalhães, P.S.G., Franco, H.C.J. 2019. Site-specific assessment of spatial and temporal variability of sugarcane yield related to soil attributes. *Geoderma* 334:90-98.

Sanches, G.M., Magalhães, P.S.G., Remacre, A.Z., Franco, H.C.J., 2018. Potential of apparent soil electrical conductivity to describe the soil pH and improve lime application in a clayey soil. *Soil & Tillage Research* 175, 217-225.

Sanches, G.M.; Paula, M.T.N.; Duft, D.G.; Magalhaes, P.S.G.; Franco, H.C.J. 2017. Ambientes de produção precisos para lavouras de cana-de-açúcar. Anais Simpósio de Agricultura de Precisão e Mecanização em Cana-de-açúcar, 2017, Jaboticabal - SP. Anais. Jaboticabal - SP, 2017. p. 6-8.

Sanchez, R.B., Marques Júnior, J., de Souza, Z.M., Pereira, G.T., Martins Filho, M.V. 2009. Spatial variability of soil attributes and of erosion factors in different landforms. *Bragantia* 68 (4), 1095-1103.

Serrano JM, Shahidian S, Marques da Silva J (2017). Spatial variability and temporal stability of apparent soil electrical conductivity in a Mediterranean pasture. *Precision Agriculture* 18(2):245-263.

Silva, C.B., Moraes, M.A.F.D., Molin, J.P., 2011. Adoption and use of precision agriculture technologies in the sugarcane industry of São Paulo state, Brazil. *Precision Agriculture* 12(1), 67–81.

Simbahan, G.C., Dobermann, A., Goovaerts, P., Ping, J., Haddix, L. 2006. Fine-resolution mapping of soil organic carbon based on multivariate secondary data. *Geoderma* 132, 471-489.

Siqueira, D. S., Marques, J., Pereira, G. T. 2010. The use of landforms to predict the variability of soil and orange attributes. *Geoderma 155*(1–2), 55–66.

Siqueira, G.M.; Silva, E.F.F.; DaFonte, D.J. 2015. Spatial distribution of soil apparent electrical conductivity measured by electromagnetic induction and sugarcane yield. *Bragantia* 74:215-223.

Souza, Z.M., Cerri, D.G.P., Colet, M.J., Rodrigues, L.H.A., Magalhães, P.S.G., Mandoni, R.J.A., 2010. Análise dos atributos do solo e produtividade da cultura de cana-de-açúcar com o uso da geoestatística e árvore de decisão. *Ciência Rural* 40, 840-847.

Stepien, M., Gozdowski, D., Samborski, S.A. 2013. A case study on the estimation accuracy of soil properties and fertilizer rates for different soil-sampling grids. *Journal of Plant Nutrition and Soil Science* 176(1):57-68.

Sudduth, K. A., Kitchen, N. R., Wiebold, W. J., Batchelor, W. D., Bollero, G. A., Bullock, D. G., et al. 2005. Relating apparent electrical conductivity to soil properties across the north-central USA. *Computers and Electronics in Agriculture*, *46*(1–3 SPEC. ISS.), 263–283.

Sudduth, K.A.; Drummond, S.T.; Kitchen, N.R. 2001. Accuracy issues in electromagnetic induction sensing of soil electrical conductivity for precision agriculture. *Computers and Electronics in Agriculture* 31: 239-264.

Razafimbelo, T., Chevallier, T., Albrecht, A., Chapuis-Lardy, L., Rakotondrasolo, F.N., Michellon, R., Rabeharisoa, L., Bernoux, M., 2003. Texture and organic carbon contents do not impact amount of carbon protected in Malagasy soils. *Scientia Agricola* 70(3), 204-208.

Tarr, A. B., Moore, K. J., Burras, C. L., Bullock, D. G., Dixon, P. M. (2005). Improving map accuracy of soil variables using soil electrical conductivity as a covariate. *Precision Agriculture*, *6*(3), 255–270.

Tian, Z., Jing, Q., Dai, T., Jiang, D., Cao, W. 2011. Effects of genetic improvements on grain yield and agronomic traits of winter wheat in the Yangtze River Basin of China. Field Crops Research 124(3), 417-425.

Triantafilis, J., Laslett, G. M., McBratney, A. B. (2000). Calibrating an Electromagnetic Induction Instrument to Measure Salinity in Soil under Irrigated Cotton. Soil Science Society of America Journal, 64(3), 1009.

Tulbure, M.G., Wimberly, M.C., Boe, A., Owens, V.N., 2012. Climatic and genetic controls of yields of switchgrass, a model bioenergy species. *Agriculture, Ecosystems & Environment* 146(1), 121-129.

Valente, D.S.M.; Queiroz, D.M.; Pinto, F.A.C.; Santos, N.T.; Santos, F.L. (2012). The relationship between apparent soil electrical conductivity and soil properties. *Revista Ciência Agronômica* 43: 683-690.

Valeriano, M.M., Albuquerque, P.C.G. 2010. *Topodata: processamento dos dados SRTM.* São José dos Campos, SP: INPE: Coordenação de Ensino, Documentação e Programas Especiais (INPE-16702-RPQ/854). 79p.

Valeriano, M.M., Rosseti, D.F. 2008. TOPODATA: seleção de coeficientes geoestatísticos para o refinamento unificado de dados SRTM. São José dos Campos: *INPE*, 50p.

Valeriano, M.M., Rossetti, D.F. 2012. Topodata: Brazilian full coverage refinement of SRTM data. *Applied Geography* 32, 300-309.

Viscarra Rossel, R.A., Bouma, J., 2016. Soil sensing: a new paradigm for agriculture. *Agricultural Systems* 148, 71–74.

Waclawovsky, A.J., Sato, P.M., Lembke, C.G., Moore, P.H., Souza, G.M., 2010. Sugarcane for bioenergy production: an assessment of yield and regulation of sucrose content. *Plant Biotechnology Journal* 8, 263-276.

Webster, R., Oliver, M. A. 1992. Sample adequately to estimate variograms of soil properties. *Soil Science* 43(1), 117-192.

Wilson, J.P., Gallant, J.C. 2000. *Terrain analysis: principles and applications.* 1st Ed. New York: John Wiley & Sons, Inc. 478p.

Wolfert, S., Ge, L., Verdouwa, C., Bogaardt, MJ., 2017. Big Data in Smart Farming – A review. *Agricultural Systems* 153, 69-80.

Yan-e, D., 2011. Design of Intelligent Agriculture Management Information System Based on IoT. In: Intelligent *Computation Technology and Automation* (ICICTA),.Guangdong, Shenzhen. 1:1045-1049.

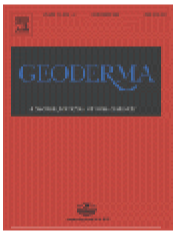
Yang, C., Peterson, C. L., Shropshire, G. J., Otawa, T. 1998. Spatial Variability of Field Topography and Wheat Yield in the Palouse Region of the Pacific Northwest. *Transactions of the ASAE*, *41*(1), 17–27.

Yost, M.A., Kitchen, N.R., Sudduth, K.A., Sadler, E.J., Drummond, S.T., Volkmann, M.R., 2016. Long-term impact of a precision agriculture system on grain crop production. *Precision Agriculture* 18(5), 823-842.

VI. ANEXOS

Copyright Clearance Center RightsLink®

Home | Create Account | Help



Title: Site-specific assessment of spatial and temporal variability of sugarcane yield related to soil attributes

Author: Guilherme M. Sanches,Paulo S. Graziano Magalhães,Henrique C. Junqueira Franco

Publication: Geoderma

Publisher: Elsevier

Date: 15 January 2019

LOGIN

If you're a copyright.com user, you can login to RightsLink using your copyright.com credentials.

Already **a RightsLink user** or want to learn more?

Please note that, as the author of this Elsevier article, you retain the right to include it in a thesis or dissertation, provided it is not published commercially. Permission is not required, but please ensure that you reference the journal as the original source. For more information on this and on your other retained rights, please visit: https://www.elsevier.com/about/our-business/policies/copyright#Author-rights

BACK | CLOSE WINDOW