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RESEARCH ARTICLE

Factors influencing the adoption of smart farming by Brazilian grain farmers

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Abstract

Smart farming (SF) is a relatively new concept referring to the use of information and communication technology in farm management, focusing simultaneously on productivity, profitability, and conservation of natural resources. However, despite the benefits, the adoption rate of some SF technologies has not been uniform in some countries. The aim of this paper was to identify the barriers and determining factors influencing the decisions of grain farmers regarding adopting SF technologies. A sample of farmers in southern Brazil (n=119) was analyzed through descriptive analysis, Logit and Poisson models. The results showed there was no strict pattern in farmers' profile, especially in terms of socioeconomic characteristics, to explain the adoption of SF technologies as a package. Adoption of some technologies requires more years of education and knowledge about how technology works, other technologies demand more scale. Broadly speaking, SF requires farmers to be open and receptive to this concept of agriculture.

Keywords: smart farming, innovation in agriculture, future farming, industry 4.0

JEL code: Q1, Q13, Q16, O1, M1

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1. Introduction

Brazil is one of the most important producers of the world's food supply, especially commodity grains, including soybean, wheat, corn, and rice. In the 2015/16 growing season, Brazil produced 186.3 million tonnes of grains, 40% of which came from the southern region of the country (CONAB, 2017). In addition, Brazil ranks second globally in soybean production, with 113.92 million tonnes in season 2016/17 (CONAB, 2017).

Over the past few decades, Brazilian soybean yields have experienced significant increases, from 1700 kg/ha in season 1979/80 to 3364.1 kg/ha in season 2016/17 (CONAB, 2017). This increase in soybean productivity has occurred due to the introduction of a set of technologies in production systems, such as fertilizers, agrochemicals, new cultivars, machines, and equipment with greater operational capacity. However, the diffusion of these technologies has not been uniform throughout Brazilian territory, and the levels of technology adoption differ throughout the country (Vieira Filho, 2014).

One set of new technologies, in particular, has arisen and attracted the interest of researchers, farmers and agribusiness managers with its potential to contribute to increased productivity. They are known as Smart Farming (SF). SF is a new concept referring to information and communication technology in farm management (Wolfert *et al.*, 2017), focusing simultaneously on productivity, profitability, and the conservation of natural resources. In general, this concept has emerged from three fields of knowledge: precision agriculture (PA), information technology (IT), and farm management information system (FMIS) (Wolfert *et al.*, 2017). While PA takes into account only in-field variability, SF goes beyond that to base management tasks on not only location but also data, enhanced by contextual and situational awareness and triggered by real-time events (Pivoto *et al.*, 2017; Wolfert *et al.*, 2017).

Some indicators predict that SF will increase the availability of technologies in the coming years. First, the average price of Internet of Things (IoT) sensors for agriculture has fallen from US\$1.50 in 2004 to US\$0.50 in 2016 (CB Insights, 2017). These sensors provide the basis for SF, because they allow collecting a lot of information and monitoring several processes in real time with precision and at low costs. Second, companies' investments in artificial intelligence are projected to rise from US\$6.0 billion in 2016 to US\$13.93 billion in 2017 (CB Insights, 2017). These data demonstrate a path of innovation in smart environments in several sectors, which could spill over to agriculture.

Given the characteristics of commodity markets, farmers usually are price-takers in grain commodity markets (Waqil *et al.*, 2010). Suppliers' profitability, thus, depends on competent financial and productive management of goods. SF use, therefore, is a frontier in productivity gains. From a macroeconomic view, due to expected challenges in food systems production in the coming decades (e.g. increased frequency and severity of climate weather events and degradation of natural resources), the adoption of SF technologies should be encouraged. In the microeconomic view (farmer viewpoint), the permanence of farmers in the activity of grain production requires either productivity gains or reduced costs; therefore, they need to advance in the adoption of technologies that lead in this direction. From economic and social perspectives, if SF technologies prove to optimize results, farmers who do not adopt them may be excluded from the agricultural activity.

In the light of the foregoing, the aim of this paper is to identify the barriers and the determining factors influencing grain farmers' decisions regarding adopting SF technologies. Behind this specific research objective, there is an effort by our research group to understand a broader issue: why is Brazilian agriculture delaying entering the digital world? In a survey carried out by Brazilian Service to Support Micro and Small Enterprises (SEBRAE, 2017), 60.5% of the farmers in Brazil did not use computers in their rural businesses. In the northern and northeastern states, the percentage of farmers that did not use computers was higher than the Brazilian average, at 78.6% and 71.0%, respectively (SEBRAE, 2017). The use of computers in rural businesses decreased as the age of the manager of the farm increased. Of Brazilian farmers, older than 55

years, less than 32% used computers. This scenario can stop the spread of several innovations in agribusiness, and increase the gap in digital and information technologies adoption with other sectors.

To the best of our knowledge, this study is the first to consider factors affecting farmers' adoption of SF in the Brazilian grain sector. The contribution of this paper is twofold: it provides empirical evidence on the role of farms' characteristics, institutional factors, information searches, and personal features in SF adoption as well as, explains the low diffusion of SF in Brazil.

2. General concepts on smart farming

The concepts on SF have come from other sectors, especially industry. Scientific advances in areas such as software engineering and computer science have led to virtually ubiquitous computing, allowing the emergence of the smart environment (Gubbi, 2013). Other areas, including agriculture, also have appropriated the concept of smart environments. The industry sector, for example cars and electronics, has become one of the main areas developing application for smart environments, resulting in a new, fundamental paradigm driving the shift of industrial production to Industry 4.0 (Brettel *et al.*, 2014; Lasi *et al.*, 2014; Liao *et al.*, 2017; Maynard, 2015).

Industry 4.0 is a denomination for the current trend of automation and data exchange in manufacturing technologies, and it includes cyber-physical systems, IoT, cloud computing and cognitive computing (Brettel *et al.*, 2014; Lasi *et al.*, 2014; Liao *et al.*, 2017; Maynard, 2015). The term Industry 4.0 was revived in 2011 at the Hannover Fair-Germany and in October 2012, where the Working Group on Industry 4.0 presented a set of Industry 4.0 implementation recommendations to the German Federal Government (Brettel *et al.*, 2014; Lasi *et al.*, 2014).

The concept of smart environments in agriculture has emerged later than in industry, although some technologies linked to the idea of smart environments, such as PA and FMIS, have already been used in agriculture for a long time. The concept of SF can be expressed using different terminologies and definitions. Zheng *et al.* (2011), for example, used the concept of digital agriculture to refer to the use of digital technology to digitalize, visualize, design, monitor, and control agricultural objects and farming processes relevant to agricultural needs. According to Beecham (2014), SF emerged from the incorporation of computing and data transmission technologies into agriculture. The concept of SF or smart agriculture is broad and interacts with another set of technologies, such as PA and information management systems in agriculture, derived from FMIS.

SF has similarities with the concept of Industry 4.0. The basis for advances in Industry 4.0 is the combination of internet technologies and future-oriented technologies, such as 'smart' objects (Brettel *et al.*, 2014; Lasi *et al.*, 2014; Liao *et al.*, 2017; Maynard, 2015). The German government has labelled this emerging concept Industry 4.0 (Lee *et al.*, 2014), but there is no established concept in agriculture (Wolfert *et al.*, 2017). In this study, SF refers to the use of the IoT with the objective of connecting virtually networked objects, starting with the progressive introduction of big data knowledge, artificial intelligence, and other areas of communication and information science to improve decision making and begin the process of automation in operational activities.

The greatest application and potential offered by the advance of the set of technologies connected to SF is the possibility to increase the efficiency and effectiveness of production systems and productive chains. With more sensor data, process automation, automatic controls, and algorithm decision making can reduce losses, increase the gains in processes, and improve understanding of the relationships among the variables that determine the outcomes of systems.

Besides the new areas such as IoT, cloud computing, cognitive computing and big data, two fields have contributed to the development of SF: PA and IT (Wolfert *et al.*, 2017). A concept introduced in the early

1990 (Tey and Brindal, 2012), PA is a production system that involves crop management based on field variability and site-specific conditions (Seelan *et al.*, 2003). Data are also collected to help farmers make guided sub-field decisions, regarding, for instance, the application of fertilizers and pesticides and the sowing density for seeds (Tey and Brindal, 2012). Overall, the set of technologies linked to PA is intended to manage crop and soil variability in a manner that increases profitability and reduces environmental impact (Fountas *et al.*, 2005).

As well, IT is the use of any computer, storage, networking, or other physical devices, infrastructures, and processes to create, process, store, secure or exchange any form of electronic data. IT is the basis for FMIS. The integration of IT into different sectors has made it possible for professionals in the IT industry to make changes that can also help other sectors, such as agriculture (Figure 1). The main challenge is to determine how SF will deal with uncertainty in agriculture. Unlike other sectors, the production process in agriculture is more dependent on biophysical conditions. Consequently, agriculture, especially when not practiced in a greenhouse, has more inconsistent final production results.

Some of the main IT devices seen in the field are smartphones, tablets, and computers. The main objectives of using such equipment in the agricultural system are to improve the decision-making process and to better plan and obtain information on and off the farm.

3. Technology adoption

Farmers tend to adopt technologies and techniques if they can realize increased profitability (De Graaff *et al.*, 2008; Feder *et al.*, 1985; Jara-Rojas *et al.*, 2012). Moreover, pioneering initiatives to adopt new technologies can generate competitive advantages for farmers compared with those who do not (non-adopters) and those who only adopt them later (Foster and Rosenzweig, 2010). It, therefore, has been observed that in agriculture, technology adoption is a process characterized by a certain level of heterogeneity (Foster and Rosenzweig, 2010).

To understand the elements that result in this heterogeneity between adopters and non-adopters, it is necessary to analyze the factors that influence the process of technology adoption. For this, we define some factors

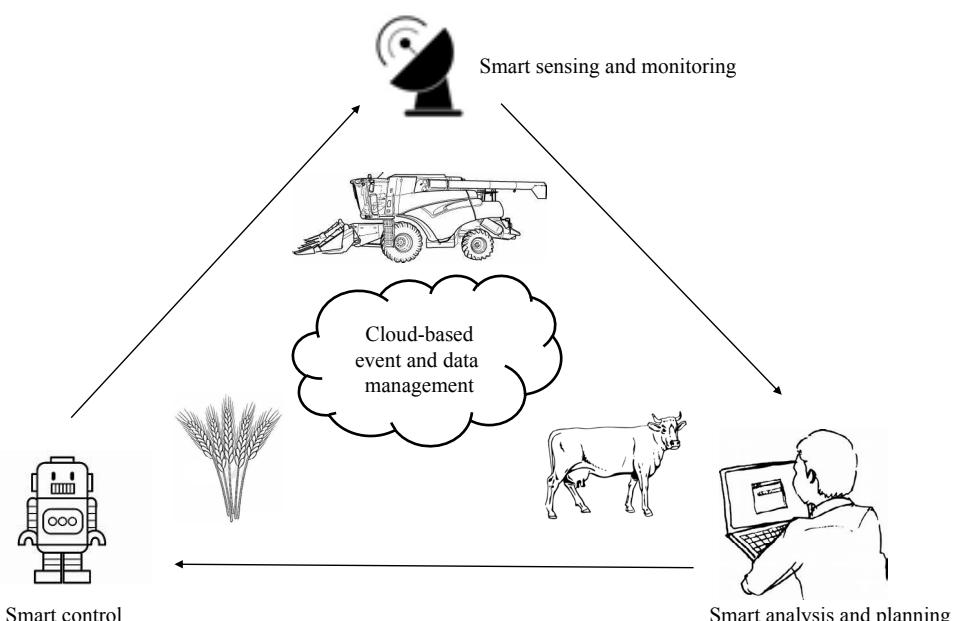


Figure 1. Concept and application of smart farming.

based on the studies of Pierpaoli *et al.* (2013), Souza Filho *et al.* (2011), and Tey and Brindal (2012). These studies focused mostly on farmers' adoption of PA and IT, which in turn are part of SF.

Adoption of SF has occurred in countless production chains around the world at different speeds (Fountas *et al.*, 2015; Kaloxylus *et al.*, 2012). Some factors may affect the likelihood of farmers adopting technologies. The most commonly analyzed dimension in the literature is the socioeconomic variables in the personal background of the farm's main decision maker. Among these personal variables, a positive relationship is expected between education and the adoption of technologies (Carrer *et al.*, 2017; Feder *et al.*, 1985), especially those linked to SF. Higher education levels potentially increases farmers' ability to process information, make decisions, and procure new management technologies (Carrer *et al.*, 2017; Feder *et al.*, 1985).

4. Material and methods

4.1 Analytical framework

In most empirical studies that used logit models, the observed decision for 'adopt' or 'non-adopt' is viewed as an outcome of a binary choice model (Carrer *et al.*, 2017; Mariano *et al.*, 2012). Thus, in this logit regression, the adoption technology decision is modeled as a binary variable, which takes the value of 1 for adopters and 0 for non-adopters:

$$Y_i = \begin{cases} 1 & \text{if the farmer adopts SF} \\ 0 & \text{if the farmer does not adopt SF} \end{cases}$$

For the Poisson regression, the adoption of technology decision is modeled as count data variables, which ranges from 1 for adopters of only one technology to 4 for farmers adopters of four technologies:

$$Y_i = \begin{cases} 1 & \text{if the farmer adopts one SF} \\ 2 & \text{if the farmer adopts two SF} \\ 3 & \text{if the farmer adopts three SF} \\ 4 & \text{if the farmer adopts four SF} \end{cases}$$

A body of empirical research assumes that utility maximization influences farmers' adoption of innovations (see Carrer *et al.*, 2017; Jara-Rojas *et al.*, 2012, Kassie *et al.*, 2009, 2015; Tey *et al.*, 2012). Accordingly, we assume that adoption occurs when the expected utility of adoption (U_n) exceeds the utility of non-adoption (U_d), i.e. $U_n > U_d$. In this context, latent variables (U_i) can define the parameters of farmers' decisions (Carrer *et al.*, 2017).

Latent variables are the functions of a set of factors, such as socioeconomic characteristics (e.g. education and age), information sources (e.g. access to technical consultants), institutional aspects (e.g. internet and credit access), and the technology characteristics of innovation (e.g. relative advantages of adoption). This set of factors has the potential to affect the farmer's perceptions of the expected utility of a particular technology, and consequently, influencing the farmer's likelihood of adopting it (Carrer *et al.*, 2017). Mathematically, this is represented as:

$$U_i = \beta X_i + e_i, \quad i = 1, 2, \dots, N, \quad (1)$$

where X_i is a vector of the independent variables, β is a vector of the parameters e_i is the error term (Hill *et al.*, 2011). This study uses two econometrics models to analyze farmers' adoption of SF: logit regression and count data (a Poisson regression model; PRM), following Carrer *et al.*, (2017), Isgin *et al.*, (2008) and Jara-Rojas *et al.*, (2012). Before running these two models, a correlation analysis is performed for the independent variables. Weak correlations are observed between the variables, except for $X1$ and $X3$ (0.852), because farmers' age is associated with length of experience in farm work.

■ Estimation of the logit regression model

The probability that the farmer adopts SF is represented as:

$$P[y_i = 1] = P(e > -X_i\beta) = 1 - F(-X_i\beta) = F(X_i\beta) = \frac{1}{1+e^{-(X_i\beta)}}, \quad (2)$$

where F is the cumulative distribution function, and the β parameters can be estimated using maximum likelihood procedures. Models constituted by binary choices differ only in the assumption of the functional form of F . The estimation of the logit model may be employed to estimate the likelihood of the adoption of SF technologies. According to Greene and Hensher (2003), it can be shown that:

$$P_i = P[y_i = 1] = \frac{e^{X_i\beta}}{1+e^{X_i\beta}}, \quad (3)$$

After obtaining the maximum likelihood estimates of X_i variables for the adoption of SF technologies, the following procedure is run to estimate the marginal effect of each variable. Typically, this is defined as the small effects of a unit change in X_i with all the other factors remaining constant. This estimation can be expressed as follow:

$$\frac{\Delta p_i}{\Delta x_i} = \frac{\partial p}{\partial x_i} = \beta_i \left(\frac{e^{-(X_i\beta)}}{(1+e^{-(X_i\beta)})^2} \right), \quad (4)$$

■ Estimation of the Poisson regression model

In addition to examining the adoption of a single technology, the present study is also intended to understand the determinants of adopting a SF package (Aldana *et al.*, 2011). Therefore, PRM are used to analyze the simultaneous adoption of a set of technologies. In this model, the dependent variables are the sum of four technologies (where 1 refers to the adoption of one technology, 2 refers to the adoption of two technologies, and so on). In this model, the dependent variable (Y) is the sum of the total number of SF technologies adopted by farmers. With Y for the random Poisson variable, the density function can be represented as:

$$P(Y = y_i|x_i) = f(y|\mu) = \frac{e^{-\mu}\mu^y}{y!}, \quad y = 0,1,2, \dots, \quad 0 \leq \mu < \infty, \quad (5)$$

where y is the number of SF technologies adopted by the farmer, and x_i are the variables that determine the adoption of SF. The expected mean parameter (μ) of this probability function is defined as:

$$\mu = E(Y) = \sum_{i=1}^N Y_i \times \frac{P(y_i, x_i)}{P(y_i|x_i)} = \exp(x_i'\beta), \quad (6)$$

Equation 6 represents the PRM in which the parameter β could be estimated using maximum likelihood procedures. In particular, the following logarithmic likelihood function is maximized:

$$\ln L(\beta) = \ln \left[\frac{e^{\lambda}\mu^y}{y!} \right] = -\lambda + y_i \ln(\lambda) - \ln(y_i!) = \sum_{i=1}^N [-\exp(x_i'\beta) + y_i(x_i'\beta) - \ln(y_i!)], \quad (7)$$

4.2 Sample, variables, and hypotheses

The data were collected in southern Brazil (Figure 2), a region that includes the states of Paraná, Santa Catarina, and Rio Grande do Sul. The main activities of these farms were livestock, dairy, and grain production (primarily soybean, wheat, corn, and rice).

The adoption of SF was analyzed by surveying farmers from April to December 2016. For the questionnaire, we defined factors based on Pierpaolia *et al.* (2013), Souza Filho *et al.* (2011) and Tey and Brindal (2012) and suggestions from 12 experts. The experts who participated in this study were professionals from machine companies and university professionals in areas such as agricultural engineering, PA, crop management, rural

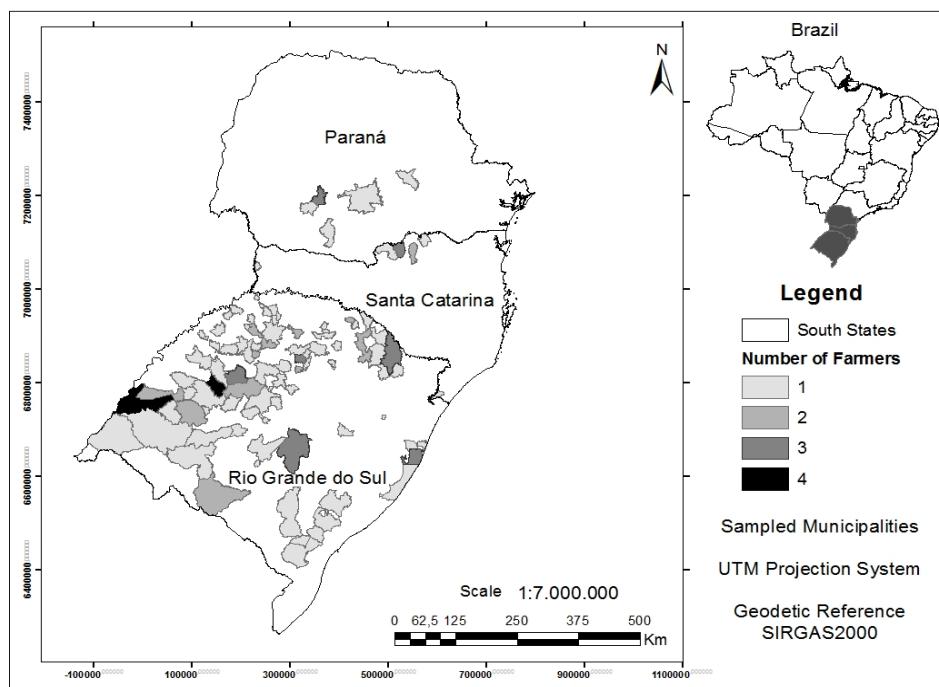


Figure 2. Geographic distribution of the sampled producers' cultivated lands.

management, and agricultural economics. To verify the appropriateness of the questions, a pilot survey was conducted with 32 farms. Afterwards, some questions were eliminated, and others modified.

The questionnaire was divided into two parts. The first part had questions on the characteristics of farmers and farms (e.g. socioeconomic variables), and the second on the barriers and factors influencing the adoption of SF technologies, called of determinants (interval scale of agreement). This section had two subsections: one on PA and one on IT. To measure the barriers and determinants, we used a 5-point Likert scale (1: totally disagree, to 5: totally agree). The questionnaire was posted on an online platform to increase the sample for data collection.

An electronic link to the questionnaire was disseminated through an e-mail lists of agricultural machinery resellers and farmers' associations. Besides online recruitment, we recruited face to face at agricultural fairs (25%) and direct application in the field (15%). The strategy to collected face to face and direct infield were used to increase the sample. Also, these different forms of sampling also allowed us to sample farmers who do not use information technology, and who would not be considered by online sampling. To be eligible to participate in this survey, farmers had to derive more than 50% of their gross revenue from grains (e.g. soybean, wheat, and corn). We sent the questionnaire to a list with 1,400 e-mail addresses and received 160 questionnaires. Some had incomplete answers, in addition, the other ways that were collected, so the final sample consisted of 119 farmers.

The analysis in this study focused on four SF technologies: three PA technologies (georeferenced soil sampling, automatic spray, and application of fertilizers and soil correctives at variable rates) and one variable linked to management tools, including management software (e.g. cost, people, productive, phytosanitary, and land management). These four technologies were chosen because they involved different applications and areas of development within SF, especially in grains. The first two were linked to soil sampling and application at variable rates to represent crop variability management. The third variable, auto-piloted spray, was related to farm automation (or attempts to do so). The fourth technology, IT, was related to information systematization or decision making.

Table 1 provides a description of the variables used in the econometric models for all the estimated parameters of the independent variables used in the regressions.

The analysis of the results centers on the general characteristics of the sample. In the following section, we present the technology adoption rate at the individual level and by level of adoption. We divide the sample into three levels of adoption: low adoption (adoption of one technology), medium adoption (adoption of two or three technologies), and high adoption (adoption of four technologies). After presenting the technologies and sample characteristics, descriptive statistics related to the farmers' perception of the barriers and the determinants of adoption are presented. Lastly, we discuss the application of the logit models and PRMs to analyze the influence of the variables on the decision to adopt these technologies. The model selection was based on an analysis of the estimators' significance criterion, Akaike selection, pseudo R^2 , and P -value of residual deviance.

Table 1. Description of the variables in the econometric analysis of the determinants of smart farming adoption.

Variables	Type ¹	Description
Y1: adoption of soil georeferenced sampling	D	1 if the farmer uses soil georeferenced sampling and 0 if not
Y2: adoption of application of variable rate fertilizers and correctives	D	1 if the farmer applies variable-rate fertilizers and correctives and 0 if not
Y3: adoption of autopilot spraying	D	1 if the farmer uses autopilot spraying and 0 if not
Y4: adoption of management software (cost, people, productive, phytosanitary, and land management)	D	1 if the farmer software for management decisions and 0 if not
SF adoption (y: Poisson model)	O	values ranging from 0 to 4, where SF is the sum of four dummy (0,1) variables for the adoption of four sf technologies: (1) soil georeferenced sampling; (2) application of variable-rate fertilizers and correctives; (3) autopilot spraying; and (4) adoption of management software (cost, people, productive, phytosanitary, and land management)
X1: farmers' age	C	years of the farmer's life
X2: education level	O	values ranging from 1 to 4: (1) elementary school; (2) high school; (3) under graduation; and (4) graduation
X3: experience	C	the farmers' years of experience in agriculture
X4: participation in a farmers' cooperative or association	D	1 if the farmer participated in a farmers' cooperative or association in the 2015/2016 harvest and 0 if not
X5: participation in a group exchanging experiences with other farmers and holding technical meetings	D	1 if the farmer participated in a group exchanging experiences with other farmers and holding technical meetings in the 2015/2016 harvest and 0 if not.
X6: technical assistance	D	1 if the farm received technical and management visits from specialists (e.g. agronomists and economists) in the 2015/2016 harvest and 0 if not
X7: frequency of consultations or technical assistance during the year	C	days per year
X8: receptivity to technology	L	values ranging from 1: fully disagree, to 5: fully agree with the following statement: 'in the purchase of machines and equipment, I prefer to acquire them with all the available technological options'
X9: total area of the farm	C	hectares
X10: soybean yield	C	bags per hectare (bag is 60 kg)

¹ D: dummy variable, C: continuous variable, L: Likert scale, O: discrete variable.

5. Results and discussion

5.1 General characteristics of the sample

Table 2 provides the descriptive statistics of the variables used in the econometric analyses. Regarding farmers' educational level, 10.9% had attended or completed elementary school, 17.8% had attended or completed high school, 52.9% had attended or completed undergraduate studies, and 19.3% had attended or completed postgraduate studies. Additionally, the sample had a mean of 1,180 ha, while half of the sample firms had less than 425 hectares. The main grains produced were soybean, wheat, corn, rice, and oat.

Table 3 shows the frequency of the adoption of the technologies analyzed in the present study. The most-used technology was soil georeferenced sampling. It was observed that not all farmers who adopted georeferenced soil sampling applied variable-rate fertilizers and soil correctives, with a difference of 8.7%. More than half of the farmers sampled used autopilot spraying. Molin (2017) found similar adoption rates in the midwestern Brazil, Matopiba,¹ and southern Brazil, with 60% of grain farmers using autopilot spraying. Unlike this work focused on spraying, Molin (2017) found that autopilot was used for several applications.

The same level of adoption was observed in the use of software for cost, people, and crop management by half of the farmers sampled. These data demonstrated farmers who are familiar with computers and software will have less difficulty making their farms connected and smarter and making better decisions about activity automation when more SF technology becomes commercially available.

After the presentation of the adoption rate for individual technologies in Table 3, the aggregate adoption of technologies was displayed, with different levels of adoption by farmers. It was seen that 13.4% of the sample did not adopt any analyzed technology². These farmers cannot be included in the context of SF and may find it difficult to introduce. We can see that 18.5% of the farmers adopted only one technology. These farms presented a low level of technology adoption. It is important to explore the factors lying behind this

¹ This Brazilian agricultural border region with a great growth in crops, including soybean, cotton, and corn, is formed by the states of Maranhão, Tocantins, Piauí, and Bahia.

² Results from *t*-test showed that there is significant difference between the groups of the low and high level of technology adoption. All means of the low-level group were lower than the high-level group: the *P*-value was 0.05 for farmers' age, experience, participation in a farmers' cooperative or association and the total area of the farm, and 0.01 for participation in a group exchanging experiences with other farmers and holding technical meetings.

Table 2. Descriptive statistics of the variables in the econometric analyses.

Variables	Mean	SD ¹	Min	Max
X1: farmers' age	41.3	13.6	20	70
X2: educational level	2.8	0.88	1	4
X3: experience	21.5	13.18	3	53
X4: participation in a farmers' cooperative or associations	0.74	0.44	0	1
X5: participation in a group exchanging experiences with other farmers and holding technical meetings	0.77	0.42	0	1
X6: technical assistance	0.37	0.49	0	1
X7: frequency of consultation or technical assistance during the year	173.8	158.4	0	365
X8: receptivity to technology	3.47	1.08	0	5
X9: total area of the farm	1,180.7	2,348.8	10	20
X10: soybean yield	59.7	11.1	35	82

¹ SD: standard deviation, Min: minimum, Max: maximum

Table 3. Adoption of smart farm technologies by grain farmers in southern Brazil.

Technologies	Adopters	Frequency of adoption (%)	Observations ¹
Soil georeferenced sampling	76	64.9	117
Application of variable-rate fertilizers and correctives	67	56.3	119
Auto pilot spraying	67	56.8	118
Uses management software (cost, people, productive, phytosanitary and land management)	60	50.8	118
Non-adopters	16	13.4	119
Adoption of one technology (low level)	22	18.5	119
Adoption of two technologies (medium level)	25	21.0	119
Adoption of three technologies (medium level)	25	21.0	119
Adoption of four technologies (high level)	31	26.1	119

¹ For some of the technologies there were observations missing.

low level of technology adoption because this low level might not be restricted to SF technologies but extend to technology in general, limiting these farmers' competitive capacity.

Farmers with a medium level of technology adoption accounted for 42.0% of the sample. These farmers were more familiar with the detailed, georeferenced IT and crop management. At the same time, the producers with high levels of SF technology adoption made up 26.1% of the sample. These farmers experienced the conditions of working in agriculture in which information was digital, decision making was aided by stored information for variables over several years, and the processes were automated with less human interference.

5.2 Determinants of the adoption of smart farming

As discussed, PA was one of the most established areas in SF. The PA determinants are presented in Table 4. The most important aspect in the farmers' perceptions of adopting PA was 'seeking yield increases.' Molin (2017) found similar reasons among farmers that adopted PA technologies and techniques, as 69% of the respondents reported increased productivity as a main reason for adoption. Additionally, Batte and Arnhold (2003) found that profitability was the biggest motivating factor in using PA tools.

Often, farmers did not make economic optimum calculations; instead, they preferred to maximize the output of grain production. Technologies that had the best effect on productivity increase tended to have greater acceptance among the farmers. This finding may have implications for policies to mitigate climate change and to make agriculture sustainable. Technologies that were environmentally less aggressive but affected negatively farmers' productivity of farmers tended not to be adopted.

Table 4. Determinants to the adoption of precision agriculture in farmers' perceptions measured by the degree of agreement (1: totally disagree, to 5: totally agree).

Variables	Mean ¹	SD
Seeking yield increases	4.77	0.63
Need to increase knowledge and information about areas of growth	4.59	0.72
Need to increase the quality of farm operations executed by employees	4.47	0.75
Reduce farm costs	4.30	0.97
Reduce the application of inputs, such as fertilizers and agrochemicals	4.17	1.05
Need to monitor agricultural operations in the field	3.96	1.16
Need to make work more comfortable for rural laborers	3.88	1.12

¹ Mean: scale of agreement, SD: standard deviation.

The variable 'need to make work more comfortable for rural workers' appeared to have the lowest score among all the questions. It was observed that concern for rural laborers was not yet a factor valued by farmers. However, farmers have been worried about shortages of rural labor, especially in southern, southeastern, and midwestern Brazil (Arns, 2016). This shortage of labor has led to increased labor prices for rural workers, especially more qualified workers (Arns, 2016). This could be another motivating element for SF adoption to increase the efficiency and the results generated by existing labor while applying more technology on the farm.

The determinants for adopting IT are presented in Table 5. The most important reason to adopt IT in the farmers' view was the 'need to improve farm management.' Farmers had increasingly available data and information to manage but also difficulty accessing, handling, and gaining knowledge from such data (Fountas *et al.*, 2015).

It was observed that much data stored and generated were not used due to a lack of methodologies or companies with data analysis services, despite the growing number of companies and startups in the sector. Lamb *et al.* (2008) argued that, in many cases, farmers' ability to collect data has exceeded their ability to understand and apply this data in a meaningful way. In the view of Lamb *et al.* (2008), developers, not users, have stifled the adoption of PA technologies.

The second most important factor for the adoption of software was related to the 'need to improve farm control costs.' Many of the applications and products sold in the market are intended to meet this demand. This was one of the first uses of IT and software in rural areas (Alvarez and Nuthall, 2006).

Another variable with a high score was the 'need to store information about soil and climate crop management'. This showed that farmers were beginning to take an interest in using information to extract more knowledge of previous harvests. This concern might have emerged due to climatic impacts and greater yield fluctuations and greater climatic variability.

It was observed that the item 'need to pass on up-to-date farm information to agronomists and consultants' was not yet an important reason in the farmers' perceptions. This was because data-sharing technologies are still in early stages. The same happened with the 'need to handle too much information, data, and documents daily', that was the last determinant score in farm view to adopting IT technologies.

Table 5. Determinants of the adoption of IT tools in farmers' perceptions measured by the degree of agreement (1: totally disagree, to 5: totally agree).

Variables	Mean ¹	SD
Need to improve farm management	4.51	0.72
Need to improve farm control costs	4.42	0.73
Need to store information about soil and climate crop management	4.12	0.90
Need to share information to agronomists and consultants	3.57	1.32
Need to handle too much information, data, and documents daily	3.45	1.17

¹ Mean: scale of agreement, SD: standard deviation.

5.3 Barriers to the adoption of smart farming

As presented earlier, the barriers to adoption SF are divided into two parts: PA and IT. The variable 'high initial investments' was the main barrier in the farmers' view. Some PA technologies had higher financial value for acquisition. Also, some services for which outsourcing had to be contracted, such as georeferenced soil analysis and variable-rate application, required a high investment, which had to be amortized over several years to become economically viable to farmers. When analyzing this investment in a timely manner for a single agricultural year, these technologies became quite costly.

The second most important barrier in the farmers' perceptions was the 'lack of a skilled workforce. Many of the respondents demonstrated through the variables analyzed that their employees did not have the knowledge or skills to make use of the new technologies being adopted in rural areas. This has been a very important topic in the economic literature. Beyond the present capacity, it is important that individuals have the capacity to absorb and assimilate knowledge, termed by Cohen and Levitt (1990) as 'absorptive capacity'. Many farmers and managers of rural enterprises have opposed the acquisition of equipment and machinery with a higher level of technology for the farm. This has sometimes occurred because the employees have not been able to handle or will not make the use of the technology acquired, preferring basic versions of equipment or machines.

In Brazil, a low level of education has been observed in the rural population, especially in regions far from urban centers (IBGE, 2006). The population older than 40 years, for example, has had less contact with technologies, such as computers. The variable in the third position reflected this finding: 'farmworkers have difficulties in handling computers and technologies in machines and equipment.' The shift to more data- and information-intensive, digital agriculture has presented the challenge of including the rural labor force to become its effective diffusion.

Information related to PA technologies was widespread among sampled farmers. The variable 'no knowledge of PA tools' had the lowest value among all. As Rogers (2003) reported, access to information is the first item in the technology adoption process. What might be happening in regard to PA then is a lack of sophisticated information about the technology.

The first barrier to the adoption of IT in the farmers' view (Table 7) was the 'need to collect and insert data manually in many programs/software'. Unlike PA, in which the farmer does not mind changing routines for adoption, farmers perceived manual data insertion as an important limitation in the adoption of management software. This limitation was beyond the focus of the farmers; that is, they were activities and processes

Table 6. Barriers to the adoption of precision agriculture in farmers' perceptions measured by the degree of agreement (1: totally disagree, to 5: totally agree).

Variables	Mean ¹	SD
High initial investments	4.21	1.08
Lack of a skilled workforce	3.40	1.41
Farm workers' difficulties handling computers and technologies in machines and equipment	3.31	1.38
Uncertain outcomes (advantages) in adoption	2.70	1.27
Neighboring producers and consultants' negative opinions on precision agriculture	2.09	1.15
Adoption of precision agriculture leading to routine changes in agricultural operations in which the farmers have no interest	1.81	1.22
No knowledge of precision agriculture tools	1.67	1.08

¹ Mean: scale of agreement, SD: standard deviation.

that farmers and employees of farms were not accustomed to monitoring and controlling, as was done in industrial areas.

Similarly, the variable 'lengthy time needed to learn the technologies' had the second highest value. Farmers had low interest in using time for administrative and control activities. Generally, they tended to spend more energy on productive and operational activities. As firms grew, there was a need for more tools and process control, leading to the creation of departments on farms. Carrer et al. (2017) noted that as citrus growers had to manage larger areas, the demand for IT, especially computers, increased due to the greater complexity of management.

Davis (1989) defined perceived ease of use, another aspect influencing the intention to adopt IT, as the belief that using a particular technology is free of physical and mental effort. According to Davis (1989), a potential user who perceives a technology as easy to use is more likely to perceive it as useful and adopt it. This view, added to the high value attributed by farmers to the barrier 'need to collect and insert data manually in many programs/software,' shows that the ease of use of IT, especially software and applications, needs to be improved by companies that sell and market products, as well as academia, which emphasizes the importance use of management tools.

The variable 'not seeing a return from adopting IT in farms' had the lowest value. In the farmers' perceptions, there were returns from adopting IT, but other factors limited the adoption process.

5.4 Factors influencing the adoption of technologies

Table 8 presents the results of the logit and Poisson econometric models. In addition to the estimated parameters, the marginal effects of each independent variable on the dependent variable of the models are also presented. These effects show the variation in the dependent variable in response to small variations in the independent variable, *ceteris paribus*.

Farmers' education level (X2) had a statistically significant, positive effect on the likelihood of adoption of soil georeferenced sampling (Y1). The estimated marginal effect for this variable indicated that the likelihood of adoption of Y1 increased by 23% among grain farmers with postgraduate degrees, *ceteris paribus*. A similar effect from education was found by Carrer et al. (2017) in computer adoption by citrus farmers, with an 20% increased likelihood of adoption. Farmers with more education and more familiarity with scientific methodologies were more willing to employ these techniques in their farms.

Table 7. Barriers to the adoption of information technology in the farmers' perceptions measured by the degree of agreement (1: totally disagree, to 5: totally agree).

Variables	Mean ¹	SD
Internet connection in the property	3.18	1.59
Need to collect and insert data manually in many programs/software	3.17	1.31
Lengthy time needed to learn the technologies	2.66	1.31
Concern that property information is sent to businesses or government agencies	2.16	1.33
No knowledge of the information tools and technologies that could help in property management	1.97	1.28
Not seeing a return from adopting information technologies in farms	1.76	1.13

¹ Mean: scale of agreement, SD: standard deviation.

Table 8. Results of the logit and Poisson models: determinants of adoption of smart farming by grain farmers.¹

Variables (Independents)	(Dependents)	Logit				Poisson Y (1,2,3,4)
		Soil Georeferenced Sampling (Y1)	Application of variable- rate fertilizers and correctives (Y2)	Auto pilot spraying (Y3)	Use management (cost, people, productive, phytosanitary and land management) (Y4)	
Intercept	β	-7.796	2.568	-5.910	1.185	-1.505
	Marginal effect					
Farmers' age (X1)	β		0.017	0.054*		
	Marginal effect		0.004	0.003		
	P-values		0.667	0.071		
Education level (X2)	β	1.791*	0.068	0.515	-0.687	0.203
	Marginal effect	0.234	0.016	0.033	0.015	0.560
	P-values	0.056	0.837	0.210	0.424	0.202
Years of agricultural experience (X3)	β		-0.022			
	Marginal effect		-0.005			
	P-values		0.590			
Participation in a cooperative or association (X4)	β	-2.719	-0.578	-0.832		-0.283
	Marginal effect	-0.259	-0.128	-0.045		-0.834
	P-values	0.151	0.391	0.329		0.303
Participation in a group exchanging experiences with other farmers and holding technical meetings (X5)	β		-0.536		-10.380	0.413
	Marginal effect		-0.119		0.032	0.952
	P-values		0.470		0.997	0.512
Has consultant or contracted technical assistance (X6)	β		0.412	1.260		
	Marginal effect		0.095	0.075		
	P-values		0.516	0.113		
Frequency of consultant or technical assistance during the year (X7)	β	-0.011				-0.001
	Marginal effect	-0.001				-0.003
	P-values	0.177				0.152
Receptivity to technology (X8)	β	1.161	0.8320***			0.268*
	Marginal effect	0.152	0.194			0.742
	P-values	0.273	0.005			0.097
Total area of the farm (X9)	β	0.05×10^{-3}		0.003***	0.003*	0.01×10^{-3}
	Marginal effect	0.06×10^{-3}		0.02×10^{-3}	0.01×10^{-3}	0.03×10^{-3}
	P-values	0.424		0.006	0.075	0.242
Productivity of soybean (sacks per hectare) (X10)	β	0.051	0.009	0.020	0.146	0.013
	Marginal effect	0.006	0.002	0.001	0.003	0.036
	P-values	0.475	0.696	0.535	0.110	0.250
P-value residual deviance		0.692	0.068	0.834	0.794	0.984
R ² McFadden		0.885	0.513	0.671	0.508	0.532

¹ Significant levels at: 10%*, 5%** and 1%***.

The independent variable of receptivity to the technology (X8) had a significant, positive effect on the adoption of the application of variable-rate fertilizers and soil correctives (Y2). The more open to new technologies farmers were, as measured by proxy, the higher their likelihood of adopting the application of variable-rate fertilizers and correctives was.

Regarding autopilot spraying technology (Y3), the variable in the model with significance at 1% was size of the total farm area (X9). This variable had a positive effect, and the probability of adopting this technology increased by 0.02390% for each additional hectare and by 23.90% for every 1,000 hectares. Previous technologies had a feature of allowing companies to provide outsourced services to producers, making the technology available to smaller areas. However, the autopilot spray was available on equipment that required a minimum area for application and did not match the market for service delivery. Consequently, the farm size factor had greater influence on adoption of autopilot spray.

The fourth technology analyzed, management software, was one of the main elements driving the emergence of SF. Regarding adoption of software for productive, technical, and financial management of the farm (Y4), it was observed that the main influencer in the adoption of this technology was farm size. Larger farmers demanded more information tools to meet the greater complexity and demand for farm organization, whereas small and medium farmers still did not have a high demand for this control and performed it in an informal and tacit manner.

Adrian *et al.* (2005) observed that the profile of adopters of PA technologies was an educated farmer who owned a larger farm with good soil quality and aimed to implement more productive agricultural practice to face growing competitive pressures. Adrian *et al.* (2005) argued that farmers with higher confidence levels, larger farms, and more education had greater intention to adopt PA technologies than farmers with lower levels of each of these variables.

When analyzing technologies in an aggregate way through the Poisson model, it was observed only one variable was significant: receptivity to technology (X8). A possible explanation of this result is that attitude (individuals' beliefs) can explain behavior (Ajzen and Fishbein, 1977). Farmers more open to technologies were more likely to adopt all four technologies or a form closer to the SF concept.

However, there was no strict pattern in farmers' profile, especially in terms of socioeconomic characteristics, to explain the adoption of SF technologies as a package. It was observed that some technologies are starting to be adopted by smaller farms. Adoption of some technologies requires more years of education and knowledge of how technology works (e.g. Y1 soil georeferenced sampling). Others demand more scale, represented by higher acreage, which could be solved by means of a market of services that meets the demands of farmers. Broadly speaking, SF requires farmers to be open and receptive to this concept of agriculture.

6. Concluding remarks

This paper aimed to analyze the determinant factors in grain farmers' decisions regarding the adoption of SF technologies. In addition, we identified factors that may be limiting the use of SF and delaying Brazilian agriculture to increasingly connect in a digital world.

The main barriers delaying Brazilian farmers' SF entry are the precariousness of Internet access in Brazilian rural regions and the need to input much data and information into software, which made analysis and interpretation difficult, characterizing problems in sources of reliable information, and technology characteristics, which can facilitate the collection and analysis of data that become in managerial information. Also, low qualifications of rural labor appear as a strong socioeconomic barrier to the diffusion of SF technologies. Training and capacity building by farmers' associations can be an important way to help in solving this barrier and spread the SF in Brazil.

Some limitations, such as the need to input much data and information into software, required more investment and development from companies. Technology developers, including machines companies, should make the applications and interfaces of equipment friendlier and more interactive for farmers. We observed numerous startups in Brazil exploring this opportunity. There are some of these enterprises development solutions to connect the machines to the office and trying to solve the gap between data available and applied knowledge to farmers. The capacity of this companies offer solution will influence the rate of SF diffusion in Brazil.

The main drivers of adopting SF were increased productivity, better process quality, reduced costs, and greater knowledge of cultivated areas. Solutions focused on improving comfort for the rural workforce and preservation of the environment are not yet the main motivators for the purchase of equipment and services in SF by farmers. Although the potential of SF to mitigate the effects of climate change, our research showed that the farmers are focus mainly on their profitability when adopting SF technologies.

Our results have shown different determinants for the adoption of individual technologies. Some technologies are more influenced by farm size, such as autopilot spraying. Another, by education level, such as adoption of soil georeferenced sampling. Although, the adoption of SF in aggregate form as a package is not determined by these variables. We observed that SF demands farmers be open to accept the risks of these new technologies. One of the important aspects for reflection in world agriculture is that we are betting strongly on these new technologies, but we still do not ask ourselves if the world's rural farmers are ready or willing to adopt these technologies. An important element to be studied are the psychological issues and aversion to technology by farmers.

It is suggested that future studies focus on the new constructs and new research questions that emerged from this work and use and deepen more specific scales. One possible direction is research on farmers' behavior. This could be investigated with farmers from Midwestern Brazil to control farm size (a variable that affects SF adoption). Another study could measure and compare whether SF adopters have a competitive advantage compared to non-adopters. This study has made the first efforts to work not merely with a single SF technology, but with a set of SF technologies.

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