Adoption of precision agriculture technologies by sugarcane farmers in the state of São Paulo, Brazil

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Abstract
This research aims at analyzing the determinants of the adoption and the intensity of adoption of precision agriculture technologies (PATs) by sugarcane farmers in the state of São Paulo, Brazil. A sample survey of 131 sugarcane farmers provided the data. Six adopted PATs were identified: GNSS and images for planting row orientation (52 adopters), tractor/harvester with automatic guidance system (32), georeferenced grids for soil sampling (15), images (satellite and/or drone) for mapping pests and yields (8), variable-rate applicators of fertilizers (8), and variable-rate applicators of pesticide (3). The adoption and adoption intensity (dependent variable) were measured as the number of PATs used by farmers. 53 farmers adopted at least one of these technologies, while 78 farmers did not adopt PATs. A count data model was used to test hypotheses on factors explaining both adoption and the intensity of adoption. The results suggested that the information provided by the sugarcane mills, the production scale and farmer perception that PATs would increase yield are determining factors for adoption. Information provided by private technical advisors and obtained at agricultural events plays an important role in the intensity of adoption. Such intensity is also affected by farmers' previous experience with PATs, their perception that PATs would increase yield, and the availability of low-cost credit.

Keywords Sugarcane · Adoption of technology · Intensity of adoption · Precision agriculture · Zero-Inflated Poisson

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Introduction

Precision agriculture (PA) has been defined by the International Society of Precision Agriculture as "a management strategy that gathers, processes and analyzes temporal, spatial and individual data and combines it with other information to support management decisions according to estimated variability for improved resource use efficiency, productivity, quality, profitability and sustainability of agricultural production (ISPA, 2021)." The diffusion of PA brings economic and environmental benefits, mainly because it improves the efficiency in the use of resources such as land, water, fertilizers, pesticides, and other agricultural inputs (Stafford, 2000; Batchelor et al., 2002; Finger et al., 2009; Shock & Wang, 2011; Amorim et al., 2019; Karatay & Aurich, 2019).

In Brazil, the Ministry of Agriculture, Livestock and Food Supply established the Brazilian Commission for Precision and Digital Agriculture as a government advisory body (Federal Decree No. 10,052, of 2019). The commission's role includes supporting the dissemination of PATs, the design of policies and the identification of trends. In 2022, the Brazilian government established the National Incentive Policy for Precision Agriculture and Livestock (Law No. 14,475, of December 13, 2022) to accelerate the diffusion of PATs.

A range of Precision Agriculture Technologies (PATs) is used in PA operations, such as GPS (Global Positioning System), soil sampling, GNSS (Global Navigation Satellite System) equipment, sensor data collection, machine guidance, controlled traffic farming, precision mapping, driver assistance and variable-rate applicators (Barnes et al., 2019). The success of policies aimed at the diffusion of PATs depends on a good understanding of the determinants of adoption. Theories on adoption and diffusion of agricultural innovations have been developed since Griliches' (1957) study on the diffusion of hybrid corn in the USA using the epidemic model. Other analytical models followed. The threshold model, for example, provided the theoretical basis for testing hypotheses on determinants of adoption (Bocquet et al., 2007; Geroski, 2000; Milgron & Roberts, 1990). Empirical studies used this theoretical approach to analyze data from samples of adopters and non-adopters of an innovation. Most studies made use of binary probit/logit statistical models, in which a binary dependent variable identifies adopters and non-adopters. This variable is then regressed on predictors of adoption, which are proxies for socioeconomic characteristics of farms and farmers, as well as institutional and environmental characteristics (Daberkow & McBride, 2003; Tamirat et al., 2018). Empirical studies on adoption of PATs have evaluated determinants of adoption using the approach. They have shown that younger farmers with better education and higher income are more likely to adopt (Watcharaanantapong et al., 2014). The role of many sources of information in adoption have also been investigated (Larson et al., 2008; Walton et al., 2008). Other studies have shown that the adoption is favored by the scale of production, usually measured by farm area and size of the agricultural activity (Walton et al., 2010; D'Antoni et al., 2012).

Empirical studies have identified farmers who adopted only one PAT, such as GNSS in tractors, while others adopted a large set of PATs, such as those for VRA operations. The adoption of two or more PATs can generate synergies and complementarities that enhance their benefits. GNSS image and the auto-guidance harvester system, for example, allow reductions in operating time, fuel, and labor in sugarcane production (Sparovek & Schnug, 2001). The number of maneuvers is reduced and, therefore, soil compaction is reduced, productivity increases and the economic life of the crop is extended (Molin et al., 2013). The use of fertilizers is also reduced with the adoption of VRA, which requires the adoption of georeferenced soil analyzes (Sanches et al.,

2021). Therefore, it is possible to identify different categories of adopters according to the number of PATs they decide to adopt (Miller et al., 2018; Barnes et al., 2019). For example, farmers who adopt more PATs can be categorized as more intensive adopters, while those who adopt only one or a few PATs are less intensive adopters. This finding has led researchers to empirically assess the determinants of this "intensity of adoption" (Giua et al., 2022; Isgin et al., 2008; Kolady et al., 2021; Paxton et al., 2011). In such case, count regression models have become preferable to binary probit/logit as a statistical tool. A count-dependent variable, which is a proxy for the intensity of adoption, assumes non-negative integer values representing the number of PATs that a farmer adopts. This variable can assume the value zero for non-adoption, followed by 1, 2, 3, and so on, representing the adopted number of PATs. Therefore, the value zero identifies a category of non-adopters, while 1, 2, 3, and so on, identify two or more ordered categories of adopters. This dependent variable is then regressed on predictor variables, which are proxies for testing factors that explain the intensity of adoption. The approach provides additional results to statistical models such as binary logit/probit, in which information on the intensity of adoption is lost.

The aim of this article is to assess the determinants of adoption and the intensity of adoption of PATs by sugarcane farmers in the state of São Paulo, Brazil. The production of sugarcane is of great importance for the economy and the environment in Brazil. It is an input not only for sugar, but also for ethanol. In 2017, Brazil produced 638.69 million tons of sugarcane. The state of São Paulo accounted for 54% of this production (IBGE, 2017). Sugarcane is produced both by the mills in their fields and by independent farmers who are their suppliers. In the 2018/2019 harvest, 88 mill companies produced 186.08 million tons of sugarcane in the state (56% of the state production), while 12,004 independent farmers produced 146.8 million tons (44% of the state production) (ORPLANA, 2020).

The cultivated area of sugarcane has increased in the state, thus increasing the competition over land and land prices (Camara and Caldarelli, 2016). The diffusion of innovations which increases efficiency in the use of resources, mainly land, water, fertilizers, and pesticides, became an important target of government policies and industry strategies. Carrer et al. (2022) found that these set of information provided by PATs improve farmers decision-making process, considerably increasing the technical efficiency in sugarcane production. The sugarcane farmers that adopted PATs operated their farms with mean technical efficiency scores 18% higher than the non-adopters—i.e., on average, the PATs adopters produced 18% more sugarcane than the non-adopters with the same level of inputs (land, machinery, labor and agrochemicals), even controlling for sample selectivity and technological heterogeneities (Carrer et al., 2022). Therefore, a greater diffusion of PATs plays an important role to improve efficiency and sustainability of sugarcane production in São Paulo state. Thus, the results of this article contribute for formulating public policies and private strategies to accelerate diffusion. Manufacturers and retailers of PATs, for example, can use the research results in their strategies of innovation and marketing. Advisors and extension services can improve their strategy, and farmers can better evaluate adoption.

A count regression approach was used to analyze primary data from a sample of 131 sugarcane farmers in the state of São Paulo. Some of these farmers have adopted one or more PATs, while others did not adopt any. Predictor variables were used to test hypotheses on factors that explain both adoption and the intensity of adoption. Section 2 presents an explanation of the data, the variables, and the count regression models. Section 3 presents results and discussion. Conclusions are in Sect. 4.

Data, adoption predictor variables, and count regression models

Data

A survey provided information on the socioeconomic characteristics of 131 independent sugarcane farmers and their farms in 47 municipalities of the state of São Paulo, Brazil (Fig. 1). Face-to-face interviews were conducted from May to November 2019, obtaining information from adopters and non-adopters regarding the 2018/2019 season. Adopters were selected with the help of the technical staff of Coplacana, a cooperative of sugarcane farmers of the state. They were asked to provide the best possible representation of farmers using PATs. For each adopter, a nearby non-adopter (counterfactual) sugarcane farmer was chosen, thus reducing the scope for discriminating adopters from non-adopters in terms of their environmental characteristics, such as soil types, topography, and climate. The sampling method could not be based on random selection due to two reasons: the number of adopters in relation to total number of farmers in the State was expected to be small, which would make it difficult to obtain a satisfactory number of observations from a random selection; and a list of adopters, from which a sample could be drawn, did not exist. The sample does not include farms owned by sugarcane mills. The municipalities where the selected farms were located accounted for 14.1% of the harvested area and 14.5% of the production of sugarcane of the state in 2017 (IBGE, 2017) (Appendix, Table 5).

The sample consisted of 53 adopters of at least 1 PAT and 78 non-adopters. Adopters have adopted at least one of the following PATs: GNSS and images for planting row orientation, tractor/harvester with automatic guidance system, georeferenced grids for soil
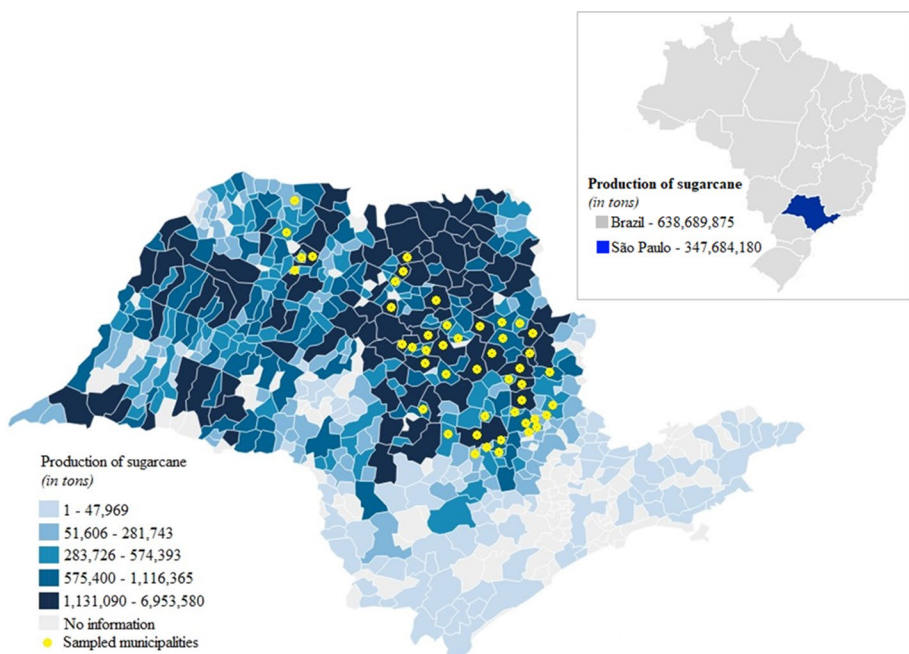

Fig. 1 Production of sugarcane and municipalities in the state of São Paulo, Brazil. Source: IBGE, 2017

sampling, images (satellite and/or drone) for mapping pests and yields, variable-rate applicators of fertilizers, and variable-rate applicators of pesticides.

GNSS and images for planting row orientation is the most adopted PAT. A map with detailed characteristics of the land is obtained, allowing the planning of planting rows and vehicle paths. Planting and harvesting follows this plan using GNSS and autopilot, so soil erosion, soil compaction and vehicle maneuvers can be reduced. In addition, the use of GNSS allows better planning of intercropping sugarcane with other crops, such as soybeans and peanuts, in the year of field renewal (every 5 or 6 year) (Bordonal et al., 2018). In this case, on a 2:8 scale, the sugarcane is planted in two rows to provide seedlings, and the other crop is planted in the remaining eight rows. After 6 to 8 months, the other crop is harvested, and the sugarcane seedlings are planted in its rows. This strategy, called Interrotational Method of Simultaneous Occurrence (MEIOSI, Portuguese acronym), aims to reduce seedling transport costs and the incidence of pests and diseases. The production of the other crop is mostly carried out in partnership with another farmer, who follows the GNSS row orientation plan.

Table 1 shows the six adopted PATs and the number of farmers who adopted each one. The number of farmers who adopted 0 (non-adopters), 1, 2, 3, 4, 5 and 6 PATs is also shown. As can be observed, 78 (60.6%) farmers chose not to adopt any of them (non-adopters). Some PATs were adopted by many farmers: 52 adopted GNSS and images for planting row orientation (satellite/drone), 32 adopted tractor/harvester with automatic guidance system, and 15 farmers adopted georeferenced grids for soil sampling. Previous studies also identified many farmers who adopted PATs that do not require special skills or additional training, such as driver assistance systems (e.g., row guidance) (Groher et al., 2020; Kolady et al., 2021). More expensive and skill-demanding PATs had few adopters: 8 farmers adopted images (satellite/drone) for mapping pests and yields, 8 farmers adopted VRA of fertilizers and 3 farmers adopted VRA of pesticides.

Some PATs were adopted individually, while others were adopted in combination with others. Column "1" of Table 1 shows that 13 farmers adopted only one PAT, GNSS and images for planting row orientation (satellite/drone). Column "2" shows that combinations of two PATs were adopted by 25 farmers, comprising two of the following PATs: GNSS and images for planting row orientation (satellite/drone), tractor/harvester with automatic guidance system, georeferenced grids for soil sampling, and images (satellite/drone) for

Table 1 Number of farmers who adopted each PAT, and number of farmers who adopted 0 (non-adopters), 1, 2, 3, 4, 5 and 6 PATs

PATs	Adopters of the PAT	Number of Adopted PATs (Y)						
		0	1	2	3	4	5	6
GNSS and images for planting row orientation (satellite/drone)	52	0	13	25	10	1	1	2
Tractor/harvester with automatic guidance system	32	0	0	21	7	1	1	2
Georeferenced grids for soil sampling	15	0	0	2	8	2	1	2
Images (satellite/drone) for mapping pests and yields	8	0	0	2	2	1	1	2
VRA of fertilizers	8	0	0	0	3	2	1	2
VRA of pesticides	3	0	0	0	0	1	0	2
Frequency of Y (n)		78	13	25	10	2	1	2
Frequency of Y (%)		59.6	9.9	19.1	7.6	1.5	0.8	1.5

mapping pests, and for mapping yields. Only two farmers adopted the six PATs combination. Different purposes and complementarities determine combinations (Giua et al., 2022; Isgin et al., 2008; Kolady et al., 2021; Paxton et al., 2011). The number of PATs (0 through 6) adopted by each farmer is the count variable which is used as a dependent variable in the statistical model described in Sect. 2.3.

Adoption predictor variables

Predictor variables were used to test the role played by five factors explaining the adoption of these PATs: agricultural information, human capital, scale, financial resources, dependence on sugarcane and perceived benefits. Table 2 shows the description of each predictor variable and a list of authors who had evaluated these explanatory factors in their empirical studies. Hypotheses on the expected effect of each variable on the adoption and the intensity of adoption are in column H.

The effect of several information sources on technology adoption has been investigated. Agricultural advisors, suppliers of machinery and equipment, technical lectures, field days and agricultural fairs are sources of information investigated in studies on the adoption of PATs (Larson et al., 2008; Walton et al., 2008; Watcharaanantapong et al., 2014; Barnes et al., 2019; Kanal et al., 2019). Walton et al. (2008) and Barnes et al. (2019) found a positive effect of information from agricultural advisors on the adoption VRA technologies. Khanal et al. (2019) identified that the greater the number of events and courses that the farmer attended, the higher probability of adopting PATs.

Human capital has also been investigated as a determinant of technology adoption. Hypotheses on the positive effect of schooling and previous experience with technology have been tested. Walton et al. (2008) and Paxton et al. (2011) found that farmers with the highest level of education are more likely to adopt PATs when compared to farmers at the lowest level. It is argued that the high level of education improves the ability to understand information and data generated by PATs. For Cohen and Levinthal (1990), the ability to absorb new information depends on the level of prior knowledge in the specific area related to the new technology. "Learning by doing" has been considered an important process for creating human capital (Bell and Pavitt, 1993). Organizations find it difficult to assess and assimilate new information without previous experience (Zahra and George, 2002). The effect of farmers' previous experience with PATs has not been evaluated to date. In the empirical approach proposed in this article, farmers were asked if they had off-farm experience with any PAT. Adopters were instructed to consider their experience prior to adoption.

The effect of production scale has been tested in several studies on the adoption of PATs, in which farm size was used as a predictor variable (Daberkow and McBride, 2003; Walton et al., 2010; D'Antoni et al., 2012; Tamirat et al., 2018; Barnes et al., 2019). In all cases, farm size had a positive effect on adoption.

The availability of financial resources is an important issue in the design of innovation diffusion policies, especially in cases of high-cost innovations. Lack of credit supply is sometimes a barrier to adoption. According to Daberkow and McBride (2003), some PATs fit the capital-intensive technology model, especially if training and education costs are considered. Therefore, lack of credit supply can delay adoption. The authors found a positive effect of access to rural credit on the adoption of PATs.

Farmer dependence on agricultural income is another predictor investigated in studies on PAT adoption (Walton et al., 2008; Watcharaanantapong et al., 2014; Paustian and Theuvsen, 2016). According to Watcharaanantapong et al. (2014), farmers whose income

Table 2 Description of predictor variables, hypotheses on expected effect on adoption and intensity of adoption, and references

Variable	Description	H	Authors
Agricultural Information			
Agricultural advisor	Binary variable: 1 if the farmer had access to private agricultural advisor in 2018; 0 otherwise	(+)	Larson et al. (2008); Walton et al. (2008); Watcharaanantapong et al. (2014); Paustian and Theuvsen (2016); Tamirat et al. (2018); Barnes et al. (2019); Khanal et al. (2019); Kendall et al. (2022); Tey and Brindal (2021)
Machinery supplier	Binary variable: 1 if the farmer had access to technical service provided by machinery and equipment suppliers in 2018; 0 otherwise	(+)	
Sugarcane mill	Binary variable: 1 if the farmer considered the Sugarcane mills as an important source of information; 0 otherwise	(+)	
Agricultural event	Discrete variable: number of agricultural events (lectures, field days and agricultural fairs) the farmer attended in 2018	(+)	
Human capital			
Schooling	Binary variable: 1 if the farmer obtained a university/college degree; 0 otherwise	(+)	Paxton et al. (2011); D'Antoni et al. (2012); Allahyari et al. (2016); Paustian and Theuvsen (2016); Kendall et al. (2022)
Experience	Binary variable: 1 if the farmer had previous experience with PATs; 0 otherwise	(+)	
Scale			
Log sugarcane area	Continuous variable: natural logarithm of the farmer's sugarcane area (hectares)	(+)	Daberkow and McBride (2003); Walton et al. (2008); Barnes et al. (2019); Gardezi & Bronson, 2020; Groher et al. (2020); Kolady et al. (2021); Kendall et al. (2022)
Financial resource			
Credit	Binary variable: 1 if the farmer had access to rural credit in the last 3 crop-years (2016, 2017 and 2018; 0 otherwise	(+)	Daberkow and McBride (2003); Allahyari et al. (2016); Kendall et al. (2022)
Dependence on sugarcane			
Sugarcane dependence	Continuous variable: ratio of sugarcane area to the farm total area. The closer to 1, the greater the farmer's dependence on sugarcane production	(+)	Walton et al., (2008); Walton et al., (2010); Watcharaanantapong et al. (2014); Paustian and Theuvsen (2016); Barnes et al. (2019)

Table 2 (continued)

Variable	Description	H	Authors
Perceived benefits			
Yield perception	Binary variable: 1 if before adopting the adopter had the perception that PATs would increase yield; 1 if the non-adopter had the perception that PATs would increase yield; 0 otherwise	(+)	Walton et al. (2008); Paxton et al. (2011); D'Antoni et al. (2012); Watcharaanantapong et al. (2014); Allahyari et al. (2016); Barnes et al. (2019); Khanal et al. (2019); Kendall et al. (2022); Kolady et al. (2021); Tey e Brindal (2021)
Cost perception	Binary variable: 1 if before adopting the adopter had the perception that PATs would increase production cost; 1 if the non-adopter had the perception that PATs would increase production cost; 0 otherwise	(−)	

comes mainly from agriculture are more likely to adopt PATs to reduce production risks. In the approach proposed in this article, the positive effect of the farmer's dependence on sugarcane production is tested.

The effect of farmers' perceptions of the benefits and the costs of an agricultural innovation has been tested in empirical studies. In the case of the adoption of PATs, a positive effect of the perception that PATs increase yield was found by Paxton et al. (2011), D'Antoni et al. (2012), Watcharaanantapong et al. (2014), and Allahyari et al. (2016). The perception of high cost of an innovation has the opposite effect. Khanal et al. (2019) found that the probability of adoption decreases when farmers perceive that production cost would increase with the adoption of PATs.

Table 3 shows means and standard deviations of the predictor variables for non-adopters and adopters of at least one of the six PATs. The hypothesis of equal means of the two groups was rejected for all variables at 10% significance level. The threshold at 0.05 commonly used in academia is an arbitrary and not fixed value. The magnitude of p-value depends on the sample size. Lower thresholds could increase sample size and cost. The cutoff for statistical significance at 0.10 has been used in empirical studies for identifying suggestive factors affecting the decision to adopt PATs (D'Antoni et al., 2012; Daberkow & McBride, 2003; Gardezi & Bronson, 2020; Isgin et al., 2008; Kolady et al., 2021; Larson et al., 2008; Paxton et al., 2011; Tamirat et al., 2018; Watcharaanantapong et al., 2014).

Count data regression models

Table 1 shows the number of PATs (0 through 6) adopted by each farmer, which is a count variable that assumes the values 0, 1, 2, 3, 4, 5 and 6. Studies on the adoption of agricultural technologies have used this type of variable as an indicator of intensity of adoption

Table 3 Means and standard deviations (in parentheses) of predictor variables, non-adopters, and adopters

Variable	Non-adopter	Adopter[a]	
Agricultural advisor (binary)	0.06 (0.25)	0.26 (0.45)	***
Machinery supplier (binary)	0.37 (0.49)	0.58 (0.50)	**
Sugarcane mill (binary)	0.45 (0.50)	0.66 (0.48)	**
Agricultural event (discrete)	7.99 (6.81)	11.51 (8.40)	***
Schooling (binary)	0.23 (0.42)	0.49 (0.50)	***
Experience (binary)	0.05 (0.22)	0.15 (0.36)	*
Log sugarcane area (continuous)	4.71 (1.31)	6.21 (1.39)	***
Credit (binary)	0.59 (0.50)	0.74 (0.45)	*
Sugarcane dependence (continuous)	0.75 (0.29)	0.86 (0.19)	***
Yield perception (binary)	0.72 (0.45)	0.86 (0.35)	**
Cost perception (binary)	0.54 (0.50)	0.38 (0.49)	*

[a] a adopters of at least one of the six PATs; Standard deviations are pointed within the parenthesis

***, ** and * indicate that, according to the results of the hypothesis test, the mean values of the variables are statistically different between the adopted and non-adopted at the significance levels of 1%, 5% and 10%, respectively. The t test was used to compare means (continuous and discrete variables) and Chi-squared test to test the equality of proportions (binary variables)

(Giua et al., 2022; Isgin et al., 2008). A count data regression model is used to test hypothesis on predictors of the intensity of adoption. The count variable is the dependent variable, Y, in these regressions. Such models have been used in other studies on the adoption of PATs (Isgn et al., 2008; Paxton et al., 2011; Barnes et al., 2019; Kolady et al., 2021).

At least eight count data regression models can be found in statistics: Poisson Regression, Negative Binomial Regression (NB), Zero-inflated Poisson (ZIP), Zero-inflated Negative Binomial (ZINB), Zero-truncated Poisson, Zero-truncated Negative Binomial, Hurdle Models and Random-effects Count Models (Cameron & Trivedi, 2013). The choice of the best model largely depends on the distribution of the dependent variable, Y. In the Poisson model, a Poisson distribution is assumed:

$$P\left[Y = y\right] = \frac{e^{-\mu}\mu^{y}}{y!} \tag{1}$$

μ is the incidence rate ratio (IRR). The mean and the variance are the same in the Poisson distribution, which is known as equidispersion. (Cameron & Trivedi, 2013; Greene, 2003). If this assumption is violated, the NB becomes more appropriate. An unobserved effect is introduced on the conditional mean to obtain a generalized Poisson model (Greene, 2003):

$$\ln u_i = x_i' \beta + \varepsilon_i = \ln \lambda_i + \ln u_i \tag{2}$$

The disturbance term, ϵ_i, holds the specification error as in the classical regression model. Therefore, the conditional distribution of the NB model keeps a Poisson distribution, but with conditional mean and variance u_i:

$$f(y_i|x_i) = \int_0^\infty \frac{e^{-\lambda_i u_i}\left(\lambda_i u_i\right)^{y_i}}{y_i!} g\left(u_i\right) du_i \tag{3}$$

An excess of zeros in the dependent variable generates a problem frequently confronted in studies that use count data models (Cameron & Trivedi, 2013). This is the case of the dependent variable in this study, which has 78 zeros (non-adopters). The ZIP and ZINB models are used to solve the problem. Both the ZIP and ZINB include a logit (or probit) regression for the group of observations at zero, followed by the Poisson estimate (if the model is ZIP), or the NB estimate (if the model is ZINB). Therefore, two internal regressions are estimated consecutively: a binary logit/probit and a count regression data. In the binary logit/probit, two groups of observations are discriminated: one with observations at zero (non-adopters) and another with observations at non-zeros (adopters). Therefore, predictors of the probability of belonging to the group at zero are estimated. In the count data regression, predictors of the count dependent variable are estimated. The choice between the ZIP and ZINB models will depend on the equidispersion of the distribution of the dependent variable, which can be tested by the Pearson goodness-of-fit tests and the likelihood-ratio test. The Vuong statistical test can be additionally performed to verify if a zero inflated model is preferable to traditional models (Poisson and NB) (Cameron & Trivedi, 2013; Greene, 2003).

Count regression models can provide additional information to binary probit/logit models. In binary probit/logit models, the dependent variable assumes two values, such as 0 for non-adoption and 1 for adoption. Heterogeneity among adopters, such as the level of intensity, is not considered. Therefore, a count data regression model is a reasonable choice for the analysis proposed in this article. The dependent count variable Y, which assumes non-negative integer values (0 through 6) and measures the intensity

of adoption, would be regressed against a vector of predictors X. The hypothesis on the role of predictors in the intensity of adoption could then be tested.

Results and discussion

The analysis started with Poisson regression estimation, as suggested by Cameron and Trivedi (2013). Stata® software was used to obtain the estimates and the correlation matrix variables, which are in the Appendix, Tables 6 and 7. Pearson's goodness of fit was then performed to test the hypothesis of equidispersion of the Poisson distribution of the dependent variable (Appendix Table 8). The p-value of the Pearson's test presented statistical significance level above 10%, indicating that the mean and the variance of the count dependent variable (the indicator of intensity of adoption) are equal. Therefore, the equidispersion assumption of the Poisson distribution was confirmed, indicating the validity of the Poisson model. The *alpha = 0* likelihood ratio test was also performed. The p-value of the test was 0.5000, indicating that the alpha dispersion parameter is equal to zero, therefore the Poisson model fits the data better than the NB model.

The dependent count variable has high incidence of zero observations, as 78 out of 131 farmers were non-adopters. The solution to this problem is the estimation of a ZIP model (Cameron and Trivedi, 2013). Estimates of this model are in Table 4. The χ^2 likelihood ratio was 27.21, with 11 degrees of freedom, and the p-value is close to zero. These results indicate that the model with predictors fits better than the model without predictors. The P > |z| = 0.0000 of the Vuong test was statistically significant, which also indicates that the ZIP model is the most suitable. The ZIP model includes a logit regression for non-adopters (observations at zero), followed by the Poisson estimate for intensity of adoption. The predictors of both models are discussed in the next two sections.

Table 4 Coefficients, IRR and OR of the ZIP regression model predictors

Variable	Logit for non-adoption			Poisson for intensity of adoption		
	Coefficient (β)		OR	Coefficient (β)		IRR
Agricultural advisor	− 2.3892		0.0917	0.5082	*	1.6623
Machinery supplier	− 0.7607		0.4674	0.1374		1.1472
Sugarcane mill	− 1.6769	*	0.1869	0.0076		1.0076
Agricultural event	− 0.0197		0.9805	0.0307	**	1.0311
Schooling	− 0.6084		0.5442	0.2487		1.2823
Experience	− 0.7087		0.4923	0.7077	**	2.0292
Log sugarcane area	− 1.6539	**	0.1913	− 0.1235		0.8838
Credit	− 2.4228		0.0887	0.4620	*	1.5872
Sugarcane dependence	− 0.1867		0.8297	0.9271		2.5271
Yield perception	− 5.0890	**	0.0062	0.5640	**	1.7576
Cost perception	0.9551		2.5990	− 0.1332		0.8753
Constant	− 3.0017		0.0497	− 0.8955		0.4084

*p ≤ 0.10; **p ≤ 0.05.; and ***p ≤ 0.01

The logit model for non-adoption

The coefficients of the logit model show the effects of predictors on the observations at zero (non-adopters). Therefore, it should be noted that the expected effect of predictors on "adoption" has the opposite effect to that shown in Table 4. The odds ratio (OR) was estimated for each coefficient of this model to provide easy interpretation. The OR is calculated as e^β. An OR greater than one indicates that the predictor has a positive effect on the probability of non-adoption. The OR can be also interpreted using the formula $[(e^\beta-1)*100]$, which shows the change in percentage points in the probability that the farmer will not adopt PAT, in response to the change in one unit in the predictor variable.

Agricultural advisors, suppliers of agricultural machinery and equipment, technical lectures, field days and agricultural fairs are some of the sources of information identified in studies on the adoption of PATs (Larson et al., 2008; Walton et al., 2008; Watcharaanantapong et al., 2014; Barnes et al., 2019; Kanal et al., 2019). Walton et al. (2008) and Barnes et al. (2019) found a positive effect of agricultural advisors on the adoption of VRA technologies. Khanal et al. (2019) found a positive effect of the number of events and courses that farmers attended on the probability of adopting PATs.

SUGARCANE MILL was one of four predictor variables used to test the hypothesis that access to agricultural information positively affects adoption. It was assumed that more information increases knowledge and reduces uncertainties about the benefits and impacts of adoption (Feder et al., 1985). The variable indicates farmer's access to technical information provided by sugarcane mills. The estimated negative coefficient shows a negative effect on non-adoption. The OR, 0.1869, is less than one, indicating that the predictor has a negative effect on the probability of non-adoption. Using OR, one can also say that the chance of a farmer being a non-adopter decreases by 81.31% $[(0.1869-1)*100]$ if he/she has access to agricultural information provided by the sugarcane mill. Conversely, the likely of being an adopter increases. This result confirms that access to agricultural information increases the chances of a farmer becoming an adopter of PAT, which corroborates other empirical findings (Barnes et al., 2019; Larson et al., 2008; Walton et al., 2008; Watcharaanantapong et al., 2014).

It can be said that the mills had a special role in adoption decision. The sample data showed that the mills were an important channel for the adoption of two of the most adopted PATs: GNSS and images for planting row orientation (satellite/drone) and tractor/harvester with automatic guidance system. In many cases, adopting these PATs is the first step towards adopting a larger set of PATs. As shown in Table 1, 52 out of 53 (98%) adopters have adopted GNSS and images for planting row orientation, and 32 out of 53 have adopted a tractor/harvester with an automatic guidance system. In fact, the mills provide services to farmers, such as planting, harvesting, loading and transporting sugarcane. Analysis of the survey data showed that many adopters of GNSS and image for planting row orientation (satellite/drone) reported the mill as the main provider of data analysis (58%) and data collection (52%). In addition, 56% of these adopters reported that the mill was their provider of planting operations, in which the mill was the owner of equipment used in these operations. The value and technical conditions of these services are defined in formal contracts, which are negotiated with the technical staff of the mills. The latter has the accumulated *learning by doing* knowledge, as some mills have already adopted planting row orientation for mechanized operations with autopilot in their own fields. This knowledge is diffused among farmers, mainly among those who buy mills' services. Therefore, the mills have become an important entry channel for the adoption.

The other variables for information sources, AGRICULTURAL ADVISOR, MACHINERY SUPPLIER and AGRICULTURAL EVENT, were not statistically significant in the logit model. However, AGRICULTURAL ADVISOR and AGRICULTURAL EVENT were significant in the Poisson model for adoption intensity, as will be shown in the next section.

The variable LOG SUGARCANE AREA was used to test the effect of production scale. Several studies on the adoption of PATs used the farm size variable as a proxy for production scale (Daberkow and McBride, 2003; Walton et al., 2010; D'Antoni et al., 2012; Tamirat et al., 2018; Barnes et al., 2019). In all cases, farm size showed a positive effect on the adoption of PATs. LOG SUGARCANE AREA had a positive and statistically significant effect on the adoption in the logit model (Table 4), corroborating the findings. The OR shows that farmers who own large areas of sugarcane are more likely to be in the adopter group. The mean area of sugarcane in the group of non-adopters was 278.7 hectares, while in the group of adopters it was 1125.5 hectares. The survey also showed that 32% of non-adopters reported farm size as a barrier to adoption. These figures clearly indicate a threshold for the adoption of even the most diffused PATs, such as the GNSS and images for planting row orientation. This result also supports the proposition that there is a critical minimum size below which adoption cannot occur, mainly due to technological indivisibilities (Feder et al., 1985). Large farms enable the adoption of high-cost technologies and services associated with them. This result corroborates the findings of Groher et al. (2020), Kendall et al. (2022) and Kolady et al. (2021).

The benefits perceived by farmers when adopting PA are centered on increased productivity and the economic benefits of reducing the use of inputs (Barnes et al., 2019; Kendall et al., 2022; Kolady et al., 2021; and Tey & Brindal, 2021). Empirical studies have identified a positive effect on adoption when farmers perceive that the adoption of PATs would increase productivity (Paxton et al., 2011; D'Antoni et al., 2012; Allahyari et al., 2016; Watcharaanantapong et al., 2014). However, a negative effect on adoption was found when farmers had the perception that PATs would increase production costs (Khanal et al., 2019). Two variables were used in the model of to test the effect of farmers' perception of PATs: YIELD PERCEPTION and COST PERCEPTION. YIELD PERCEPTION measured farmers' perception that the adoption of PATs would increase yields, while COST PERCEPTION measured farmers' perception that the adoption of PATs would increase cost. Non-adopters reported perceptions which they had at the time of the interview, while adopters reported the perceptions they had before adopting a PAT. A positive and statistically significant effect of YIELD PERCEPTION was found in the logit model. This result corroborates the findings of other empirical studies. However, the statistically non-significant parameter of COST PERCEPTION did not show an effect on adoption, therefore the hypothesis of a negative effect was not confirmed.

SCHOOLING and EXPERIENCE were used to test the positive effect of the human capital hypothesis. They have been used to measure farmer's ability to perceive and interpret new information (Mizumoto, 2009). Studies have shown that the higher the level of education of the farmer, the greater the chance of PATs being adopted (Paxton et al., 2011; Walton et al., 2008). These studies showed that farmers with a higher level of education have greater ability to interpret information and data generated by PATs and, therefore, have a higher probability of adoption when compared to farmers with lower level of education. However, the statistically non-significant parameters of SCHOOLING and EXPERIENCE showed no effect on adoption. Nevertheless, EXPERIENCE had an effect on adoption intensity, as will be shown in the next section.

Some PATs are high-cost and capital-intensive technologies that require availability of sufficient financial resources. (Daberkow and McBride, 2003). Consequently, access to credit can promote the adoption of PATs. The variable CREDIT was used as proxy for the availability of financial resource. Kendall et al. (2022) showed that access to credit positively affects the adoption of certain PATs. This predictor was not significant in the logit model, although it was significant in the Poisson regression for adoption intensity, as will be discussed in the next section.

The dependence of farmers on farm income has been investigated in studies which analyze the adoption of PATs (Walton et al., 2008; Watcharaanantapong et al., 2014; Paustian and Theuvsen, 2016). According to Watcharaanantapong et al. (2014), farmers whose income comes mainly from agriculture are more likely to adopt PATs to reduce production risks. The variable SUGARCANE DEPENDENCE was used as a proxy for this type of dependence, but the parameter was not significant in the logit model, and the hypothesis of a positive effect on adoption was not confirmed.

As seen, the parameters of AGRICULTURAL ADVISOR, AGRICULTURAL EVENT and EXPERIENCE were not significant in the logit model, but were significant in the Poisson model. This stems from the binary dependent variable in the logit model, which takes the value 1 for all adopters, regardless of the number of PATs adopted. Therefore, the adoption intensity is not considered, as is the case with the Poisson model.

The poisson count model for intensity of adoption

Table 4 shows the coefficients (β) and the Incidence Rate Ratios (IRR) of the Poisson count model for intensity of adoption. The IRR is e^β, and does the exact same thing as the OR used in the logit model. However, the IRR indicates how changes in a predictor variable affect the mean of the number of PATs adopted by a farmer, keeping the other variables constant. An IRR greater than one shows that the mean of the expected number of PATs adopted by a farmer increases when the predictor variable increases by one; the expected number of adopted PATs decreases if IRR is less than one. Farmers who had access to private technical advisor (AGRICULTURAL ADVISOR, for which the IRR is 1.66), for example, adopt, on average, 66% more PATs than those who did not.

The results showed that agricultural information plays a role in the intensity of adoption. Two predictors were statistically significant, AGRICULTURAL ADVISOR and AGRICULTURAL EVENT. Both have a positive effect on the number of PATs adopted. The Poisson model shows that access to private agricultural advisors increases the number of PATs adopted by 66%, which is a substantial impact. The survey data showed that technical advisors were hired by only 14.5% of all farmers in the sample (adopters and non-adopters). This proportion rises to 26.4% of all adopters and 60% of the adopters of four or more PATs. Furthermore, Table 1 showed that both the georeferenced grids for soil sampling and the images for mapping pests and yields were mainly adopted by farmers who adopted three or more PATs. These PATs require site-specific knowledge to interpret the data and make recommendations. Unlike them, GNSS and Images for planting row orientation, which was adopted individually, do not require as much new knowledge and effort, thus hiring private advisors may not be necessary. Therefore, access to agricultural

information provided by private technical advisors has played an important role in the process of scaling up the use of PATs. This result corroborates the findings of Paustian and Theuvsen (2016); Barnes et al. (2019); and Tey and Brindal (2021).

The information obtained in agricultural events (lectures, field days and agricultural fairs) played a minor role in the intensification, even though the estimate for AGRICULTURAL EVENT was statistically significant. The IRR in the Poisson model shows that farmers who participated in a agricultural events adopt 3% more PATs on average than those who do not. Nevertheless, the positive effect supports the findings of Watcharaanantapong et al. (2014); Tamirat et al. (2018); and Khanal et al. (2019). Many of these agricultural events are sponsored by farmer organizations such as cooperatives and associations, research organizations and government extension services. These events are an opportunity to share information and experience about the new technology with technicians and peers. Most of the knowledge brought by farmers to these events was acquired in a learning-by-doing process, and are generally seen by their peers as a more reliable source of information (Buck & Alwang, 2011). This kind of information helps to improve farmers' evaluation of risks, which may favor intensification.

The parameter of the variable SUGARCANE MILL was significant in the logit model of Sect. 3.1, but not in the Poisson model. It can thus be said that the mills are entry channels for the adoption of PATs, however they do not play a role in intensification. Farmers would depend on information provided by private advisors and agricultural events to increase the number of PATs, as shown in the Poisson model.

The parameter of MACHINERY SUPPLIER did not show statistical significance in the Poisson model, replicating the result of the logit model. Therefore, the hypothesis that information provided by machinery suppliers would have a positive effect on adoption and adoption intensity was rejected. In addition, the survey data showed that 19% of adopters reported the lack of assistance from suppliers as a problem they faced when deciding to adopt. It can be suggested that suppliers improve strategies to be considered a relevant source of information.

The parameter of EXPERIENCE was statistically significant at 10% level in the Poisson model, which shows that previous experience with PATs positively affects intensification. This result indicates that the accumulated knowledge in a *learning-by-doing* process increases the ability to evaluate an innovation and ultimately affects the decision to adopt (Bell & Pavitt, 1993). The learning performance is higher and its marginal cost is lower when the learning object is related to what is already known (Zahra and George, 2002). Kendall et al. (2022) found that adopting unknown PATs requires additional learning time to obtain the necessary skills for using information systems and interpreting data outputs. Thus, previous experience reduces the time spent on learning and increases the likelihood of adoption. This result corroborates the findings of Paxton et al. (2011), D'Antoni et al. (2012), Allahyari et al. (2016) and Paustian and Theuvsen (2016).

Access to rural credit, measured by the variable CREDIT, had a positive and statistically significant effect on the intensity of adoption. The survey data showed that 80% of adopters of three PATs had access to rural credit. This percentage rises to 100% of adopters of four or more PATs. Brazilian credit programs provide subsidies to promote the diffusion of agricultural technologies. For example, farmers can apply for the program INOVAGRO (acronyms for rural credit for precision agriculture technologies), which provides credit for the adoption PATs. The amount committed to INOVAGRO was 3.25% of the total amount of subsidized rural credit in Brazil in the 2022/23 season (BNDES, 2023). This

result corroborates the findings of Daberkow and McBride (2003) and Isgin et al. (2008). It should be noted that 67% of non-adopters in the sample reported the high cost of PATs as a barrier to adoption, highlighting the importance of rural credit in overcoming financial restrictions.

The parameters of YIELD PERCEPTION were statistically significant in the Logit and Poisson models. The variable measures farmers' perception that PATs could increase sugarcane yield. This predictor had a positive effect on both adoption and adoption intensity. The IRR in the Poisson model shows that farmers who have this perception adopt 75% more PATs on average than those who do not. Therefore, the Poisson model reveals the important role of this type of perception in intensification. However, the COST PERCEPTION parameter was not statistically significant in both models. Therefore, the hypothesis of a negative effect caused by the perception that PATs increase the cost was not confirmed. These results suggest that farmers see PATs as productivity-enhancing innovations, and cost is not seen as a barrier to adoption. The benefits perceived by farmers are centered on increasing productivity and reducing the use of inputs.

The variable LOG SUGARCANE AREA was used to test the effect of production scale. In the logit model, the parameter of this variable was significant and indicates that size can be a barrier to the adoption of even the most diffused PATs, such as GNSS and images for planting row orientation. However, it was not significant, indicating that, once a critical size is reached, the scale does not affect the intensity of adoption. This finding corroborates the proposition by Giua et al. (2022) on the adoption of smart agricultural technologies in Italy, where large scale is a necessary condition for adopting, but it was not determinant for the intensity of adoption.

The parameters of the variables MACHINERY SUPPLIER, SCHOOLING, and SUGARCANE DEPENDENCE were not statistically significant in the Poisson and logit models.

Conclusion and implications

The production of sugarcane has economic, social and environmental relevance in several countries. It is assumed that PATs can increase resource use efficiency and environmental sustainability in sugarcane production (Carrer et al., 2022). Therefore, understanding the factors that affect farmers' adoption decisions is useful for designing policies aimed at their diffusion.

The results showed that GNSS and images for planting row guidance (satellite/drone) is the most diffused PAT, followed by tractor/harvester with automatic guidance system, and georeferenced grids for soil sampling. Few farmers adopted images (satellite/drone) for mapping pests and yields, and VRA of fertilizers and pesticides. However, many farmers in the sample did not adopt any of these PATs, while some adopted one, and others adopted a combination of two or more, suggesting complementarity among them.

A ZIP model was used to test hypotheses on determinants of this heterogeneity. The logit model of this approach showed that the information provided by sugarcane mills, the scale of production and the farmer's perception that PATs increase productivity affect the adoption of at least one of these PATs. The Poisson model showed that information from agricultural advisors, information from agricultural events, farmer's previous experience

with PATs, access to credit, and farmer's perception that PATs increase productivity affect the number of PATs adopted, that is, the intensity of adoption.

The ZIP regression provided results that would not be obtained by estimates of a binary logit/probit model alone. In the analysis on the role of information, the logit model showed that information from mills positively affects adoption, and suggested they are an important entry channel. The logit model also showed that agricultural advisors and agricultural events did not affect adoption. However, the Poisson model showed that information from agricultural advisors and agricultural events are important determinants of intensity of adoption, while mills had no role in this. Therefore, the ZIP regression expanded the scope of the analysis, bringing additional results.

The Poisson model showed that the intensity of adoption is also affected by access to credit, farmers' previous experience with PATs, and their perception that PATs would increase yield. These results contribute to the scarce empirical literature on these types of determinants.

It can be said that the mills had a prominent role in the adoption. The information provided by them is transmitted through their transactions with farmers. They are not only buyers of sugarcane, but also providers of services to farmers, such as planting, harvesting, and loading and transporting sugarcane. They provide, for example, planting operations, which can be carried out with machinery equipped with PATs. Data collection and analysis can also be performed by the mills' personnel.

Despite the relevance of some sources of information, such as mills and private advisors, they were not sufficient to intensify use of PATs, notably in the case of small farmers. There is room for rural organizations, research institutes and public rural extension to act on this matter. The results of the logit model showed that small farmers face barriers to becoming adopters, mainly adopters of several PATs. Their small scale does not cope with the indivisibility of some PATs. A possible strategy to overcome the problem could be, for example, collective actions carried out by farmers' organizations, such as cooperatives and pools. These organizations could create their own extension service and provide other services at a lower cost. Some cooperatives in the region provide paid services related to the PATs, such as renting autopilot for tractors, renting equipment for georeferenced soil sampling, and data analysis. However, their business approach has not reached the small farmers, as the diffusion among them is still low.

The estimates also showed that the suppliers of machinery are also failing to become an important source of information. Therefore, they should improve their strategies, which can be done jointly with farmers' organizations, and public extension services. The main objective is to reduce the cost of information and the cost of using PATs.

Access to rural credit was determinant for the intensity of adoption (Poisson model), which involves large areas of sugarcane. Although the Brazilian government has a low-cost rural credit policy for small and medium-sized farmers, it has not been sufficient to increase the number of PATs adopted by these farmers. Farmer organizations and PAT suppliers can take advantage of the availability of this policy to enhance PAT diffusion. It may be necessary to adapt terms and interest rates to the needs of small farmers.

Appendix

See Tables 5, 6, 7, 8.

Table 5 Sample counties

Sampled municipalities	Area with cane				Sugarcane produced			
	Municipality*		Sample		Municipality*		Sample	
	(ha)	%[1]	(ha)	%[2]	(tn)	%[1]	(tn)	%[2]
Aguaí	11.417	0,2	5.107	6,3	772.504	0,2	513.585	7,2
Americana	4.648	0,1	575	0,7	93.960	0,0	50.775	0,7
Anhembi	4.541	0,1	31	0,0	288.939	0,1	1.432	0,0
Araraquara	28.819	0,6	2.173	2,7	2.260.290	0,7	192.724	2,7
Araras	32.647	0,7	8.647	10,6	2.751.237	0,8	813.941	11,3
Artur Nogueira	3.043	0,1	2.720	3,3	240.629	0,1	226.371	3,2
Boa Esp. do Sul	30.143	0,6	401	0,5	1.953.107	0,6	34.460	0,5
Cardoso	4.816	0,1	300	0,4	277.630	0,1	29.440	0,4
Charqueada	6.495	0,1	37	0,0	397.755	0,1	2.783	0,0
Colina	24.174	0,5	1.111	1,4	1.739.822	0,5	93.652	1,3
Cordeirópolis	4.888	0,1	600	0,7	421.219	0,1	60.651	0,8
Cosmópolis	5.657	0,1	326	0,4	453.357	0,1	25.738	0,4
Descalvado	27.125	0,6	2.809	3,5	2.012.669	0,6	213.799	3,0
Gavião Peixoto	12.271	0,3	824	1,0	863.705	0,3	73.256	1,0
Holambra	71	0,0	23	0,0	3.398	0,0	2.101	0,0
Jaboticabal	43.252	0,9	702	0,9	3.719.451	1,1	71.331	1,0
Jaguariúna	2.740	0,1	27	0,0	177.495	0,1	3.053	0,0
Laranjal Paulista	3.003	0,1	494	0,6	175.030	0,1	48.686	0,7
Leme	17.044	0,4	1.020	1,3	1.401.390	0,4	84.145	1,2
Luís Antônio	25.295	0,5	38	0,0	1.870.606	0,6	3.696	0,1
Matão	16.555	0,4	1.414	1,7	1.368.468	0,4	147.327	2,1
Mogi Mirim	5.201	0,1	700	0,9	362.955	0,1	62.982	0,9
Mombuca	6.404	0,1	154	0,2	359.562	0,1	13.339	0,2
Monte Aprazível	22.503	0,5	5.746	7,1	1.372.135	0,4	501.913	7,0
Monte A. Paulista	14.551	0,3	2.809	3,5	1.142.215	0,3	296.738	4,1
Motuca	7.195	0,2	587	0,7	611.419	0,2	55.483	0,8
Nova Europa	11.592	0,2	638	0,8	879.150	0,3	64.847	0,9
Paraíso	9.355	0,2	1.277	1,6	702.767	0,2	142.663	2,0
Piracicaba	40.975	0,9	8.190	10,1	2.933.390	0,9	584.471	8,1
Pirassununga	29.568	0,6	779	1,0	2.271.499	0,7	83.082	1,2
Poloni	4.173	0,1	1.915	2,4	305.830	0,1	184.813	2,6
Ribeirão Bonito	14.078	0,3	2.767	3,4	859.476	0,3	240.951	3,4
Riodas Pedras	8.259	0,2	3.718	4,6	588.517	0,2	343.417	4,8
Saltinho	2.193	0,0	319	0,4	128.640	0,0	22.696	0,3
Snta Adélia	23.329	0,5	536	0,7	1.769.926	0,5	40.853	0,6
Snta C. Conceição	3.956	0,1	153	0,2	303.350	0,1	15.563	0,2
Snta C.Palmeiras	16.346	0,4	4.872	6,0	1.455.953	0,4	468.181	6,5
Snta Lúcia	8.167	0,2	56	0,1	635.965	0,2	5.193	0,1
Snta R. P. Quatro	14.901	0,3	3.562	4,4	1.044.489	0,3	256.209	3,6
Snta R.Viterbo	8.371	0,2	170	0,2	574.393	0,2	10.350	0,1
São Carlos	27.848	0,6	192	0,2	2.001.903	0,6	15.563	0,2
São Simão	15.119	0,3	447	0,5	1.068.372	0,3	32.229	0,4

Table 5 (continued)

Sampled municipalities	Area with cane				Sugarcane produced			
	Municipality*		Sample		Municipality*		Sample	
	(ha)	%[1]	(ha)	%[2]	(tn)	%[1]	(tn)	%[2]
Tabatinga	17.631	0,4	843	1,0	1.263.331	0,4	78.335	1,1
Tambaú	20.329	0,4	4.239	5,2	1.501.553	0,4	410.861	5,7
Tietê	7.386	0,2	5.107	6,3	499.515	0,1	363.141	5,1
União Paulista	3.574	0,1	1.081	1,3	259.919	0,1	82.388	1,1
Votuporanga	7.322	0,2	1.149	1,4	495.561	0,1	103.884	1,4
Total	658.970	14,1	81.390	12,4	48.634.446	14,5	7.173.090	14,7
Total do estado	4.660.068	100		1,7	336.055.867	100		2,1

*Data on the area and production of sugarcane from the Municipality were extracted from IBGE (2017). [1]Percentage of the area with sugarcane or production in the Municipality in relation to the total area or production of the state; [2]Percentage of the area with sugarcane or sample production in the Municipality in relation to the total sample area

Table 6 Poisson Model

Variable	IRR	Coefficient	p > |Z|
Agricultural consulting	1;974	0;680	0;007
Machinery supplier	1;018	0;018	0;934
Sugarcane mill	1;411	0;344	0;078
Agricultural event	1;033	0;033	0;005
Schooling	1;208	0;189	0;388
Experience	1;635	0;492	0;049
Log sugarcane area	1;230	0;207	0;019
Credit	1;275	0;243	0;300
Sugarcane dependence	2;339	0;850	0;092
Yield perception	1;070	0;068	0;781
Cost perception	0;684	-0;380	0;078
Constant	0;051	-2;978	0;000

Table 7 correlation matrix variables

		a	b	c	d	e	f	g	h	i	j	k	1
Agricultural consulting	a	1											
Machinery supplier	b	0,143	1										
Sugarcane mill	c	– 0,006	0,213	1									
Agricultural event	d	– 0,016	– 0,003	– 0,013	1								
Schooling	e	0,212	0,092	0,080	0,262	1							
Experience	f	0,094	0,026	– 0,021	0,079	0,054	1						
Log sugarcane area	g	0,336	0,338	0,099	0,323	0,362	0,172	1					
Credit	h	– 0,014	0,098	0,050	0,142	– 0,086	0,067	0,275	1				
Sugarcane dependence	i	– 0,020	0,213	0,155	0,142	0,183	0,023	0,295	0,091	1			
Yield perception	j	– 0,066	0,034	0,072	0,067	– 0,051	– 0,107	– 0,123	– 0,125	– 0,148	1		
Cost perception	k	0,130	– 0,073	– 0,034	– 0,029	– 0,220	– 0,036	– 0,211	0,024	– 0,112	– 0,026	1	
Credit_mill	1	– 0,195	– 0,137	– 0,102	0,045	– 0,070	– 0,145	– 0,147	– 0,134	– 0,078	0,044	– 0,067	1

Table 8 Pearson test goodness-of-fit poisson model

Deviance goodness-of-fit	148;6055
Prob > chi2(119)	0;2570
Pearson goodness-of-fit	179;5530
Prob > chi2(119)	0;2000

Author contributions All authors contributed to the study conception and design. CIM, MdMBV and MJC: The data collection and analysis were performed. CIM and HMdSF: The first draft of the manuscript was written, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Data availability The data are available from the corresponding author upon request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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