Impacts of the use of biological pest control on the technical efficiency of the Brazilian agricultural sector

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Abstract

This paper aimed to assess the impact of the intensive use of biological control on the technical efficiency of the Brazilian agricultural sector. The study also considered the influence of factors such as technical assistance, rural financing, and membership in cooperatives or class entities on efficiency measures. It was estimated stochastic production frontiers for regions intensively using and not using biological control, considering potential selection bias. Results demonstrate that areas with intensive use of biological pest management have a 0.863 technical efficiency score, while this score is 0.823 for nonintensive areas. This means that the intensive regions would be closer to their efficiency frontiers. Additionally, technical assistance and membership in cooperative or class entities increase efficiency by 6 and 2.5%, respectively. It can be concluded that the intensive adoption of biological control can raise the productive performance of the Brazilian agricultural sector. Therefore, it must be highlighted the importance of formulating joint policies (e.g., credit+rural extension) for the adoption of biological control to be a feasible option to promote the sustainable development of the Brazilian agricultural sector.

Keywords Entropy balancing · Productivity · Stochastic production frontier · Sustainability

Introduction

The search to guarantee food security in the face of population growth, which increases the demand for food, has led to the development of new technologies aimed at increasing agricultural productivity. Considering that pests and diseases cause significant crop losses, crop protection is essential for food security (Oerke and Dehne 2004; Hawkins et al. 2019).

The use of pesticides has been one of the main alternatives that farmers have adopted to prevent these losses. According to data from the Agricultural Census, in 2006, while 26.97% of the Brazilian agricultural establishments used pesticides, only 9.72% used alternative methods to control pests and plant diseases. The excessive and incorrect use of agrochemicals has caused incalculable damage to the environment and the health of the population through the

contamination of soil, water, food, and animals; poisoning of farmers; biodiversity reduction; development of resistance to certain active ingredients of pesticides; and destruction of beneficial organisms (Bettiol et al. 2017).

It is noteworthy that the development of resistance to certain active ingredients and the effect of pesticides on natural predators have made the pesticide control of pests and pathogens increasingly difficult (Wilson and Tisdell 2001; Bale et al. 2008). According to Hawkins et al. (2019), the evolution of resistant pathogens, weeds, and pests has been a threat to the effectiveness of pesticides.

In this context, biological control emerges as an alternative for phytosanitary control, due to its agronomic advantage of reducing the chances of pests and pathogens developing resistance to pesticides (Bale et al. 2008; Fontes and Valadares-Inglis 2020). In addition, given a scenario in which pest control alternatives that preserve natural resources and environmental quality are sought, biological control becomes fundamental for sustainable management (Naranjo et al. 2015).

According to the Brazilian Agricultural Research Corporation (EMBRAPA), biological control is a technique that seeks to suppress the population of a certain pest, making it less abundant or less harmful, through living organisms.

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These organisms, the biological control agents, are beneficial insects, predators, parasitoids, and microorganisms, which may be native or exotic (from other countries), with pathogenic potential against insect pests. In summary, biological control is premised on controlling pests and pathogens using natural enemies that are harmless to the environment and the health of the human population (EMBRAPA 2020).

Fontes and Valadares-Inglis (2020) state that the products used in biological control do not generate residues or pose toxicological risks. Therefore, they do not harm the environment or health. Another advantage over pesticides is the likely specificity against certain species of pests. Biological control does not affect other organisms (nontarget species) that benefit the agricultural environment, which provides increased control over time (Bale et al. 2008). In other words, biological control becomes a useful tool for the sustainable development of the agricultural sector.

Despite these benefits, the use of biological control is still incipient in Brazil. According to data from the 2006 Agricultural Census, only 1.30% of the rural establishments used biological control in the reference period. According to Parra et al. (2002), difficulties in the transfer of biological control technology limit its adoption by farmers. Colmenarez et al. (2016) highlight the lack of knowledge and technical assistance as limiting factors for the implementation of biological control.

Additionally, pesticides have a relatively quick and thorough effect, which ensures the death of a significant number of pests in the absence of resistance (Bale et al. 2008) and makes farmers prioritize this method of pest control.

However, although in the short term the use of pesticides has a relatively low cost and increases agricultural yields, this relationship can be reversed in the long run, with increased production costs and reduced yields (Wilson and Tisdell 2001). At the same time, the search for sustainable development highlights concerns about the health of the population that is exposed to pesticides through direct contact with the product (agricultural workers) or indirectly, through residues in food (final consumers), and the health of the environment in which nontarget species are affected by the pesticide (Seiber et al. 2018).

In this context, assuming that farmers will adopt a profit-maximizing behavior, it is important to carry out research that demonstrates both the technical and economic benefits arising from the use of more sustainable agricultural practices, such as biological control, to promote their adoption. It is noteworthy that few studies analyze the economic impacts of the implementation of this technology (McFadyen 2008; Naranjo et al. 2015; Türkten et al. 2017). In addition, most studies analyze specific cultures (Van Den Berg et al. 2000; Bokonon-Ganta et al. 2002; Fronzaglia 2006; Monteiro et al. 2006; Bueno et al. 2011; Colloff et al. 2013).

Therefore, this research aims to evaluate the effect of the intensity of the adoption of biological control on the agricultural performance of Brazilian producers. Technical efficiency, which represents the maximum product obtained through the optimal allocation of inputs in the production process, according to Lima (2006), is used as a performance measure. It is noteworthy that the results from the measurement of efficiency can help farmers make decisions about the adoption of new technologies to increase their production (Tupy and Yamaguchi 1998).

Thus, to meet the proposed objective, data from the 2006¹ Brazilian Agricultural Census, published by the Brazilian Institute of Geography and Statistics (IBGE), were used and initially paired using entropy balancing, which enabled evaluation between municipalities that intensively adopt the biological control with those that adopt it less intensively. The stochastic production frontier for each group was estimated using the two-stage procedure developed by Heckman (1979). The combination of these approaches generates results less susceptible to selection bias in observable and unobservable variables.

The results of this research, in addition to contributing to the scarce literature on the subject, will help guide policies by revealing economic benefits from the adoption of biological control. Thus, the development and implementation of policies that encourage the adoption of this technique for phytosanitary control can help the sustainable development of the Brazilian agricultural sector.

The article consists of three sections in addition to this introduction. In the next section, the empirical strategy is presented; in the third section, the results are presented and discussed; and in the fourth section, the study is concluded.

Materials and methods

To assess the effects of the intensity of biological control adoption on the technical efficiency of producers, the potential selection bias caused by the characteristics of farmers and rural properties must be considered. Thus, an estimation procedure divided into two parts was adopted.

The entropy balancing method was used first to find a control group as similar as possible to the group of adopters, to reduce the selection bias caused by observable characteristics. Second, stochastic production frontiers were estimated through the two-stage procedure described by Heckman

¹ In the 2017 Brazilian National Agricultural Census, there is no question on the adoption of biological control by the producer responsible for the establishment. Thus, the 2006 Brazilian Agricultural Census was used in the present study. Because the analysis is aggregate and structural, it does not diminish the meaning of the analysis.

More details can be found in section “2.4 Variables and Data”.

(1979): (i) in the first stage, the selection equation is run using the probit model that seeks to explain the probability of representative farms intensively adopting biological control; and (ii) in the second stage, the stochastic production frontier is estimated for each group adopting intensive and nonintensive biological control, incorporating the inverse Mills ratio (IMR) obtained in the first stage, in addition to the sample being weighted with the entropy balance results.

The combination of these two approaches can provide mean technical efficiency scores less susceptible to biases caused by both observable and unobservable characteristics. This strategy has been recently used by Bravo-Ureta et al. (2012), Duangbootsee and Myers (2014), Reyna et al. (2020), Freitas et al. (2021).

Next, each method used to carry out this study is briefly presented, in addition to the source and treatment of the data.

Entropy Balancing

Entropy balancing was proposed by Hainmueller (2012) as a data preprocessing technique that allows researchers to obtain balanced samples in observational studies with binary treatment. Through a reweighting scheme, a set of weights is adjusted in such a way that an exact balance is reached in the first, second, and third moments of the distribution of the explanatory variables (covariates) in the treatment and control groups. This allows the selection of a control group as similar as possible to the group treated according to the observable characteristics.

Unlike other matching methods, entropy balancing directly estimates the weights of a set of equilibrium constraints that exploit the researcher's knowledge about sample moments. Thus, entropy balancing generalizes the propensity score weighting approach and has the advantage of directly adjusting the unit weights to the known moments of the sample and ensuring a better balance at all times of the covariate included in the reweighting (Hainmueller 2012).

Furthermore, according to Hainmueller (2012), entropy balancing dispenses with an iterative process to obtain the propensity score and eliminates the need to constantly verify whether the balancing property was satisfied.

To demonstrate the proposed method, imagine a sample composed of n_1 treated units and n_0 control units that are randomly drawn into populations with sizes N_1 and N_0 , respectively, where $n_1 \leq N_1$ and $n_0 \leq N_0$.

Assume a binary treatment indicator, $D_i \in \{1, 0\}$, with value 1 if i belongs to the treatment group (uses biological control) and 0 if not. Let X be a matrix composed of the data of j exogenous pre-treatment variables; X_{ij} corresponds to the value of the j -th variable for unit i so that $X_i = [X_{i1}, X_{i2}, \dots, X_{ij}]$ refers to the feature line vector for unit i , and X_j refers to the column vector with j -th covariates.

The entropy balancing weight determined for each control unit (w_i) is selected by a weighting scheme that minimizes the metric entropy distance, as shown below:

$$H(w) = \sum_{\{i|D=0\}} w_i \log \left(\frac{w_i}{q_i} \right) \quad (1)$$

This is subject to the following balancing and normalization restrictions:

$$\sum_{\{i|D=0\}} w_i c_{ri}(X_i) = m_r, \text{ with } r \in 1, \dots, R \quad (2)$$

$$\sum_{\{i|D=0\}} w_i = 1 \quad (3)$$

$$w_i \geq 0, \forall_i / D = 0 \quad (4)$$

in which $q_i = 1/n_0$ is a basis weight, and $c_{ri}(X_i) = m_r$ denotes a set R of restrictions imposed on the moments of the covariates in the reweighted control group.

The variables that will be included in the reweighting must be defined initially. Subsequently, for each variable, a set of equilibrium constraints (Eq. 2) is specified to equalize the moments of the distribution of the covariates between the treatment and control groups. Moment constraints can include mean, variance, and asymmetry, which correspond, respectively, to the first, second, and third moments. A typical balancing constraint is formulated so that m_r contains the moment of order r -th of a specific variable X_j of the treatment group, and the moment function is specified for the control group as $c_{ri}(X_{ij}) = X_{ij}^r$ or $c_{ri}(X_{ij}) = (X_{ij} - \mu_j)^r$, where μ_j is the mean.

In this context, entropy balancing seeks a set of weights $W = [w_1, \dots, w_{n_0}]$ which minimizes the entropy distance between W and the base weight vector $Q = [q_1, \dots, q_{n_0}]$ (Eq. 2), given the restrictions of equilibrium (Eq. 3), normalization (Eq. 5), and non-negativity (Eq. 4). In other words, this procedure ensures that the weights are adjusted so that the equilibrium constraints are met while keeping the maximum proximity to the evenly distributed base weights, to retain information in the weighted data.

The moment restriction used in this study ensures that the first moment (average) of the covariates is met. These variables were selected because they have the potential to influence the rural producer's decision to use biological control. Thus, for all covariates, the means in the treatment group were calculated, and a set of weights was defined, by which the weighted means in the control group were similar. Once the distributions of independent variables were adjusted, those weights were used in subsequent estimates free from any selection bias caused by observable variables.

Sample selection model

The first stage of Heckman's (1979) procedure consists of estimating the binary probit model to predict the probability of intensive adoption of biological control. From this perspective, the selection equation represented by Eq. 5 is defined as follows:

$$BC_i = \delta_0 + \sum_{j=1}^n \delta_j V_{ij} + \varepsilon_i \quad (5)$$

where BC is the binary variable that takes on the value of 1 if the representative farmer makes intensive use of biological control and 0 otherwise. Furthermore, the term ε refers to the random error, such that $\varepsilon \sim N(0, I)$. V_{ij} refers to the variables used in the estimation of the probability model, which are specified in Sect. 2.4.

Then, through the error of the estimated probit model, the IMR was calculated as described by Heckman (1979). The IMR is defined in Eqs. 6 and 7:

$$\lambda_i^{BC}(\alpha_\varepsilon) = \frac{\varphi(\alpha X_i / \sigma_\varepsilon)}{\Phi(\alpha X_i / \sigma_\varepsilon)} \quad (6)$$

$$\lambda_i^{NBC}(\alpha_\varepsilon) = \frac{\varphi(\alpha X_i / \sigma_\varepsilon)}{1 - \Phi(\alpha X_i / \sigma_\varepsilon)} \quad (7)$$

where φ is the standard normal probability density function, and Φ is the cumulative normal distribution function. $\lambda_i(\alpha_\varepsilon)$ is the IMR. According to Heckman (1979), it is inserted as an independent variable in the main regression (stochastic production frontier) to minimize the sample selectivity bias, since this bias is similar to a specification error originating in the omission of covariates.

Following the estimation, it was analyzed the statistical significance of the parameter ρ that accompanies λ and its sign. In this study, ρ is statistically significant, which reveals the importance of the selection bias correction implemented.

Stochastic production frontier

After entropy balancing, the technical efficiency levels of the representative producers are estimated, considering whether or not to adopt biological control intensively, using the stochastic production frontier model, corrected for selectivity bias.

Technical efficiency results in the maximum possible production, given a set of factors and the adoption of a given

technology. In other words, for any agricultural establishment with a certain level of technology, the quantity produced can be above or below the production frontier. In this sense, according to Taylor and Shonkwiler (1986), the extent to which the production of an establishment is below the frontier becomes a measure of technical inefficiency.

Aigner et al. (1977), Meeusen and Van Den Broeck (1977), Taylor and Shonkwiler (1986), Battese (1992), Coelli and Battese (1996), and Coelli et al. (1998) are some of the authors who suggest that the stochastic production frontier be used to measure the technical efficiency of the agricultural and livestock sector. Based on this recommendation, this study uses the stochastic frontier procedure to estimate technical efficiency. The data used for estimation are a cross section from the 2006 Agricultural Census.

The analysis of stochastic production frontiers follows a parametric approach with an econometric approach, simultaneously introduced by Aigner et al. (1977), Meeusen and Van Den Broeck (1977). The Cobb–Douglas function was selected as the form of the production function to be estimated. This function in the logarithmic form becomes linear within our parameters, which is more appropriate for Heckman's procedure (1979). Furthermore, Chambers (1988) and Silva (1996) list other advantages of using this functional form, such as (i) the regression coefficients are the production elasticities; (ii) the sum of the coefficients results in the return to scale, as it is a homogeneous function; and (iii) having a smaller number of estimated parameters compared to the functional form of the translog reduces the probability of multicollinearity in the estimation of the production function.

Taylor and Shonkwiler (1986) argue that the stochastic nature of the model is directly related to the possibility of the existence of factors that cause border deviations and that cannot be controlled by the producer responsible, such as climatic variations, pests, and diseases. In this study, boundaries for intensive and nonintensive biological control were estimated. A pooled model for Brazil was also estimated, to verify the distance of each group (intensive and non-intensive) to its efficiency frontier. The function of a stochastic production frontier in its generic form is given by Eq. 8:

$$Y_i = f(X_i \beta) e^{(v_i - u_i)} \quad (8)$$

where Y_i is the value of the quantity of production by representative producer i in 2006, X_i is a vector of expenses with inputs used in the same period, and β is a vector of

the parameters to be estimated, which define the production technology. The error terms v_i and u_i are vectors that represent different components of the error. The term v_i refers to random error and has a normal, independent, and identical distribution (*iid*), truncated at zero and with variance σ_v^2 ($v \sim iid N [0, \sigma_v^2]$). In addition, this error term captures the stochastic effects over which the productive unit has no control (natural disasters, measurement errors, etc.).

The term u_i refers to the technical inefficiency of the i -th representative producer, whether intensive or not in their use of biological control. According to Coelli et al. (2005), this is the part of the error that represents a downward deviation from the production frontier and non-negative random variables ($u_{ij} \geq 0$). Technical efficiency is measured by the unilateral component. The condition greater than or equal to zero ensures that all observations are located below the boundary.

$$u_i = \mu Z_i + \varepsilon_i \quad (9)$$

The vector of variables that explains the technical inefficiency is represented by Z , and μ is a vector of parameters related to Z . The technical inefficiency u_j , by hypothesis, is independently distributed, but it is not identically distributed, with normal distribution truncated at zero ($u_i \geq 0$), averaged μZ_i and variance σ_ε^2 , since $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$.

The stochastic production frontier function is added to the dummy variables representing the Brazilian regions² (Reg_w), as well as the climatic variables (CV), the IRM ($Mills_i$) obtained after estimating the selection equation, and the weight (W_i) given by the entropy balancing procedure. Therefore, Eq. 8 in the Cobb–Douglas general functional form results in Eq. 10.

$$\ln Y_i = \beta_0 + \sum_{k=1}^n \beta_k \ln X_{ki} + \sum_{w=1}^3 \beta_w Reg_w + \beta_j CV + \rho Mills_i + v_i - u_i \quad (10)$$

To obtain the measure of technical efficiency after estimating the stochastic production frontier function, the procedure by Jondrow et al. (1982) and the separation of the deviations from the frontier into their random and inefficiency-related elements were carried out. Thus, the technical efficiency of a given observation can be obtained with the ratio between the observed product and the potential product of the sample, defined by Eq. 11.

$$TE_i = \frac{Y_i}{Y_i^*} = \frac{Y_i}{f(X_i)} = \frac{\exp(X_i \beta + v_i) \exp(-u_i)}{\exp(X_i \beta + v_i)} = \exp(-u_i) \quad (11)$$

² These dummies were inserted to capture the fixed characteristics of each Brazilian region, in addition to controlling for a possible spatial autocorrelation, as an alternative to obtain an estimate of the technical efficiency, free from these effects.

The TE_i value is in the interval $[0; 1]$, where 0 is the total inefficiency and 1, the total efficiency. Therefore, the present study aimed to estimate the parameters of Eqs. 9, 10, and 11.

Variables and data

Secondary data from the 2006 Brazilian Agricultural Census,³ the latest census released by the Brazilian Institute of Geography and Statistics (IBGE) with information on the use of biological control, were used. It must be highlighted that microdata from the 2006 Agricultural Census was not available. Therefore, the data used are not at the farm level, but at the level of administrative units (municipalities), publicly available in the IBGE Automatic Recovery System (SIDRA)⁴ (IBGE 2006). Thus, information from farms in a given municipality is aggregated to preserve the identification of rural producers. As a result, in this study, the concept of representative farms was used, and the value of each variable was divided by the number of agricultural establishments in the respective municipality. These variables represent an average, and each Brazilian municipality is considered a representative farm. A similar procedure was adopted by Rada et al. (2019), Freitas et al. (2020), Reyna et al. (2020). Thus, the maximum number of observations corresponds to 5548 municipalities visited by the Brazilian Agricultural Census in 2006. These include 67,221 farms in which biological control was used (IBGE 2006).

In this context, it is important to point out that, to create the dependent dummy variable and identify whether the municipality is intensive in agricultural establishments with the adoption of biological control, it was used the average adoption in Brazil plus half a standard deviation as the threshold, which in this research is equivalent to 4%

³ The Agricultural Census is a survey carried out by the IBGE aimed to present the Brazilian agricultural scenario by collecting information from all farms in the country. The data from this Census are made available by the IBGE in different ways and levels of aggregation and detailing of the variables: (i) online access via SIDRA, where data previously aggregated at the municipality level are stored in a table retrieval system, without the possibility to cross-reference information besides that already available; (ii) access in person, after a rigorous process to obtain authorization for use, to the Restricted Data Access Room (SAR), where microdata are available at the level of each Brazilian farm, which contain all the variables of the Agricultural Census, the most disaggregated information possible (IBGE 2006). However, due to the COVID-19 pandemic, SAR is closed. Thus, this study used aggregated data from the 2006 Agricultural Census, available from the SIDRA website, using techniques already adopted in the literature.

⁴ Brazilian Agricultural Census 2006 data can be retrieved from the IBGE Automatic Recovery System (Sistema IBGE de Recuperação Automática – SIDRA), accessible at <<https://sidra.ibge.gov.br/pesquisa/censo-agropecuario/censo-agropecuario-2006/segunda-apuracao>>.

(or 0.04). In other words, those municipalities where the percentage of farms that adopted biological control exceeds 4% are considered intensive in the use of this technique and, therefore, are included in the treated group. Those below this threshold are non-intensive municipalities (control groups). A similar procedure was performed by Silva et al. (2018), Freitas et al. (2020), Reyna et al. (2020). In common, these authors used the same strategy to work with data from the Brazilian Agricultural Census aggregated at the municipal level.

To perform the entropy balancing and run the equation of sample selection (Eq. 5), variables able to affect the intensity of the use of biological control were selected. The variables used are defined as follows: gender is a categorical variable identifying whether the farm's manager is male or female (base); age is a categorical variable related to the farm manager's age: up to 25 years old (age_25), between 25 and 35 years old (age_25to35), between 35 and 45 years old (age_35to45), between 45 and 55 years old (age_45to55), between 55 and 65 years old (age_55to65), or over 65 years old (age_65; base); schooling is a categorical variable related to the farm manager's education level: do not read and write (base), literate, incomplete elementary school, complete elementary school, agricultural technician, high school, or college degree; experience is a categorical variable that refers to the years the manager has led farm activity: up to one year (exp_1), between 1 and 5 years (exp_1to5), between 5 and 10 years (exp_5to10), over 10 years (exp_10; base). Farm ownership was also explored by including a categorical variable: owner (base), tenant, partner, or occupant.

Other characteristics, such as the association of the producer with a cooperative or class entity (association), access to rural financing (financing), access to technical assistance, the presence of skilled labor in the farm workforce (qualification), and the use of agricultural practices and tillage systems, can play an important role in the likelihood of intensive use of biological control. Farm size was also explored by including a categorical variable by area: up to 10 ha (very small), between 10 and 50 ha (small), between 50 and 500 ha (medium), and above 500 ha (large; base).

The gross value of production (GVP) was used in the production function as a proxy for the output (dependent variable), which corresponds to the sum of the value of animal and plant production in thousands of R\$ in 2006. The following elements were used as inputs: land, which is the total area of crops and pastures in hectares; labor, which is the number of people over 14 years of age employed in agriculture and livestock; capital, which is the sum of tractors, machinery and agricultural equipment in the establishment; and purchased inputs, which is the spending on fertilizers, soil correctives, pesticides, seeds, animal medicines, salt and rations, machines and fuels, in thousands of R\$, in 2006.

The climatic dataset was obtained from the Terrestrial Hydrology Research Group (THRG) at Princeton University, following the procedures described in Sheffield et al. (2006). The data for the average monthly temperature in degrees C and the accumulated monthly precipitation in millimeters for the period from December 1979 to December 2005 were used to calculate the seasonal (summer and winter) averages for precipitation and temperature. The use of climate variables in these specifications is due to the significant changes observed in the Brazilian climate between these seasons (Cunha et al. 2015; Morais et al. 2021).

Results and discussion

Descriptive analysis and entropy balancing

Table 1 presents the descriptive statistics of the variables used and the results of the entropy balancing. Before balancing, the means of most variables between treatment and control groups were statistically different. Only the values exp_5to10, exp_10, partner, and medium farm presented no statistically significant differences between the groups.

Regarding the other variables, municipalities with intensive use of biological control have, on average, farm managers aged between 35 and 65 years, with higher education levels, compared to municipalities that adopted nonintensive biological control. Education is identified as a determining factor in the adoption of agricultural technologies (Ramírez and Schultz 2000; Challa and Tilahun 2014; Sankoh et al. 2016; Zhang et al. 2018b). According to Challa and Tilahun (2014), farmers with a higher level of education are expected to have more information and better knowledge about technological innovations. Consequently, they are more likely to adopt them than farmers with a lower level of education.

The percentage of rural establishments whose producers are owners is higher in intensive (which adopted biological control) municipalities, and the percentage of producers who are occupants is higher in nonintensive (which adopted biological control) municipalities. Studies reveal that producers who are not owners are more likely to use agrochemicals, in search of better results in the short term (Dasgupta et al. 2001; Kassie and Holden 2007; Kassie et al. 2013; Gao et al. 2019). Furthermore, the incentive structure intrinsic in property rights and thus land tenure has a significant influence on environmental management (Dasgupta et al. 2001). As such, landowners are expected to make decisions that account for their long-term interests more often and thus take actions to reduce the damage to local ecosystems.

It was also observed significant differences in financing and technical assistance. In general, intensive municipalities have a higher proportion of agricultural establishments that received rural credit and technical assistance (25.30%

Table 1 Mean of the variables used in entropy balancing, selection, and stochastic production frontier equations

Variables	Unbalanced sample		Balanced sample	
	Intensive	Nonintensive	Intensive	Nonintensive
Gender (men)	91.04	88.83*	91.04	91.05 ns
Age_25	1.79	2.68*	1.79	1.78 ns
Age_25 to 35	9.75	11.88*	9.75	9.69 ns
Age_35 to 45	21.72	21.33**	21.72	21.74 ns
Age_45 to 55	26.81	24.25*	26.81	26.90 ns
Age_55 to 65	22.13	21.32*	22.13	22.14 ns
Age_65	17.82	18.54*	17.82	17.75 ns
Do not read and write	6.32	19.01*	6.32	6.30 ns
Literate	3.98	8.15*	3.98	3.98 ns
Incomplete elementary school	48.35	43.31*	48.35	48.39 ns
Complete elementary school	13.44	10.14*	13.44	13.46 ns
High school	11.65	7.81*	11.65	11.68 ns
Agricultural technician	2.91	1.72*	2.91	2.92 ns
Higher education	8.94	4.43*	8.94	8.94 ns
exp_1	2.79	3.08**	2.79	2.80 ns
exp_1 to 5	17.33	18.10**	17.33	17.31 ns
exp_5 to 10	18.73	18.41 ns	18.73	18.82 ns
exp_10	61.16	60.41 ns	61.16	61.08 ns
Owner	83.52	79.38*	83.52	83.59 ns
Tenant	6.41	4.30*	6.41	6.44 ns
Partner	1.84	2.12 ns	1.84	1.85 ns
Occupant	3.41	6.53*	3.41	3.36 ns
Association	46.10	37.83*	46.10	46.23 ns
Financing	25.30	17.09*	25.30	25.40 ns
Technical assistance	50.33	27.67*	50.33	50.44 ns
Agricultural practices	110.31	73.52*	110.31	110.81 ns
Tillage systems	57.94	41.96*	57.94	58.14 ns
Qualification	8.24	4.92*	8.24	8.24 ns
Very small farm	37.57	41.46*	37.57	37.64 ns
Small farm	36.89	33.06*	36.89	37.04 ns
Medium-sized farm	19.36	18.30 ns	19.36	19.22 ns
Large farm	4.18	2.93*	4.18	4.19 ns
Gross Value Production (thousand R\$)	153.16	48.18	—	—
Land (ha)	96.66	60.78	—	—
Labor (Number)	5.16	3.22	—	—
Purchased inputs (thousand R\$)	57.82	17.87	—	—
Capital (Units)	1.14	0.43	—	—

Source: Research results. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, ^{ns}not significant. The value of agricultural practices exceeds 100% because agricultural establishments in certain municipalities may have adopted more than one type of agricultural practice

and 50.33%, respectively) than nonintensive municipalities (17.09% and 27.67%, respectively). This difference highlights the importance of rural credit and technical assistance to promote the adoption of technological innovations. Access to formal credit increases farmers' propensity to adopt technological innovations (Million and Getahun 2001; Saleem et al. 2011; Akudugu et al. 2012; Beshir et al. 2012). Extension services, on the other hand, can make producers

aware of the importance of technology and provide precise technical assistance in its implementation (Challa and Tilahun 2014). In other words, while financing can help producers with the short-term investments needed for biological control practices to be adopted effectively, technical assistance is paramount to disseminate knowledge of the techniques and their effective implementation.

In this context, it is worth pointing out that the lack of knowledge and the difficulty in spreading information are barriers that must be overcome to increase the adoption of biological control (Parra et al. 2002; Colmenarez et al. 2016). Participation in cooperative or class entities can be a means of spreading information and knowledge and promoting the adoption of new technologies. The data reveals that, on average, the percentage of producers associated with such entities is higher in intensive municipalities. According to Cullen et al. (2008) and Gao et al. (2019), cooperation among farmers favors the adoption of sustainable practices, such as biological control, as it goes beyond technology transfer by allowing farmers to observe the performance of farmers who have adopted the technique and learn from them. In addition to the technical knowledge required for the adoption of biological control, more skilled labor can be found in municipalities where biological control is used intensively. Since the implementation of this technique requires a certain level of knowledge (Colmenarez et al. 2016; Zhang et al. 2018a), establishments with skilled labor may find it easier to implement.

Intensive municipalities have a higher proportion of establishments adopting sustainable agricultural practices and soil preparation systems than nonintensive municipalities, which demonstrates that, along with the use of biological control, intensive municipalities adopt other techniques to ensure crop yields. Furthermore, municipalities that intensively adopt biological control have some knowledge about sustainable development, which justifies the increased adoption of other sustainable practices. According to Ooi and Kenmore (2005) and Zhang et al. (2018a), knowledge of agroecological mechanisms is fundamental for the adoption and diffusion of biological control.

In terms of farm size, there is a higher proportion of very small farms in nonintensive municipalities compared with intensive municipalities. The opposite is observed when small and large properties are considered. In this context, it is worth mentioning that 47.86% of Brazilian rural properties have an area of less than 10 ha (IBGE 2006), which highlights the importance of public policies aimed at this group of producers.

Significant differences in the value of production can be observed between the groups; the average production value of intensive municipalities is more than three times the average of nonintensive municipalities, which indicates that the adoption of this technique may increase the value of the products. According to Soesanto and Kusnaman (2016), one of the benefits of using biological pest control is the possibility of increasing the price of the products and, consequently, farmers' income.

Additionally, it is possible to observe that, on average, the area used is larger in intensive than nonintensive municipalities, but the difference is smaller than that observed between

Table 2 Estimation of stochastic production frontier for the total sample, intensives and non-intensives in biological control adoption

Variables	Intensive	Nonintensive	Total sample (pooled)
lx1 (Area)	0.155*** (0.037)	0.249*** (0.041)	0.146*** (0.012)
lx2 (Labor)	0.360*** (0.059)	0.237*** (0.085)	0.412*** (0.026)
lx3 (Input)	0.409*** (0.044)	0.486*** (0.036)	0.517*** (0.010)
lx4 (Capital)	0.135*** (0.037)	0.040** (0.016)	0.033*** (0.07)
Mills (Intensive)	0.900** (0.401)	— —	— —
Mills (Nonintensive)	— —	1.257*** (0.417)	— —
Constant	2.272*** (0.664)	1.362** (0.613)	0.294 (0.183)
Determinants of inefficiency (<i>Usigma</i>)			
Technical assistance	−0.059*** (0.010)	0.007 (0.261)	−0.054*** (0.007)
Association	−0.025** (0.010)	0.008 (0.009)	−0.005 (0.004)
Financing	0.052*** (0.012)	−0.053 (0.050)	0.041*** (0.009)
Constant	−1.115** (0.553)	−2.756* (1.528)	−2.602*** (0.220)
<i>Vsigma</i>	−1.256*** (0.096)	−1.286*** (0.045)	−1.002*** (0.022)
<i>Lambda</i>	0.89	2.14	2.60
Wald-Test	1649.70	2908.77	12,041.95
<i>Prob > chi²</i>	0.000	0.000	0.000
Fixed effects (regions)	Yes	Yes	Yes
Climatic variables	Yes	Yes	Yes
Observations	617	4,910	5,548

Research results. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Robust standard error in brackets

GVPs, which suggests that municipalities that adopt intensive biological control may achieve higher productivity.

Table 1 also presents the result of entropy balancing for the first moment of the sample (mean of the covariates). Before entropy balancing, the differences in the means of most variables between intensive and nonintensive municipalities were statistically significant. After entropy balancing, the first moment of the distribution of the variables is adjusted, since the means of all variables are significantly equal in both groups. Therefore, for each treatment group, there is a similar control group differing only in the intensity of the adoption of the biological control.

Stochastic frontier of production and determinants of technical inefficiency

It was estimated the stochastic production frontier for the total sample, intensive and nonintensive municipalities. The results are presented in Table 2. Wald statistics indicates a good fit of the models and rejects the null hypothesis of joint insignificance of the variables for all models estimated at 1%. The hypothesis of selection bias in unobservable is confirmed since the estimated coefficients for the IMR are statistically significant for intensive and nonintensive municipalities. This validates the methodological procedure adopted in this research.

Table 2 also presents the elasticities of the factors of production and their effects on the value of the agricultural production of intensive and nonintensive municipalities. This is possible because the frontier estimates were based on the Cobb–Douglas functional form and all variables were transformed into natural logarithms.

The estimated model for all Brazilian agricultural systems (pooled) indicates that purchased inputs and labor are the production factors that contributed most to the GVP in 2006. A 10% increase in inputs and labor results in an average increase of 5.17% and 4.12% in GVP, respectively. These results corroborate the findings of Helfand et al. (2015), Fortini et al. (2018), Reyna et al. (2020), Morais et al. (2021).

The comparison between intensive and nonintensive farms reveals differences in production elasticities. Although purchased inputs have the greatest impact on the GVP in both groups, the area is the second most important factor contributing to the production value of nonintensive farms, where a 10% increase in the area of crops and pastures results in an average increase of 2.49% in GPV. In intensive biological control farms, a 10% increase in the area results in a 1.55% increase in GPV. This may be due to the larger size of the area used in these farms compared to that used in nonintensive farms. Consequently, the return on the expansion of the area of crops and pastures is proportionally higher in nonintensive farms.

A 10% increase in labor provides 3.6% and 2.37% increases in the GVP for intensive and nonintensive farms, respectively. A 10% increase in the expenses of purchased inputs raises the GVP of intensive farms by 4.09% and that of nonintensive farms by 4.86%. The higher labor elasticity on intensive farms may be a result of the proportionally higher presence of skilled labor on these farms, as shown in Table 1.

The number of tractors, machines, and agricultural implements (a proxy for capital) was the least influential factor on GVP in both types of farms. Nevertheless, there were significant differences in the coefficients estimated between intensive and nonintensive farms. For intensive farms, a 10%

increase in capital leads to an average increase of 1.35% GVP. For nonintensive farms, this increase is only 0.4%.

In summary, it was observed that the contribution of labor and capital to GVP was higher in intensive farms, while the share of purchased inputs and area was higher in nonintensive farms.

The lambda parameter is another relevant piece of information presented in Table 2. It is obtained by dividing the variance of the error term concerning inefficiency (U_{σ}) by the variance of the random error term (V_{σ}). This parameter is used to test for the significance of technical inefficiency. Values higher than 1 indicate that most of the error is due to inefficiency. The value of this parameter is higher in nonintensive farms than intensive ones, which reveals that the effects of inefficiency are decisive in explaining the failure to achieve maximum results.

The determinants of technical inefficiency are presented in the second part of Table 2. A negative sign indicates that the variable decreases the inefficiency variance. The results are distinct among the three models. For intensive farms, all variables (technical assistance, association, and financing) are statistically significant. The availability of technical assistance and the association with cooperatives or class entities are associated with increased efficiency. These results agree with those obtained by Freitas et al. (2019), who demonstrated that irrigation, technical assistance, and membership in cooperatives are the main factors for increasing efficiency.

Fortini et al. (2018) also found that technical assistance and cooperative membership increased the technical efficiency levels. According to the authors, the members share their experience with the use of production techniques and commercial practices, while technical assistance promotes knowledge and behavioral changes through the provision of training or technical instructions on the use of productive systems, thus contributing to the optimal allocation of resources.

These results indicate the relevance of these factors in both the adoption and the effective use of biological control. Therefore, policies for the expansion of technical assistance services should be prioritized, since, besides promoting the adoption of sustainable agricultural practices, they increase technical efficiency. Cechin (2014) and Neves et al. (2021) emphasize the relevance of cooperatives for the Brazilian rural producer as channels of access and guidance for the use of diverse technologies related to inputs, management, and production harvesting.

Access to credit, on the other hand, is associated with higher inefficiency. This was an unexpected result since the availability of financial resources contributes to the adoption of productive technologies, purchase of modern inputs, and acquisition of support services for production, which favors the efficient allocation of production factors (Freitas et al.

Table 3 Mean of technical efficiency scores by Brazilian regions

Regions	Intensives	Non-intensives	Total sample
North	0.823	0.818	0.845
Northeast	0.752	0.808	0.799
Midwest	0.846	0.826	0.870
Southeast	0.872	0.810	0.879
South	0.882	0.875	0.886
Brazil	0.863	0.823	0.851

Source: Research results

2020). However, it is worth mentioning that the Brazilian agricultural model linked rural financing to the purchasing of certain inputs, such as pesticides, which leads to their intensive use (Porto and Soares 2012). Furthermore, the variable solely represents the acquisition of rural credit and does not consider the specific purposes of the credit nor the financial agent responsible for the financing. Thus, this result should be analyzed with caution. Anyway, this result may indicate that rural credit needs to be accompanied by technical assistance that gives farmers support for the adoption of biological pest control techniques. As reported by Kabir et al. (2017), institutional support, through credit and technical guidance, is an important incentive for farmers to adopt more environment-friendly practices.

For nonintensive (in biological control adoption) farms, all coefficients presented signs opposite to those obtained in the intensive (in biological control adoption) model. However, none of them presented statistical significance.

Regional analysis of technical efficiency

Table 3 exhibits the technical efficiency scores by region. The average efficiency of farms that intensively use biological control exceeds the average of those that do not, which corroborates the hypothesis that farms that adopt intensive biological control are more technically efficient than those that do not. In other words, this result implies that, on average, farms that intensively use biological control operate closer to their production frontier than nonintensive farms; that is, intensive farms use their resources more efficiently than nonintensive farms.

This result may be related to pesticide cost reduction due to the use of biological control instead of agrochemicals to combat pests (Collof et al. 2003; Medeiros et al. 2006; Monteiro et al. 2006; Cullen et al. 2008). According to Bale et al. (2008), natural enemies are more economical than pesticides, considering both use and development costs.

The results obtained in the present study corroborate those found by Türkten et al. (2017) for pepper producers in Turkey and converge with those presented by Tzouvelekas et al. (2001), who reported greater efficiency in

organic olive cultivation than in conventional cultivation in Greece. However, they do not corroborate the results of Beltrán-Estevé and Reig-Martínez (2014), who found that the efficiency of organic citrus cultivation in Spain is lower than that of conventional cultivation. According to the latter authors, regulatory and technological factors may impose limits on the efficiency of organic citrus fruit production. It is important to observe that the studies by Tzouvelekas et al. (2001) and Beltrán-Estevé and Reig-Martínez (2014) analyzed organic agriculture rather than the biological control per se. Therefore, even though organic agriculture does not use agrochemicals to combat pests and pathogens, when the biological control method is used (Bueno et al. 2011), the comparison of the results must consider these particularities.

Similarly, Rahman and Norton (2019) revealed that bitter gourd growers in Bangladesh that adopted integrated pest management (IPM) achieved greater technical efficiency than non-adopters. In Brazil, Bueno et al. (2011) demonstrated that the use of IPM is an efficient alternative for soybean crops, as it reduces the amount of pesticides used. It is important to point out that the use of biological control to combat pests and diseases is one of the IPM pillars. However, in certain cases, it allows the selective use of pesticides (Naranjo et al. 2015).

In general, it is observed that the use of sustainable practices for pest and disease management can enhance agricultural efficiency. These results reveal that the increased adoption of biological control for pest management may bring the farm closer to its production frontier. In other words, intensifying the use of biological control can increase the productive performance of farms. In addition, the adoption of this method for pest management can contribute to the insertion of the producer into an expanding market, given the increased preference of customers for sustainable products (Cullen et al. 2008; Oleynikova et al. 2020). It is possible to state that, besides the environmental benefits, the producers who adopt this technique obtain economic gains.

These benefits may be more significant in the long term since biological pest control does not damage the environment and does not harm beneficial organisms in the agricultural environment (Landis et al. 2000), but rather allows natural enemies to play their role in controlling the pest population (Colmenarez et al. 2016). Bueno et al. (2011) point out that biological control and integrated pest management are ecologically sustainable practices as they reduce agricultural dependence on expensive and environmentally damaging chemicals.

It is noteworthy that the advantages of reducing the use of pesticides go beyond the environmental benefits. The intensive use of pesticides is associated with damage to health (Pignati et al. 2014, 2017; Sankoh et al. 2016; Kim et al. 2017; Rodrigues and Féres 2022), which can interfere with

worker productivity and the formation of human capital. Thus, in addition to its greater efficiency in the agricultural sector resulting from environmental and ecological benefits, biological control is good for human health (Soesanto and Kusnaman 2016) and, as a result, favors long-term economic development.

It is estimated that the world population will exceed nine billion by 2050, which requires an increase of approximately 70% in food production between 2005/2007 and 2050 (FAO 2009). Therefore, increasing agricultural productivity becomes crucial for food security. Focus on technical efficiency is a way of increasing productivity since it maximizes the output from the available resources. This study reveals that biological control may be an effective tool to deal with the growing food demand by demonstrating that farms that intensively use biological control are more technically efficient (Table 3).

However, farmers using both intensive and nonintensive control can achieve productivity gains and cost savings by increasing technical efficiency. Similar results were found by Tzouvelekas et al. (2001) and Beltrán-Estevé and Reig-Martínez (2014), who revealed that production costs can be reduced by increasing technical efficiency in conventional and organic farming systems.⁵

In terms of Brazilian regions, in general, the farms of the south, southeast, and midwest regions are more technically efficient. According to Reyna et al. (2020), these results may be due to the well-developed agricultural tradition in these regions, in which more advanced and market-oriented technologies are used. Moreover, these regions are the most intensive in adopting biological control,⁶ which corroborates the potential relationship between biological control and technical efficiency. On nonintensive farms, the highest efficiency measures are found in the south, midwest, and north regions.

When comparing intensive and nonintensive farms by region, the technical efficiency in the southeast would benefit most from the intensified use of biological control. Furthermore, this region is among those with the highest technical efficiency scores, which means that the southeast optimizes resource allocation, efficiently transforming inputs into outputs. In the meantime, it is worth mentioning that this is the largest sugarcane-producing region in Brazil. This crop is a classic example of the use of biological control in the country, whose program is among the best in the world

(Parra 2014; Parra and Coelho Júnior 2019). Additionally, this region presented the highest percentage of establishments with managers with college degree (6.5%) and was the second region with the highest percentage of rural properties that received technical guidance (30.69%) (IBGE 2006). As reported in Tables 1 and 2, these factors can contribute to the adoption of biological control and technical efficiency measures of agricultural production.

The northeast, where nonintensive farms are more technically efficient than intensive farms, must also be highlighted. This may be due to the low overall adoption of biological control in the region. On average, only 0.51% of the agricultural establishments in the northeast used this practice to control pests in 2006 (IBGE 2006). This region presents the lowest proportion of managers with college degree (1%) and with less access to technical assistance and rural extension services. Only 8.38% of the rural establishments received some type of technical guidance, whether regular or occasional, in the analyzed period (IBGE 2006). Once again, the potential relationship between these factors and the adoption of biological control is highlighted. Therefore, it must be emphasized the importance of developing policies and programs for these regions, to expand the adoption of sustainable practices and increase agricultural efficiency. Educational and training programs and the expansion of ATER services can be effective strategies for regional development, given the low level of education and restricted access to technical guidance.

In general, all regions except the northeast would gain technical efficiency with the intensified use of biological control. Therefore, biological control is recommended as an effective alternative for pest management and a tool for sustainable agricultural development.

In this context, it is worth mentioning that one of the main limitations for the effective implementation of biological control is the lack of information and the dependence of farmers on the use of pesticides (Parra et al. 2002; Colmenarez et al. 2016; Zhang et al. 2018a). The expansion of ATER services can help overcome such limitations, through the dissemination of knowledge and incentives for the adoption of more sustainable practices. This can be explained by the fact that the lack of information/knowledge makes producers overuse pesticides and consequently become dependent on the use of agrochemicals, which hinders the adoption of alternatives for pest management, such as biological control. According to Wyckhuys et al. (2011) and Zhang et al. (2018a), understanding how organic products work increases the confidence of producers in their efficiency. Given this, Colmenarez et al. (2016) emphasize the importance of transmitting information to farmers in an appropriate language, considering the particularities of these producers. In Brazil, for example, the low level of education of farmers must be

⁵ As mentioned, biological control is an essential component in organic agriculture because the use of pesticides is prohibited in such production systems (Bueno et al. 2011).

⁶ In 2006, the percentage of agricultural establishments that adopted biological control in the North, Northeast, Mid-West, Southeast, and South was, respectively, 0.72%; 0.51%; 1.61%; 1.63%, and 3.08% (IBGE 2006).

considered. In 2006, only 18.6% of the rural establishments had managers with a college degree (IBGE 2006).

In addition, an appropriate natural habitat is critical to effective biological control (Collof et al. 2013; Naranjo et al. 2015; Tschardt et al. 2016). Tschardt et al. (2016) point out that the following aspects interfere with the effectiveness of biological control: (i) the absence of effective natural enemies in the region; (ii) the habitat benefits the development of pests to the detriment of natural enemies and/or lack the appropriate conditions for the development of natural enemies in the amount necessary to combat the pests; and (iii) the adoption of agricultural practices that neutralize the action of natural enemies. Therefore, such factors must be considered before adopting the biological control method.

Specifically for Brazil, the tropical climate, the mindset of farmers concerning the intensive use of pesticides, and the considerable size of cultivated areas are the main challenges to be overcome (Parra 2014; Parra and Coelho Júnior 2019). However, Brazil has a remarkable level of biodiversity, which is one of the favorable factors for the development and implementation of biological control (Parra and Coelho Júnior 2019). Therefore, it is important to emphasize the importance of investments in R&D for the expansion of this technology. Baker et al. (2020) highlight the relevance of education and extension through universities and research institutes to expand the adoption of biological control. In Brazil, the involvement of specialists trained in Brazilian universities was fundamental for the development of biological control methods (Parra 2014).

In short, the effectiveness of biological control, as well as of integrated pest management (IPM), is the result of the adequacy of recommendations, institutional guidelines, and technical elements to the ecological and socioeconomic circumstances of those involved (Maumbe et al. 2003; Kabir et al. 2017; Zhang et al. 2018a; Gao et al. 2019). Therefore, for a successful biological control, it is important to consider the multiple aspects inherent to adopters, institutional support, and soil and climate conditions, as well as which crops are grown on-site.

Conclusion

Biological control is considered an alternative for sustainable phytosanitary control. Despite the effectiveness of several biological products, their adoption is incipient in Brazil,

and few studies reveal the economic impacts of adopting biological pest control. This study aimed to evaluate the effect of the intensive use of biological control on the productivity of Brazilian agriculture.

It was applied a method that allowed the comparison of municipalities with very similar characteristics, differing only in the intensity of the use of biological pest control. The results reveal that municipalities that adopt intensive biological control are more technically efficient than nonintensive ones. It means that, in general, intensive biological control municipalities use their available resources more effectively than nonintensive ones. Technical assistance and association with cooperatives or class entities promote greater technical efficiency on intensive farms.

In addition, the most efficient regions (the South, Southeast, and Midwest) are also the most intensive in the use of biological control. Therefore, it is possible to conclude that the adoption of this phytosanitary control technique can increase the technical efficiency of Brazilian producers.

The long-term effects may be greater than this study suggests. Fertilizer expenses may be reduced, since biological control, unlike pesticides, does not affect nontarget microorganisms which are fundamental for soil health and plant nutrition and development. Besides increasing biodiversity and the presence of natural enemies that help to balance the ecosystem, biological pest control may reduce the need for agrochemicals to fight pests.

The numerous benefits associated with biological control and its incipient adoption in Brazil highlight the importance of government policies designed to disseminate information and knowledge of this agricultural practice. Designing credit programs intended to foster the implementation of biological control for pest management, as well as training agricultural technicians, extension workers, and farmers, can be effective strategies to promote the adoption of biological pest control. In summary, institutional support for environmentally friendly agricultural practices can be a very important tool to promote their adoption and increase their efficiency among Brazilian rural producers.

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Declarations

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

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