139. The impact of digital technologies on technical efficiency of soybean farms in São Paulo State, Brazil

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Abstract

Despite extensive studies on the economics of digital technologies (DTs), such as feasibility and adoption, their impact on technical efficiency (TE) and productivity in crop production using large microdata sets remains unclear. TE refers to the relationship between the maximum attainable output and the observed farm output considering the same endowment of inputs and available production technology. This study fills this gap by evaluating the effects of DT adoption on TE and productivity of soybean farms in the state of São Paulo, Brazil. Microdata from 148 farms (2023–2024 crop season) were collected via structured questionnaire). Econometric models of stochastic production frontier were applied to investigate the effects of DT adoption on farm TE and productivity. The results show that yield maps and management software increase productivity and all four DTs (yield map, autopilot, drone and management software) reduced technical inefficiency, offering insights into the potential of DTs in improving managerial capability.

Keywords: adoption, managerial capabilities, stochastic frontier analysis, technological impacts

Introduction

The adoption of new digital technologies (DTs) in agriculture has been widely studied in recent years from various perspectives, such as technical, economic, and environmental impacts. Other studies aim to estimate and identify the determinants of adoption and the barriers to better understand the diffusion of these technologies. However, the success of adoption does not depend exclusively on the innovations itself but also on how efficiently farms operate these innovations to achieve gains in productivity and efficiency (Carrer *et al.*, 2022; Delay *et al.*, 2021; Villano *et al.*, 2014).
In this context, econometric studies have sought to identify and measure factors that impact the efficiency of agricultural enterprises. Most of these studies analyze the ability of a firm to maximize production given a specific amount of inputs and a particular technological package, which Farrell (1957) seminally defined as technical efficiency (TE) of production. Production at the frontier occurs when firms achieve the maximum possible output given the quantity of inputs they use and the available technology. A key practical challenge is the estimation of the production frontier, which requires up-to-date data on input use and the adoption of technologies at the firm level (also referred to as a production unit or a farm), especially in the agricultural sector.
In a literature review, Čechura *et al.* (2021) used stochastic production frontier (SPF) models to evaluate the impact of adopting these technologies on the TE of cereal producers in the Czech Republic using a panel data. However no significant impact of DT adoption on farm efficiency was found. Delay *et al.* (2021) estimated four different production frontiers after clustering farmers into late adopters, laggards, late majority, and early adopters. On average, the meta-frontier technical efficiency (TEm) of early adopters of precision agriculture technologies was 16% higher than that of laggards. Nevertheless, the authors found no significant differences in the technological gap ratio (TGR) among the four groups of producers, concluding that the main impact of adopting precision agriculture technologies lies in improving farms' managerial capabilities rather than narrowing the

technological gap. The same conclusion was established by Carrer *et al*. (2022) assessed the impact of precision agriculture technologies on the TE of Brazilian sugarcane producers. The meta-frontier technical efficiency (TEm) of adopters was, on average, 18.5% higher than that of non-adopters. The authors also attributed this difference to the greater managerial capacity provided by precision agriculture technologies rather than a pure technological shock (TGR).

There is, therefore, limited understanding of how DT adoption – particularly those related to precision agriculture – impacts technical efficiency in agricultural production.

In the context of precision agriculture (PA) in Brazil, soybean production stands out. Borghi (2016) and Molin (2017) observed that soybean producers were the ones who most frequently adopted PA practices. According to Vegro and Martins (2022), São Paulo State recorded the largest expansion in soybean cultivation area (91%) over the last 10 years, increasing from 637 000 ha in the 2012–2013 season to 1.215 Mha in 2021–2022. The growing international demand for soybeans, combined with the possibility of cultivation in areas of sugarcane renewal (Zeferino, 2019) and the high average productivity of São Paulo's soybean production (3.576 kg/ha in 2021–2022, as reported by Vegro and Martins (2022)), explain this growth in the region. As soybean production expands in São Paulo, a state with high production costs, soybean farmers must become more competitive, and digital technologies may be a determining factor for their survival in the sector.

By addressing these topics, this study aims to assess the impacts of DT adoption on technical efficiency and productivity in soybean farms in São Paulo State, Brazil. This article also seeks to contribute to policymakers, the academic and private sectors by estimating the impacts of these technologies on the production of small and medium-sized soybean farmers in São Paulo. These results will contribute to the development of strategies to increase resource-use efficiency, environmental sustainability, and the economic viability of soybean production in Brazil.

Methodology

The proposed methodology consists of two main steps. The first involves the collection of primary data through the application of a structured questionnaire conducted *in loco*. The second step consists in the estimation of econometric models of stochastic production frontier to verify whether the adoption of DTs can impact the productivity and reduce technical inefficiency, as described below.

Sample

The data were collected through the application of a structured questionnaire to 148 farmers or managers of crop farms, in person. The *in loco* interview aimed to avoid biased responses and ensure the depth of the data required for the intended analyses. All of the farms in the sample are located in the State of São Paulo, counting for 76 municipalities. The producers in these regions are relatively homogeneous in terms of production system, weather conditions, and biome, thus enabling the comparison of farms without the inclusion of regional dummies. The data collection was carried out from July to October 2024, referring to the crop year 2023–2024 (cross-sectional data).

The questionnaire was organized into three sections: (1) personal, social, and behavioral characteristics of the farmers; (2) structural characteristics of production (use of inputs, production methods, and technology); and (3) aspects of the decision-making process.

The data set used in this paper is part of an ongoing project. So, for all the DTs investigated in the questionnaire, this paper focuses on four (yield map, GNSS auto-steer, drone and management software). Further analyses are needed to incorporate additional technologies and inputs in the SPF models.

Stochastic frontier and inefficiency effects model

The application of production frontier methodologies for analyzing technical efficiency (TE) has been widely used in empirical studies across various sectors of economic activity (Fried *et al*., 2008). In the agricultural sector, the use of this methodology began in the late 1970s with the works of Battese and Corra (1977). More recently, and following considerable methodological advancements, some studies have investigated the impacts of technological innovations on the TE of farms (Čechura *et al.*, 2021; Delay *et al.*, 2021; Carrer *et al.*, 2022).

In the present study, a stochastic production frontier model with a Cobb–Douglas functional form representing the technology was applied, while the firm-specific heteroscedasticity inefficiency model (Caudill *et al.*, 1995; Hadri *et al.*, 2003) was also applied to identify the effects of digital technologies on the (in)efficiency of farms. The proposed econometric model can be described by the following specific form:

$$\ln y_i = \beta_0 + \beta_1 \ln x_{1i} + \beta_2 \ln x_{2i} + \beta_3 \ln x_{3i} + \beta_4 \ln x_{4i} + \alpha d_i + v_i - u_i \quad (1)$$

in which y_i denotes the production of the i-th firm; x_i is a vector of logarithms of physical quantities of inputs used by the farm (land, labor, machinery and seed), β is a vector of parameters of the production function to be estimated; d_i are dummy variables that represent the adoption of different digital technologies that might affect production frontier, as defined in Table 1; α is the parameter that shows the effects of digital technologies on production frontier – these unknown coefficients represent the technological changes that digital technologies might provide; v_i is a random error term, independent and identically distributed (i.i.d.); u_i is an asymmetric non-negative random error associated with the technical inefficiency of the i-th farm; and i denotes the i-th of 148 farms in the sample. Table 1 presents the definition of the variables used in the analysis and their statistical description.

Additionally, as proposed by Hadri *et al.* (2003), the following multiplicative heteroscedasticity for the one-sided error (inefficiency) term was also estimated:

$$\sigma_{ui} = \exp(d_i \gamma) \quad (2)$$

where d_i are the variables that represent digital technology adoption, and γ are the unknown parameters that is assumed to include an intercept parameter. These parameters show the effects of DTs adoption on technical efficiency (management efficiency). The standard deviation of the two-sided error term is also written in exponential form:

$$\sigma_v = \exp(\delta_0) \quad (3)$$

Measures of TE can be obtained from econometric estimations of SPF models (Aigner *et al.*, 1977; Battese and Coelli, 1992), defined as the relationship between the observed output and the maximum output (y_i^{MAX}) – frontier output – that could be produced by the firm/farm *i* using the same quantity of inputs and available technology, as follows:

$$\text{TE}_i = \frac{y_i}{y_i^{\text{MAX}}} = \frac{e^{x_i\beta_i - u_i + v_i}}{e^{x_i\beta_i + v_i}} = e^{-u_i} \quad (4)$$

A technically efficient farm produces the maximum output from a given quantity of inputs and production technology (output-oriented TE) (Koopmans, 1951). The TE index ranges from 0% to 100% and can also be interpreted as a proxy for the managerial capacity of the firm (Greene, 2010; Martin and Page, 1983; Villano *et al.*, 2014).

The smaller this gap, the greater the TE of the farm. This analysis complements the technological effects analysis (provided by the coefficients α of production frontiers) and shows the associations between the adoption of DTs and managerial capabilities of farms.

Summarizing, two econometric modelling strategies were applied to estimate the effects of DTs on farm productive performance. The first strategy consists in the use of dummy variable on production

Table 1. Descriptions and statistics of variables.

Variable	Mean	SD	Minimum	Maximum	Description
Output (y)	1421.83	2519.98	10.43	20630.40	Total production of soybean in the crop year 2023–2024 (t)
Area (x_1)	477.58	670.54	10.50	4912.00	Harvested area of soybean in the crop year 2023–2024 (ha).
Labor (x_2)	8015.17	15140.96	240.00	120640.00	Hours worked by permanent and temporary/day laborers in the crop year 2023–2024
Machinery (x_3)	4.24	2.59	1.00	19.00	Number of tractor and self-propelled machinery used in soybean production
Seed (x_4)	25.38	39.80	0.52	294.42	Quantity of seed used in the crop year 2023–2024 (t)
Digital technologies variables					
Yield map (d_1)	0.26	0.44	0.00	1.00	Dummy=1 if yield maps was used.
GNSS autopilot (d_2)	0.56	0.49	0.00	1.00	Dummy=1 if GNSS auto-steer was adopted in at least one machine.
Drone (d_3)	0.13	0.34	0.00	1.00	Dummy=1 if a drone or aircraft was used to monitor the filed or apply inputs.
Software (d_4)	0.41	0.49	0.00	1.00	Dummy=1 if the farmer adopted management software to collect, organize, store, integrate, process and share data.
Alltech (d_5)	0.06	0.25	0.00	1.00	Dummy=1 if the farmer adopted all four precision agriculture technologies above in the 2023–2024 crop year.

frontier to estimate the effects of DTs on farm productivity – a pure technological effect. The second one consists in the use of dummy variables in the distribution of inefficiency variance to estimate the effects of DTs on technical efficiency – a pure managerial effect.

Results and discussion

Table 2 presents the SPF estimates of five econometric models to assess the effects of DTs on farm productivity – the technological shock. Regarding the output partial elasticities, the coefficients for Area and Seed were significant at the 1% level across all four technologies. Thus, considering farmers who adopted all four technologies, a 1% increase in land can improve soybean production by 0.64%, *ceteris paribus*. Similarly, a 1% increase in the quantity of seed can lead to 0.37% increase in crop production, ceteris paribus. This indicates that further increases in production are highly dependent on additional inputs of land and seed.

Regarding the technologies, only yield map and management software had a positive and significant effect on production frontiers of soybean farms. If a farmer adopts yield map, soy production can potentially increase by 20%, *ceteris paribus*. In turn, the effect of software adoption on soy productivity was 16%. The adoption of GNSS auto-steer and drone did not show technological effects on production. The same applies to farmers who used all for technology. Notwithstanding, all the estimated coefficients were positive.

Table 2. Partial elasticities from the five stochastic production frontier models: technological effects of DTs on farm productivity (n=148).

Variable	Yield map	Autopilot	Drone	Software	All technologies
Constant	2.29***	2.49***	3.03***	2.66***	2.68***
lnx_1 (area)	0.67***	0.64***	0.60***	0.71***	0.64***
lnx_2 (labour)	−0.01	−0.01	−0.05	−0.06	−0.04
lnx_3 (machinery)	0.13	0.10	0.00	0.01	0.11
lnx_4 (seed)	0.30***	0.33***	0.42***	0.33***	0.37***
z_1 (yield map)	0.20***	–	–	–	–
z_2 (GNSS autopilot)	–	0.11	–	–	–
z_3 (drone)	–	–	0.09	–	–
z_4 (software)	–	–	–	0.16**	–
z_5 (alltech)	–	–	–	–	0.09

***, **, * represent statistical significance at the 1, 5 and 10% level, respectively. x_i is a vector of the logarithms of the physical quantities of inputs used by the farms, as described in Table 1.

The Hadri *et al.* (2003) model examines how digital technologies affect production inefficiency. It focuses not only on how production inputs (land, labour and machinery and seeds) affect output but also on how inefficiency changes with the adoption of these technologies. The coefficients of the production inputs (lnx_1,...,lnx_4) indicate the direction of their impact on productivity (positive or negative), but their numerical values should not be interpreted as direct elasticities. The key is to understand the direction of the effect and how these factors influence inefficiency and productivity with DT adoption.

In this way, Table 3 presents the estimates of five stochastic frontier models with inefficiency effects. These econometric models were applied to assess the effects of DT adoption on technical (in)efficiency of farms – the pure managerial effects of these technologies. The coefficients Area and Seed were also significant at the 1% level across all four technologies, shown positive effects on soy production, with partial elasticities very similar across the models.

All the four DTs, as well as their joint adoption, showed negative and statistically significant associations with the technical inefficiency of farms. In other words, these technologies can provide a positive impact on the technical efficiency of soybean production.

In fact, these technologies provide management enhancement, both through the collection, storage and processing of data to generate accurate information for decision-making (software and yield map), and through improvement in agricultural operations (auto-steer, drone and yield map). For yield map, similar results were found by McFadden *et al.* (2021), who observed both direct (frontier-shifting) and indirect (efficiency-enhancing) productivity effects between USA Midwest corn production and the information contained in yield maps.

The sign and significance of $\ln x_1, \ldots, \ln x_4$ indicate the direction of the impact on productivity (positive or negative), but the numerical value should not be interpreted as a direct elasticity Hadri *et al.* (2003).

Conclusions

Digital technologies (DTs) have transformed agriculture by optimizing input allocation, automating systems and providing real-time farm management control. Using primary data, this study estimated

Table 3. SPF econometric estimates for DTs: inefficiency effects (n=148).

Variables	Yield map	Autopilot	Drone	Software	All technologies
Constant	2.99***	2.99***	2.96***	2.07***	3.03***
$\ln x_1$(area)	0.55***	0.54***	0.57***	0.56***	0.56***
$\ln x_2$ (labour)	–0.01	–0.01	–0.02	–0.02	–0.03
$\ln x_3$ (machinery)	–0.00	–0.00	0.00	0.00	–0.00
$\ln x_4$ (seed)	0.44***	0.45***	0.44***	0.44***	0.45***
Inefficiency drivers					
Constant	–0.04	0.00	–0.14	–0.08	–0.17
u_1 (yield map)	–0.88***	–	–	–	–
u_2 (GNSS autopilot)	–	–0.44**	–	–	–
u_3 (drone)	–	–	–1.04***	–	–
u_4 (software)	–	–	–	–0.36*	–
u_5 (alltech)	–	–	–	–	–1.21**
Mean technical efficiency (TE)	0.77	0.77	0.75	0.75	0.76

Note: ***, **, * represent statistically significance at 1%, 5% and 10%, respectively.

stochastic production frontiers (SPF) econometric models to evaluate the impact of DT adoption on the productivity and technical efficiency (TE) of soybean farms.

The results show that, among the four DTs analyzed, yield maps and management software had a positive impact on production technology, leading to productivity increases of 20% and 16%, respectively. Despite yield map and GNSS auto-steer presenting the highest TE score, all four technologies – including their combined use – demonstrated the potential to reduce inefficiency on farms. In other words, DTs were shown to be valuable tools for improving farm management.

This study contributes to the understanding of DTs by providing empirical insights into their potential benefits and impacts on agricultural performance, addressing the lack of studies on technical efficiency and the absence of updated official data on digital technologies in Brazilian agriculture.

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