UNIVERSIDADE FEDERAL DE SÃO CARLOS
CENTRO DE CIÊNCIAS EXATAS E DE TECNOLOGIA
DEPARTAMENTO DE ENGENHARIA DE PRODUÇÃO
PROGRAMA DE PÓS-GRADUAÇÃO EM ENGENHARIA DE PRODUÇÃO

RODRIGO DAMASCENO

DETERMINANTES DA ADOÇÃO DE TECNOLOGIAS DE AGRICULTURA DIGITAL POR PRODUTORES DE SOJA DO ESTADO DE SÃO PAULO

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Dissertação de Mestrado apresentada ao Programa de Pós-Graduação em Engenharia de Produção da Universidade Federal de São Carlos como requisito para a obtenção do título de Mestre em Engenharia de Produção

Orientador: Prof. Dr. Marcelo José Carrer

Agência Financiadora: FAPESP - Processo: 2023/14459-7

São Carlos-SP
2025

UNIVERSIDADE FEDERAL DE SÃO CARLOS

Centro de Ciências Exatas e de Tecnologia
Programa de Pós-Graduação em Engenharia de Produção

Folha de Aprovação

Defesa de Dissertação de Mestrado do candidato Rodrigo Damasceno, realizada em 10/07/2025.

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O Relatório de Defesa assinado pelos membros da Comissão Julgadora encontra-se arquivado junto ao Programa de Pós-Graduação em Engenharia de Produção.

AGRADECIMENTOS

Expresso minha profunda gratidão à minha família, especialmente aos meus pais, José Roberto e Iraildes, pelo amor incondicional e pelo apoio constante em todas as etapas da minha formação pessoal e profissional. Ao meu irmão, Henrique, agradeço pela presença constante, pelo companheirismo, incetivo e por celebrar comigo cada conquista.

Ao professor Marcelo Carrer, registro minha gratidão pela orientação dedicada, pelas valiosas contribuições acadêmicas e pela confiança depositada ao longo desta jornada.

Agradeço também às pessoas que contribuíram para o processo de coleta de dados em diversas regiões do estado de São Paulo – Marcelo, Marcela, Hildo, Larissa Pagliuca, Larissa Lopes, Leticia – cuja parceria foi essencial, especialmente no último ano, durante as reuniões de equipe, nas estradas do estado de São Paulo e na tabulação dos dados.

Aos professores Hildo e Rodrigo Lanna, membros da banca examinadora, agradeço pelas sugestões criteriosas e pelas contribuições que enriqueceram este trabalho desde o processo de qualificação.

Sou grato à UFSCar pela estrutura, pelas oportunidades e pelos recursos oferecidos ao longo do curso de mestrado.

Em especial, agradeço ao grupo de estudos GEPAI e agregados, e aos amigos que estiveram ao meu lado nesses últimos dois anos – Adailton, Yago, Flavia, Thais, Fernanda, Renato, Guilherme, Raul, Luis, Mari, Vitor, Gilberto, Pâmella, Rogê, Sofya, Cinthya, Adriele, Camila e Alex – pelas trocas de conhecimento, pela parceria e pelo convívio enriquecedor.

Um agradecimento especial à Professora Sílvia Miranda, da ESALQ, por sua valiosa parceria desde os tempos da graduação em Economia e pelos anos de convivência no CEPEA, durante os quais me apresentou à oportunidade de ingressar no mestrado na UFSCar.

Agradeço à FAPESP pelo apoio financeiro, fundamental para o desenvolvimento desta pesquisa.

Finalmente, a todos que, de alguma forma, contribuíram para a realização deste trabalho, meu sincero agradecimento.

RESUMO

As tecnologias digitais vêm transformando processos produtivos e modelos de negócio em diversos setores ao ampliar a eficiência técnica, fomentar a inovação e facilitar o acesso a dados e informações. Esta dissertação possui dois objetivos complementares: (i) identificar e descrever as principais Tecnologias de Agricultura Digital adotadas por produtores de soja no estado de São Paulo; e (ii) identificar os determinantes da adoção e da intensidade de uso dessas tecnologias pelos agricultores. Inicialmente, foi realizada uma revisão sistemática da literatura sobre a adoção de tecnologias digitais por produtores de grãos. Com base nessa revisão e em reuniões com pesquisadores e agentes da cadeia produtiva, foi elaborado um questionário estruturado para a coleta de microdados primários. Um banco de dados referente a 150 produtores de soja na safra 2023/2024 (cross-section) foi obtido para a análise empírica. Os dados foram coletados por meio de pesquisa de campo conduzida entre maio e outubro de 2024. Modelos econométricos de escolha qualitativa (regressão logit) e de dados de contagem (Poisson) foram aplicados para identificar os fatores determinantes da adoção e da intensidade de uso de oito tecnologias de agricultura digital: amostragem georreferenciada de solo, plantio a taxa variável, aplicação de fertilizantes a taxa variável, monitor de produtividade, mapa de produtividade, piloto automático, software de gestão e uso de drone. Os resultados indicam que a área cultivada com soja, a experiência do produtor, o acesso à consultoria privada e o nível de escolaridade exercem influência positiva sobre a adoção das tecnologias digitais, enquanto a percepção do custo elevado da tecnologia constitui um fator limitante. Os resultados do modelo de Poisson revelam que os produtores com adoção mais intensiva de tecnologias digitais tendem a ser mais inovadores e experientes, apresentam maior escolaridade, gerenciam propriedades maiores, contratam serviços de consultoria e possuem menor percepção de custo associado às tecnologias digitais. Os resultados empíricos obtidos podem contribuir para orientar as decisões de alocação de recursos pelos agricultores, além de subsidiar a formulação de políticas públicas e apoiar as estratégias de agentes de extensão rural, consultores e desenvolvedores de tecnologias. Recomendações para pesquisas futuras incluem a investigação dos efeitos da adoção dessas tecnologias digitais sobre os indicadores de produtividade total dos fatores (PTF). Além disso, sugere-se a incorporação de variáveis climáticas nas análises de produtividade, com o objetivo de proporcionar uma compreensão mais aprofundada dos fatores ambientais que influenciam a eficiência agrícola e os resultados de adoção dessas tecnologias.

Palavras-chave: soja; Tecnologia de Agricultura Digital; Agricultura 4.0; adoção de tecnologia; intensidade de adoção.

ABSTRACT

Digital technologies have been changing production processes and business models in various industries by enhancing technical efficiency, fostering innovation, and enabling unprecedented access to data and information. This dissertation has two complementary objectives: (i) to identify and describe the main Digital Agriculture Technologies (DAT) adopted by soybean producers in the state of São Paulo; (ii) to identify the determinants of adoption and intensity of use of these technologies by farmers. First, a systematic literature review on digital technology adoption by grain farmers was conducted. Following this review and meetings with researchers and supply chain agents, a structured questionnaire was developed for microdata collection. A primary dataset of 150 soybean farms in the 2023/2024 crop year (cross-sectional survey) was obtained to perform empirical analysis. The data were collected in field research carried out between May and October of 2024. Econometric models of qualitative choice (logit regression) and count data (Poisson) were applied to identify the determining factors for the adoption and intensity in use of eight different DAT - grid soil sampling, variable rate seed application, variable rate fertilizer application, yield monitor, yield map, GPS auto-steer (autopilot), management software, and drone. The findings indicate that soybean area, farmer experience with soybean production, access to private consultancy, and education positively influence the adoption of most DA technologies, while cost perception negatively affects these farmers' decisions. The results of Poisson model showed that more intensive adopters of digital technologies are more innovative and experienced, have higher levels of schooling, manage larger farms, hire consultancy services, and have a lower perception of digital technology costs. The empirical results of the work can contribute to farmers' resource allocation decisions and can also guide public policy design, helping agricultural extension agents, consultants, and technology developers in their strategies. Recommendations for future research include the investigation of the relationship between the adoption of digital agriculture technologies and their effects on total factor productivity (TFP) indicators. Additionally, the integration of climate-related variables into productivity analyses is suggested, as this may offer more robust insights into the environmental factors influencing agricultural efficiency and technological outcomes.

Keywords: soybean; Digital Agriculture Technology; Agriculture 4.0; technology adoption; intensity of adoption.

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Sumário

1. Introduction

The necessity to conserve natural ecosystems, coupled with the continued expansion of urban territories, has imposed significant constraints on the availability of arable land, thereby limiting its use for agricultural purposes and compromising food production potential. Simultaneously, the global demand for food is escalating in response to rapid population growth, which is projected to rise by approximately 30% by 2050, underscoring the urgent necessity to enhance agricultural productivity to ensure global food security (FAO, 2018). In this context, the adoption of advanced agricultural technologies is essential, such as the utilization of certified seeds (Baglan et al., 2020), site-specific input management through variable-rate application techniques (McFadden et al., 2022), and integrated production systems (Carrer et al., 2020). These innovations not only optimize the efficiency use of inputs but also contribute to the mitigation of greenhouse gas emissions, thereby fostering the sustainable intensification of agricultural systems (Perosa et al., 2021).

In recent decades, Brazilian agriculture has undergone profound transformations in both its technical and organizational paradigms, particularly since the mid-2000s. These changes have been largely driven by the diffusion of innovations associated with digital agriculture and by the emergence of novel governance structures within agro-industrial value chains. The progressive adoption of data-intensive technologies, including georeferenced systems, remote sensors, unmanned aerial vehicles (UAVs), and integrated management information systems, has increasingly across Brazilian farming enterprises (Carrer et al., 2017; Bolfe et al., 2020; Milanez et al., 2020).

Within the framework of technological adoption and dissemination, the interrelated concepts of invention, innovation, adoption, and diffusion are fundamental to understanding the mechanisms driving technological advancement and its wider societal ramifications. Invention refers to the origination of novel ideas or artifacts and represents the foundational stage in the technological development continuum (Schumpeter, 1939). Innovation occurs when these inventions are effectively integrated into market systems, facilitating the reconfiguration of existing resources and processes in ways that catalyze economic development.

Consequently, innovation extends beyond the act of invention by incorporating novel solutions into established production and operational frameworks, often precipitating profound transformations throughout multiple stages of the production process. The initial adoption of such technological innovations is observed among innovators, the pioneering segment of producers who first integrate emergent technologies. This is subsequently followed by the early adopters and the early majority, marking a progressive increase in acceptance. Once the innovation reaches a critical threshold of acceptance within the sector, it transitions into the diffusion stage, wherein adoption is further propagated by the late majority and ultimately by the laggards, the final cohort to assimilate the innovation into practice (Rogers, 1983)

The expansion of agritechs underscores the increasing strategic relevance of digital technologies within Brazil's agribusiness sector. According to Dias et al. (2023), a total of 1,574 agritech startups are currently operating in the country, with approximately 48.09% headquartered in the state of São Paulo. These enterprises are engaged in the development and dissemination of digital solutions that support a broad spectrum of agribusiness functions, encompassing technical, managerial, and commercial dimensions across diverse segments of the agricultural production chain.

Despite initial limitations in technological infrastructure, data from the 2006 Agricultural Census (IBGE, 2006) indicated that only 4.54% (183,623) of Brazilian agricultural establishments possessed computers, and 1.87% (75,407) had internet access on-site. A decade later, the 2017 Agricultural Census (IBGE, 2017) revealed an increase in digital connectivity, with approximately 1.4 million rural establishments reporting access to the internet via broadband, mobile networks, or dial-up connections, representing 28% of the national total.

In the state of São Paulo, survey data from the LUPA project (2016–2017) demonstrated that while 75% of farms utilized electricity in agricultural operations, only 12.46% employed computers and 13.82% accessed the internet specifically for agricultural purposes. Although these figures have likely evolved substantially in recent years, the absence of up-to-date official statistics constrains the ability to accurately assess this progression (Milanez et al., 2020). Nevertheless, empirical research has consistently emphasized the growing relevance of digital agriculture technologies as critical instruments for enhancing on-farm decision-making processes (Bolfe et al., 2020; Carrer et al., 2022; de Souza Filho et al., 2023; Mozambani et al., 2023).

The soybean sector constitutes one of the most economically significant components of Brazilian agriculture, with national production reaching 152,144,238 tons in 2023. In the state of São Paulo, the cultivated area dedicated to soybeans has expanded considerably over the past decade, increasing from 495,833 hectares in 2010 to 1,360,285 hectares in 2023 (IBGE, 2023). In the same year, the soybean production chain generated an estimated value of R$ 12.4 billion, positioning it as the third most valuable agro-industrial chain in the state (Monteiro et al., 2023). These figures underscore the sector's strategic importance to regional and national agribusiness. However, to the best of our knowledge, no empirical studies to date have employed micro-level datasets combined with econometric modeling to examine the adoption of eight specific digital agriculture technologies and their respective impacts on soybean production within the state of São Paulo. This gap in the empirical literature provides the basis for the central research question addressed by the present study:

- What factors affect the decisions of digital agriculture technology adoption by soybean farmers?

The main objective of the dissertation is to identify the determinants of DA technology's adoption and intensity in use by soybean farmers in the state of São Paulo, Brazil. The specific objectives are: i) to identify and describe the main DA technologies adopted by soybean producers in the state of São Paulo; ii) to test the effects of managerial, behavioral, structural, institutional, and human/social capital variables on the probability of adoption of different DA technologies by soybean producers, and to test the effects of these variables on the intensity of the adoption of these technologies.

The insights derived from addressing these questions hold substantial value for informing farmers' decision-making processes regarding the allocation and utilization of productive resources, directing strategic initiatives aimed at technology dissemination by actors within agricultural innovation systems, and underpinning the formulation of evidence-based public policies. Achieving growth in rural production without a commensurate escalation in the use of primary inputs—particularly land and agrochemicals—relies on the widespread adoption of innovations that enhance producers' technical efficiency.

Consequently, identifying the determinants that influence the adoption of digital agriculture (DA) technologies is of critical importance for advancing sustainable intensification strategies in the agricultural sector.

This M.Sc. thesis adopts an article-based format. Chapter 2 comprises a conceptual study that served as the basis for the design of a structured questionnaire administered to soybean producers in the state of São Paulo. In addition, this chapter offers a succinct synthesis of the theoretical framework guiding the literature contributions on the adoption of digital technologies in grain production. In this context, a systematic literature review (SLR) was conducted to identify the predominant digital agriculture technologies and the determinants influencing their adoption. Chapter 3 presents the empirical study, which draws upon primary data collected from soybean producers in São Paulo and employs econometric techniques to examine both the adoption and the intensity of adoption of DAT. Chapter 4 concludes the thesis by summarizing its principal contributions and implications, as well as proposing future research opportunities.

2. Determinants of digital agriculture technology adoption by grain producers: a systematic literature review[1]

2.1. Introduction

Digital agriculture refers to the application of a suite of digital technologies designed to collect, store, integrate, process, and analyze extensive datasets related to the production, commercialization, and organizational dynamics of agricultural enterprises (Tummers et al., 2019; Barnes et al., 2019a; Carrer et al., 2022). The implementation of these technologies, which encompass big data analytics, data science, cloud computing, advanced data storage and processing architectures, production automation, and artificial intelligence, facilitates the efficient allocation and utilization of production inputs, thereby enhancing agricultural productivity, operational efficiency, and overall profitability (Carrer et al., 2022; Mühl & de Oliveira, 2022).

The concept of precision agriculture is extensively referenced in scientific literature as encompassing a suite of technologies aimed at enhancing the digitalization and optimization of agricultural processes. It is formally defined as a data-driven management strategy that involves the collection, processing, and integration of temporal, spatial, and site-specific data from agricultural properties, which, when synthesized with complementary datasets, serves to inform strategic decisions regarding the use and management of production inputs (Balafoutis et al., 2017; ISPA, 2021). Although the terms 'digital agriculture' and 'precision agriculture' are frequently used interchangeably, the present study delineates precision agriculture as a specialized domain within the broader framework of digital agriculture.

The advancement of Information and Communication Technologies (ICT) has played a pivotal role in the evolution of digital agriculture technologies. Empirical studies have investigated the use of smartphones as tools for accessing field-collected data, market pricing information, and essential documentation (Ma et al., 2020; Michels et al., 2020), as well as for facilitating communication through messaging platforms (Mendes et al., 2023). Moreover, the deployment of wireless sensors for field monitoring and the development of digital applications for plant disease detection, fertilizer calculation, and georeferenced data collection have been extensively documented (Ogutu et al., 2014; Michels et al., 2020). Further research has examined the implementation of integrated agricultural management information systems, commonly referred to as Farm Management Information Systems (FMIS), alongside enterprise resource planning (ERP) solutions within rural production environments (Carrer et al., 2017; Tummers et al., 2019; Junior et al., 2019; Carrer et al., 2020; de Souza Filho et al., 2023). Collectively, these studies elucidate the key technological instruments employed in the acquisition and analytical processing of agricultural data.

There are also analyses of the adoption of digital technologies aimed at improving the application of inputs in the production process. These include automatic guidance systems (autopilot) for tractors and harvesters, georeferenced soil sampling, application of inputs (fertilizers or pesticides) at variable rates (Barnes et al., 2019a; Carrer et al., 2022; Mozambani et al., 2023; Gabriel; Gandorfer, 2023), and drip irrigation technologies (Rossi et al., 2020). The adoption of these technologies is justified by the need to adapt

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[1] This article was presented at the "62º Congresso da SOBER" (Brazilian Society of Economics, Administration and Rural Sociology), held between 07/28/2024 and 08/01/2024 at the Federal University of Tocantins (UFT), in the city of Palmas (TO).

rural production to meet global food supply demands, ensuring origin, quality, food safety, and environmental preservation in compliance with international agreements.

Existing systematic literature reviews have examined the adoption of digital technologies in agriculture from various perspectives. Some address the topic in a generalized manner, without specifying the agricultural activity under consideration (Shang et al., 2021; Aparo et al., 2022; Mühl & de Oliveira, 2022; Moreno et al., 2024; Papadopoulos et al., 2024), while others focus on particular technological domains, such as farm management information systems (Tummers et al., 2019; Giua et al., 2020) or mobile-based applications (Aparo et al., 2022), or on distinct segments of the agri-food supply chain, such as post-harvest storage (Goulart et al., 2024). Nevertheless, there is a notable absence of systematic reviews specifically addressing digital technology adoption in grain production—a sector that constitutes a foundational component of the Brazilian agricultural economy—along with the key determinants influencing such adoption.

Brazil ranks among the foremost global producers of grains. According to estimates by the National Supply Company (CONAB, 2024), the country's grain output for the 2023/24 harvest is projected to reach 295.6 million metric tons. Between 2000 and 2023, there has been a 363.56% increase in soybean production volume, measured in metric tons, whereas the expansion of cultivated area reached 224.63% over the same period (IBGE, 2023).

Projections by the Brazilian Ministry of Agriculture and Livestock (MAPA, 2023) indicate an anticipated increase of 75 million metric tons in grain production and an expansion of 14.8 million hectares in cultivated area between the 2022/2023 and 2032/2033 harvest seasons. In this context, the adoption and widespread dissemination of digital agriculture technologies are positioned as strategic mechanisms for enhancing the efficiency of production input utilization and improving overall grain productivity.

Accordingly, this paper seeks to identify the main digital agriculture technologies and the key determinants influencing their adoption by grain producers. In addition, it aims to propose an analytical framework that integrates these variables to enhance the understanding of the adoption process of digital technologies in agricultural contexts. To achieve these objectives, the article is structured into five chapters, beginning with this introductory section. Chapter 2 outlines the methodological approach employed for article selection and presents the corresponding results. Chapter 3 follows with the presentation of findings, organized into descriptive and content analysis. Chapters 4 and 5 are dedicated to the discussion of results and the final considerations, respectively, including proposals for future research agendas based on the thematic dimensions addressed throughout the study.

2.2. Method

The systematic literature review seeks to establish a replicable research protocol capable of addressing the study's central questions, in accordance with the principle that all methodological procedures must be transparently documented (Tranfield et al., 2003; Snyder, 2019). Within this framework, the review is guided by the following research questions: (i) Which digital technologies have been adopted by grain producers? and (ii) What are the key factors influencing the adoption of digital agriculture technologies within this context?

Accordingly, the search string was systematically developed through the decomposition of the research questions and the application of Boolean operators to facilitate a structured search within two major scientific databases: Scopus and Web of Science. To capture a comprehensive set of relevant publications, a series of synonyms for key conceptual terms were employed. For the concept of 'determinants,' the following terms were included: ('determin' OR 'factor' OR 'driver*' OR 'enabler*' OR 'predictor*'); while for the concept of 'adoption,' the search string incorporated: ('use' OR 'adopt*' OR 'invest*' OR 'diffus*' OR 'transf*'). The term relating to digital agriculture technologies was operationalized by combining synonymous descriptors for both 'agriculture' and 'digital' components using the Boolean proximity operator (W/0), thereby ensuring the co-occurrence of these terms, regardless of word order, within the title, abstract, or keywords. The final expression used was: (('digit*' OR 'precision' OR 'smart' OR 'modern' OR 'intelligent' OR 'automat*' OR '4.0') W/0 ('agri*' OR 'farm*' OR 'rural' OR 'crop*' OR 'field crop*')).

"The final component of the search string was designed to target studies involving grain producers. Broad terms such as 'grains,' 'cereal,' and 'seed' were intentionally excluded to minimize the retrieval of articles outside the scope of this review, which prioritizes research based on fieldwork and the use of primary data. Accordingly, specific crop terms were selected in alignment with the grain classification established by CONAB (2023), including: ('cotton' OR 'peanut' OR 'rice' OR 'bean' OR 'sesame' OR 'sunflower' OR 'castor bean' OR 'corn' OR 'soy' OR 'soybean' OR 'sorghum' OR 'oat' OR 'canola' OR 'rye' OR 'barley' OR 'wheat' OR 'triticale'). This term group was integrated with the three preceding components of the search strategy using the Boolean operator AND."

Table 1. Inclusion and Exclusion Criteria

Items	Inlcusion	Exclusion
Language	English	Other languages
Document type	Peer-reviewed articles	Grey literature and others (published in conferences, book chapters)
Sample	Farm level data (microdata)	Literature review (theoretical articles) or use of aggregated data
Object	Grain producers	Other stakeholders in the soybean production chain and other crops
Approach	An examination of the determinants influencing the adoption of specific digital agriculture technologies, as perceived by rural producers	An analysis of rural producers' intention to adopt digital technologies, examined from the perspective of the technological solutions under development
Scope	Digital agriculture technologies – information and communication technology (IoT, data science) that collect, store and transmit information relevant to agricultural production (BALAFOUTIS et al., 2017; CARRER et al., 2022)	Other practices and technologies, such as climate smart agriculture

Language and document type criteria were applied in advance through the filtering functions of the selected databases (Web of Science and Scopus) and are summarized in Table 1. The searches were conducted on August 9, 2024, resulting in the identification of 692 records in Scopus and 764 in Web of Science.

The retrieved records were imported into Parsifal for the identification and removal of duplicate entries, resulting in the exclusion of 465 articles. Subsequently, an initial screening was conducted based on the titles, abstracts, and keywords, leading to the exclusion of 934 articles. As a result, 57 articles were retained and downloaded for full-text analysis. As detailed in Table 1, the primary exclusion criteria at this stage pertained to the study sample, research focus, and methodological approach. During the subsequent phase of the review protocol, 10 additional articles were excluded due to reliance on secondary data, and one article was removed because the full text was available only in Portuguese, with only the title, abstract, and keywords translated into English.

Furthermore, 27 articles were excluded based on scope-related criteria, as their primary focus was on climate-smart technologies rather than digital agriculture technologies.

Figure 1 illustrates the PRISMA protocol, following the guidelines proposed by Liberati et al. (2009) and Moher et al. (2009), summarizing the key procedural stages involved in the identification, screening, eligibility assessment, and inclusion of articles selected for both descriptive and content analyses.

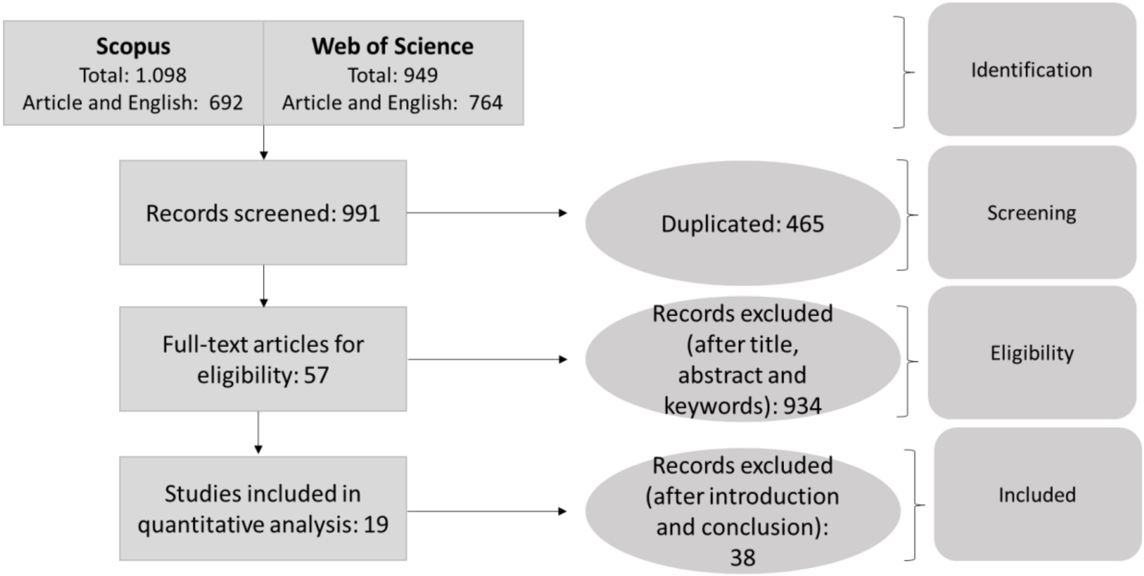

Figure 1. PRISMA protocol flow diagram

2.3. Results

This chapter is structured in two sections. The first section presents a content analysis of the 19 selected articles, emphasizing their temporal distribution, geographical provenance, and the specific types of grain production addressed in the respective studies. The second section focuses on the identification and systematic codification of the primary digital agriculture technologies, as well as the key determinants associated with their adoption.

2.3.1. Descriptive Analysis

Figure 2 highlights the geographic distribution of the analyzed studies, revealing a marked predominance of research conducted in the United States, which represents approximately 60% of the total sample. Figure 3 categorizes the agricultural commodities investigated in the selected articles. In cases where the specific crop type was not explicitly mentioned, the studies were assigned to the general classification of "crop farmers." This designation was applied to works such as that of Paustian and Theuvsen (2017), whose primary focus was on assessing the economic impacts of adopting digital technologies in agricultural systems, rather than analyzing a particular crop.

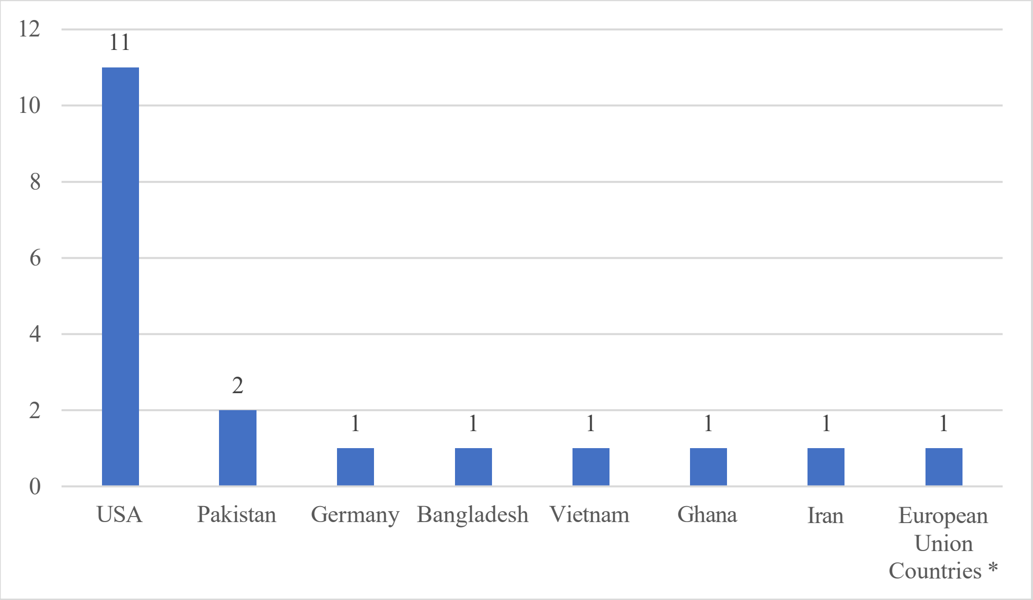

Figure 2. Distribution of articles in relation to countries

* European Union Countries: UK, Germany, Netherlands, Belgium and Greece

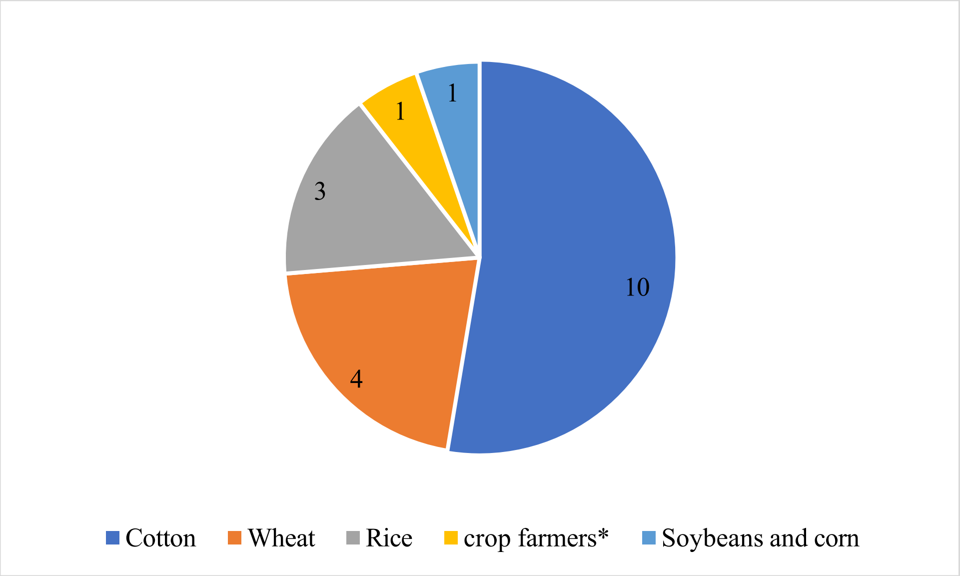

Figure 3. Types of crops studied in each article

* Crop farmers: The article does not specify what specific crop was analyzed

Table 2 summarizes the academic journals in which the selected articles were published. Among them, *Precision Agriculture* accounted for the highest proportion of publications, comprising 26% of the total reviewed articles. Notably, *Computers and Electronics in Agriculture* and the *Journal of Agricultural and Resource Economics* also contributed significantly, each with two articles included in the systematic review.

Table 2. Distribution of articles in relation to journals

Journal	**Articles**
Precision Agriculture	5
Computers and Electronics in Agriculture	2
Journal of Agricultural and Resource Economics	2
Agricultural and Resource Economics Review	1
Applied Sciences-Basel	1
Environmental Science & Policy	1
Evaluation Review	1
Geojournal	1
International Journal of Social Economics	1
Journal of Soil and Water Conservation	1
Science ofthe Total Environment	1
Sustainability	1
Water	1

Figure 4 illustrates the temporal distribution of the publications included in the review, revealing a notable increase in research activity in 2022, which marked the highest number of publications within the analyzed period. In contrast, all other years exhibited only a single publication addressing the topic under investigation.

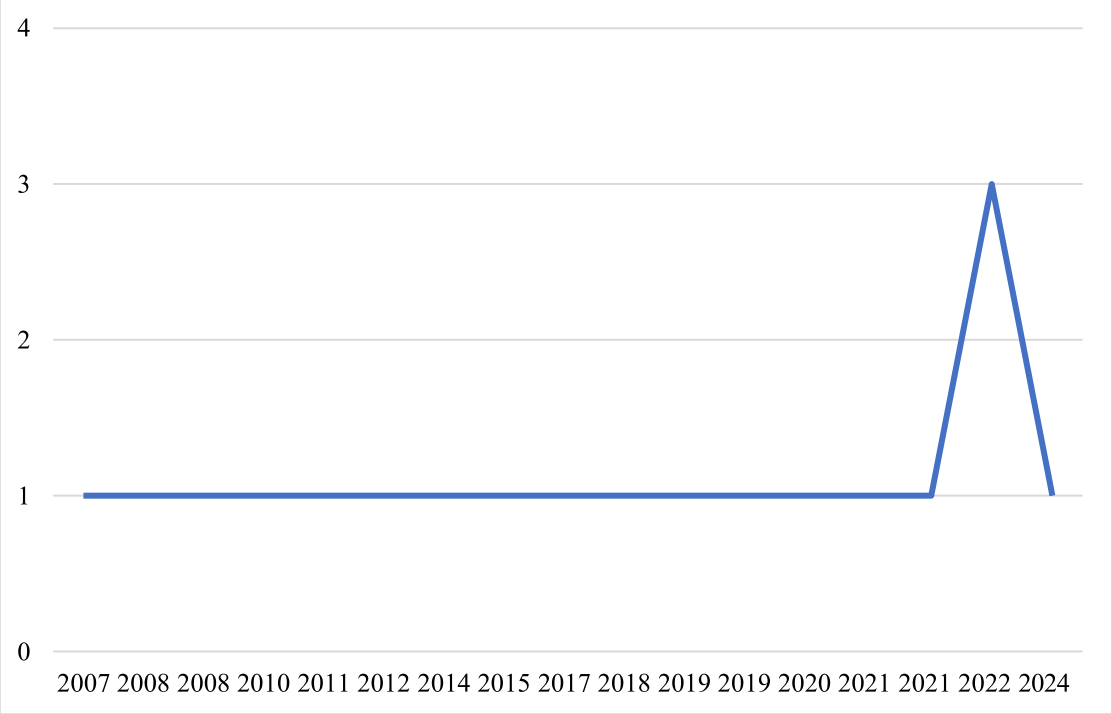

Figure 4. Distribution of articles over time

Figure 5 outlines the primary methodological approaches employed to estimate key parameters and identify the determinants influencing the adoption of digital technologies in agriculture.

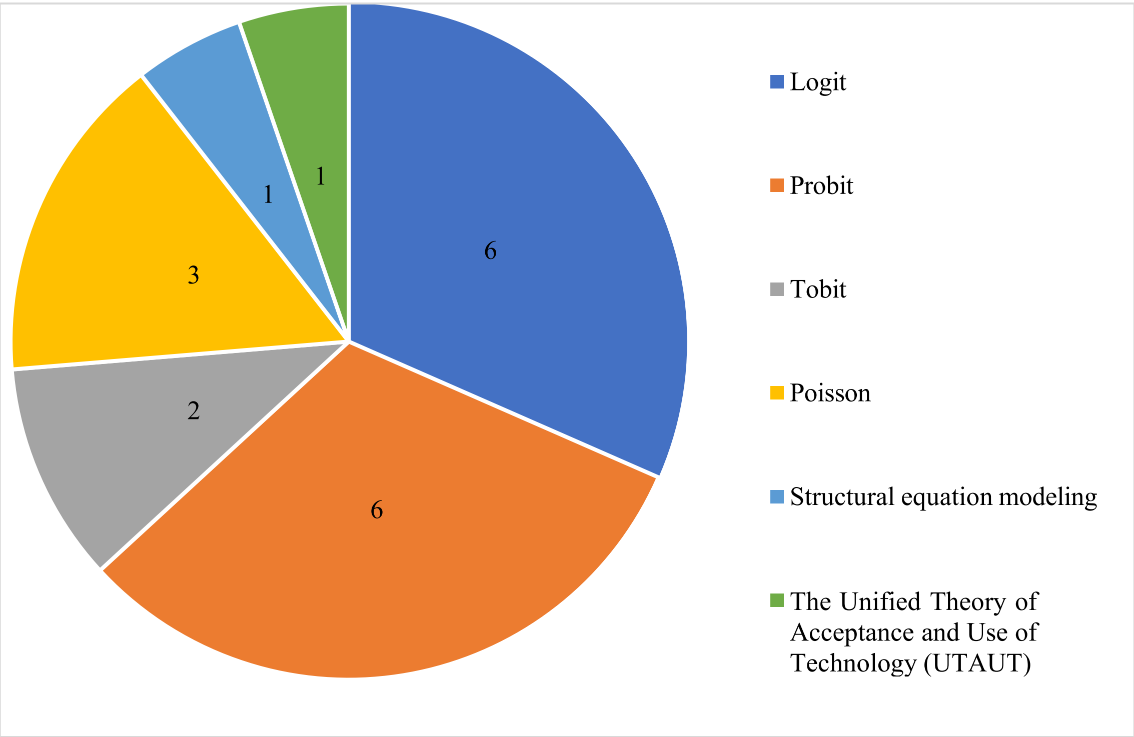

Figure 5. Methodologies used in the articles to define the determinants of adoption of digital technologies

It is noteworthy that linear regression-based models—specifically Logistic (Logit), Probit, Tobit, and Poisson regressions—constitute the predominant methodological approaches in the analyzed literature, appearing in 16 out of the 19 studies reviewed.

2.3.2. Content Analysis

Table 3 lists the digital agricultural technologies identified across the reviewed articles. These technologies can be broadly categorized into two main groups: production management and field application. The production management category encompasses tools designed to collect, organize, analyze, and deliver data to support informed decision-making by producers and farm managers. In contrast, the field application group comprises technologies aimed at enhancing operational efficiency and optimizing input utilization within agricultural production systems.

This classification framework draws on the typology proposed by Moreno et al. (2024b), who delineated a more comprehensive categorization encompassing eight distinct technological domains: automation/control/robotics, biotechnology/bioengineering, cloud computing technologies, data acquisition and communication technologies, data science and artificial intelligence, information systems, manufacturing technologies and equipment, and resource-related technologies. Additionally, it incorporates the more targeted classification scheme developed by Balafoutis et al. (2017), which groups technologies into three functional categories: data acquisition, data analysis, and input application.

Table 3. - Mapping and Categorization of Digital agriculture technologies

Digital Agriculture Technologies	Coding (*)	Authors

Soil sampling	DAT.F	TORBETT et al., 2007; WATCHARAANANTAPONG et al., 2014; WALTON et al., 2010; PAXTON et al., 2011; LAMBERT et al., 2015; LUTHER et al., 2020; WALTON et al., 2008
Variable rate application	DAT.F	TORBETT et al., 2007; BARNES et al., 2019b; LARSON et al., 2008; LUTHER et al., 2020
Machine guidance system	DAT.F	BARNES et al., 2019b
Mechanization	DAT.F	ADDAI et al., 2022; VORTIA et al., 2021
Row planting	DAT.F	ADDAI et al., 2022
Precision agriculture technologies (generic term) **	DAT.F	NGUYEN et al., 2023; PAUSTIAN; THEUVSEN, 2017
Automatic controls – GPS or lightbar	DAT.F	D'ANTONI et al., 2012; KHANAL et al., 2019; LAMBERT et al., 2015
Water-efficient irrigation technologies	DAT.F	POKHREL et al., 2018
Handheld devices - GPS/PDA	DAT.F	PAXTON et al., 2011
Yield monitor	DAT.M	TORBETT et al., 2007; WATCHARAANANTAPONG et al., 2014; PAXTON et al., 2011; LAMBERT et al., 2015; LUTHER et al., 2020
Remote sensing	DAT.M	TORBETT et al., 2007; WATCHARAANANTAPONG et al., 2014; LARSON et al., 2008
Satellite imagery/aerial photography	DAT.M	TORBETT et al., 2007; PAXTON et al., 2011; LAMBERT et al., 2015
Topography mapping	DAT.M	TORBETT et al., 2007
Digitized mapping	DAT.M	PAXTON et al., 2011
Communication and Information Technologies – Mobile Internet	DAT.M	KHAN et al., 2022a; KHAN et al., 2022b
Early warning systems (for drought)	DAT.M	SHARAFI et al., 2021

* DAT.F digital agriculture technologies applied in the field – e DAT.M - digital agriculture technologies for management

** As the authors did not explicitly identify the specific precision agriculture technologies examined, the term was retained in its generalized form to maintain consistency and avoid unwarranted assumptions.

The determinants influencing the adoption of digital agricultural technologies were categorized into five distinct dimensions: biophysical (attributes of the farm or rural property—DF.F), sociodemographic (characteristics of the rural producer—DF.S), behavioral (psychological and personality-related traits of individuals—DF.B), institutional (the nature and extent of support provided by public institutions or other organizations—DF.I), and technological (producers' perceptions regarding the specific features of the technologies—DF.T) (Shang et al., 2021; Aparo et al., 2022). Table 4 provides a detailed classification of these determinants as identified in the analyzed studies.

Table 4. Codification of determinants for the adoption of digital agriculture technology

Determinants	**Number of articles**	**Codification**
Distance to the road	1	DF.F
Planted area	3	
Percentage of area allocated to rotation	1	
Diversification of production	4	
External factors	1	
Farm location	[illegible]	
Distance to water resources	1	
Land ownership	5	
Labor force on the property	1	
Number of agricultural machinery	2	
Portion of irrigated land	1	
Size of the property	7	

Risk aversion	1	DF.B.
Relationship between farmers	1	
Perception of potential improvement in environmental quality	1	
Perceptions of current profits and future importance of technologies	1	
Years of schooling (formal education)	8	DF.S.
Years of experience	2	
Gender	4	
Age of the owner	9	
Age of the operator	1	
Family income	4	
Occupation outside the rural property	1	
Access to credit	1	DF.I.
Agricultural insurance	1	
Consultancy	5	
Participation in cooperatives	3	
Agricultural extension service	1	
Training	2	
Perception of the importance of technology	1	DF.T
Perception of technology performance	1	
Perception of ease of use	1	
Expectation of future profit	1	
Perception of the importance of using climate information	1	
Support from private companies	1	
Use of computer	4	
Use of portable GPS - Personal Digital Assistant (PDA)	1	
Use of maps and information generated by third parties	1	

Among the various determinants influencing the adoption of digital agriculture technologies in grain production, farmers characteristics, particularly age and educational attainment, emerged as the most frequently examined factors, being highlighted in eight of the reviewed studies. Age was found to exhibit a predominantly negative association with technology adoption, indicating that older producers are generally less likely to adopt those technologies. This trend is commonly attributed to greater conservatism in decision-making and heightened risk aversion among older rural producers, especially in relation to technologies that are unfamiliar or demand additional time and effort to learn and integrate into existing production systems.

The most salient biophysical factors associated with rural properties (DF.F) influencing the adoption of digital technologies were the geographic location of the property, which was cited in six studies, followed by farm size and land ownership status, each identified as significant variables in five of the reviewed publications

The primary factors influencing the adoption of variable rate input technologies include the engagement of consultancy services, defined as the hiring of specialized agricultural service providers, and the type of labor utilized on the farm. In the case study presented by Torbett et al. (2007), farms that did not employ family labor demonstrated a significantly higher likelihood of adopting variable rate practices, suggesting a potential association between non-family labor structures and technology uptake.

Similarly, Larson et al. (2008) identified consultancy as a key determinant in the adoption of remote sensing technologies for variable rate of inputs implementation, with particular emphasis on services related to the generation of spatial maps derived from remote sensing data to enhance precision input application. This indicates the relevance of specialized services not only in facilitating adoption but also in optimizing the effective use of such technologies. Furthermore, the study highlighted that producers who utilized laptops for consulting maps, were younger, possessed higher levels of education, and generated their own maps exhibited a greater propensity to adopt these digital tools.

Four studies (Barnes et al., 2019; Nguyen et al., 2023; Paxton et al., 2011; Paustian & Theuvsen, 2017) addressed precision agriculture technologies in general terms, each employing distinct methodological perspectives. For instance, Barnes et al. (2019) conducted a comparative analysis of adopters and non-adopters of precision agriculture across five European countries. Their findings indicated that while farm size and income are initial predictors of adoption, these variables lose explanatory power when evaluating adoption intensity among users. In contrast, variables such as the educational level of the producer, employee training, and the use of consultancy services were found to significantly influence both the likelihood of adopting precision agriculture technologies and the extent of their use.

Nguyen et al. (2023) conducted a qualitative investigation into the factors shaping the behavioral intention of Vietnamese smallholder rice farmers to adopt precision agriculture technologies, drawing on farmers' subjective perspectives and experiences. The study identified several key determinants influencing adoption decisions, including institutional support from private enterprises, involvement in agricultural cooperatives, social interactions among farmers, governmental assistance, and farmers' perceptions of the perceived benefits and usability of the technologies.

Farmers characteristics, particularly age and educational attainment, have been explored by various authors as determinants of technology adoption. Paxton et al. (2011), in a study on U.S. cotton producers, identified age as a significant factor, reporting that older farmers are less inclined to adopt new technologies due to their shorter planning horizons and lower expectations of long-term returns. In contrast, Paustian and Theuvsen (2017), found no statistically significant relationship between age and the adoption of precision agriculture technologies, suggesting that the influence of age may vary depending on regional or structural factors when examining the context of German agriculture.

Conversely, despite being conducted in distinct national contexts, both studies reached a similar conclusion regarding the influence of farm location, defined at the subnational level (e.g., states), on the adoption of precision agriculture technologies. Specifically, both authors found that properties situated in regions characterized by elevated grain production levels and/or superior market infrastructure exhibit a higher propensity to adopt digital agricultural innovations.

Based on the spatial distribution of service providers, Paustian and Theuvsen (2017) observed that the location of rural properties, defined at the state level within Germany, was a statistically significant factor influencing the adoption of precision agriculture technologies. The higher concentration of suppliers in specific regions was associated with increased uptake, suggesting that local availability of technological support infrastructure plays a critical role in facilitating adoption

Paxton et al. (2011) operationalized the variable "location" as a binary indicator representing whether or not a farm was situated within a specific U.S. state. Their analysis revealed a statistically significant relationship between this locational variable and the number of precision agriculture technologies adopted. As further emphasized by the authors, the explanatory power of the location variable may also be attributed to regional heterogeneity in producer characteristics, such as age and average educational attainment, as well as agroecological conditions, including climate and soil attributes, which collectively influence the propensity for technology adoption

In this context, the studies did not specify particular precision agriculture technologies, as their primary focus was on adoption intensity, measured by the number of technologies adopted by producers, rather than on specific technological tools. Watcharaanantapong et al. (2014) and Walton et al. (2010) found that younger producers and those holding land ownership exhibited a greater propensity for adoption of grid soil sampling. Additional factors positively associated with the uptake of this technology included the use of agricultural consultancy services, producers' perceptions of enhanced environmental quality (Watcharaanantapong et al., 2014), the extent of land allocated to the focal crop (cotton, in both U.S.-based studies), production diversification, and the utilization of digital tools such as computers and portable GPS devices (Walton et al., 2010).

In addition to grid soil sampling, Watcharaanantapong et al. (2014) also examined the adoption of other precision agriculture technologies, including yield monitoring and remote sensing. The adoption of yield monitoring was primarily influenced by producer age and the perceived enhancement of environmental quality. Similarly, perceived environmental benefits were identified as a key determinant, alongside the engagement of specialized consultancy services to support implementation for remote sensing technologies.

Mobile internet technology adoption is positively associated with farm size and the educational attainment of producers. Additional determinants identified include access to credit, participation in agricultural cooperatives and services, as well as engagement with rural extension programs (Khan, Ray, Kassem, Khan et al., 2022; Khan, Ray, Kassem, and Zhang, 2022). Furthermore, Khan, Ray, Kassem, and Zhang (2022) emphasize that younger farmers, particularly those with a heightened awareness of agricultural risk dynamics, and the locational context of the property also significantly influence the likelihood of technology adoption.

Gender demonstrated inconsistent statistical significance across the studies, indicating variability in its role as a determinant of technology adoption within different empirical contexts. Khan, Ray, Kassem, Khan et al. (2022) identified a negative association between female-headed households and the adoption of digital agricultural technologies, implying that gender may serve as a relevant explanatory variable in certain contexts. Conversely, the results presented by Khan, Ray, Kassem, and Zhang (2022) indicated no statistically significant relationship between gender and technology adoption. This divergence highlights the contextual variability in the role of gender as a determinant, potentially reflecting differences in sample characteristics, methodological approaches, or socio-cultural dynamics.

According to Addai et al. (2022), the adoption of agricultural machinery and row planting technologies is positively associated with male gender and participation in cooperatives or producer organizations. Conversely, factors such as the owner's educational attainment, as well as the size and geographic location of the property, demonstrated a negative relationship with the likelihood of adopting these technologies.

In the context of autopilot technology adoption, D'Antoni et al. (2012) identified that farm size and the utilization of computers were positively associated with its uptake. Larger agricultural properties tend to present greater operational complexity and scale-related demands, thereby increasing the incentive for automation through technologies such as autopilot. Moreover, the use of computer systems are often integral to operating and managing autopilot functionalities. Conversely, the age of the farm operator exhibited a negative relationship with adoption, suggesting that older individuals are less likely to incorporate autopilot technology, potentially due to lower familiarity with digital systems or greater resistance to change.

Sharafi et al. (2021) offers an alternative analytical perspective in examining the determinants influencing the adoption of drought early warning systems. Although the study does not provide a detailed breakdown of specific variables, it identifies three overarching categories that contribute to adoption: (i) individual-level characteristics, including personal attributes and personality traits; (ii) external and agro-environmental factors, encompassing farm-level variables such as property attributes, climate, topography, and soil conditions; and (iii) perceptual factors, particularly producers' recognition of the relevance and utility of climate information for agricultural decision-making. These dimensions collectively shape the likelihood of integrating early warning systems into rural property management strategies.

According to Pokhrel et al. (2018), the adoption of drip irrigation systems is positively influenced by a combination of biophysical and sociodemographic factors. Specifically, key biophysical determinants include the geographic location of the farm and the extent of irrigated land, while relevant sociodemographic variables comprise the educational level of the producer, land ownership status, and the use of computers.

Figure 6 illustrates the proposed analytical framework derived from the literature review, synthesizing the principal determinants associated with the adoption of digital agriculture technologies.

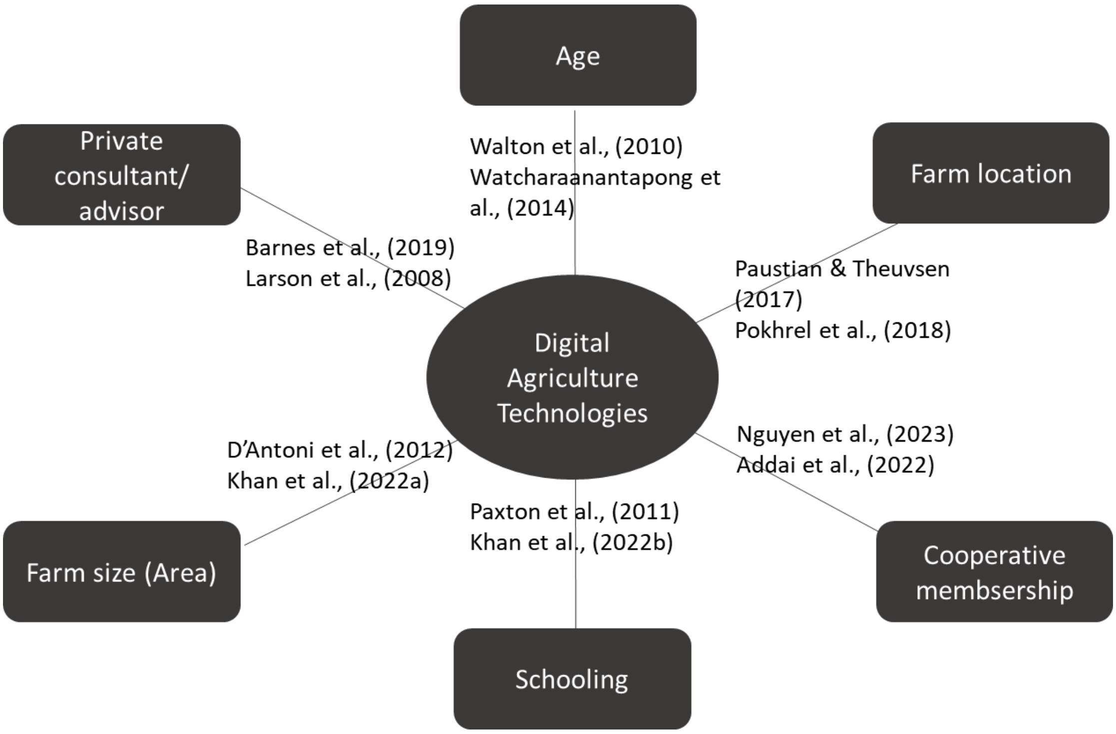

Figure 6. Summary of the main determinants for the adoption of digital agriculture technologies

The literature reviewed identified three primary categories of determinants influencing the adoption of digital technologies in grain production: biophysical, demographic, and institutional factors. Biophysical factors encompassed rural property attributes, particularly geographic location and land area. Demographic variables included farmers characteristics such as age and educational attainment. Institutional factors were associated with the engagement of external support mechanisms, notably the hiring of consultancy services and participation in agricultural cooperatives or other rural producer organizations.

2.4. Discussion

Studies examining the adoption of digital technologies in agriculture employ a range of methodological approaches, including binomial and multinomial logistic regression models, Poisson regression, among others. The selection of explanatory variables and the interpretation of outcomes vary across studies. While some analyses focus on identifying factors that significantly increase the likelihood of technology adoption, others also highlight variables that do not attain statistical significance within their specified models.

It is important to acknowledge that, in certain instances, the methodological approaches employed by the respective authors did not explicitly address specific research questions related to the determinants of technology adoption. Consequently, these studies did not allow for reliable inferential analysis regarding the factors influencing adoption. As a result, such cases were excluded from the present review to ensure analytical consistency and the validity of comparative insights.

This paper primarily concentrated on identifying specific digital agriculture technologies. However, an examination of the excluded literature revealed that, in the context of grain production, several studies focused on climate-smart technologies, understood both as technological innovations (e.g., genetically modified seeds) and as sustainable agricultural practices (e.g., no-tillage systems, crop-livestock-forest integration) aimed at reducing greenhouse gas emissions. These findings underscore the importance of broadening the analytical scope to include a wider array of technologies and management strategies that contribute to the efficient use of natural resources and the mitigation of environmental impacts.

Digital agriculture technologies can be broadly categorized into two interrelated domains: field-level technologies and farm management systems. These domains are functionally integrated, as data generated through field operations require processing and interpretation via software tools and digital platforms classified under property or farm management technologies. This interdependence is evidenced by the consistent identification of computer use as a significant determinant in the adoption of various digital technologies, including autopilot systems (D'Antoni et al., 2012), grid soil sampling (Walton et al., 2010), drip irrigation (Pokhrel et al., 2018), and broadly to precision agriculture technologies as a unified category, without detailing the specific tools or systems under analysis (Paxton et al., 2011).

Accordingly, it is imperative to conduct targeted studies examining the complementarities and integrative potential of various digital agricultural technologies, alongside their potential interdependencies and interactions across distinct technological levels.

2.5. Conclusions

Based on a systematic literature review, this paper identified the predominant digital agriculture technologies employed in grain production, including variable-rate input application, grid soil sampling, yield monitoring, remote sensing, and mobile internet technologies. Furthermore, the review synthesized the principal determinants associated with the adoption of these technologies, providing insights into the conditions and characteristics that facilitate or constrain their uptake in agricultural production.

The most frequently reported determinants across the reviewed studies include farmers characteristics, such as age and educational attainment, and farm-level attributes, including geographic location, landholding size, and land tenure arrangements. Additionally, the engagement of consultancy services emerged as a key institutional factor. Collectively, these findings underscore that the adoption of digital agriculture technologies is influenced by a multifaceted set of variables, particularly those of economic and social nature. Accordingly, public policies and dissemination strategies aimed at promoting these technologies should be tailored to account for such heterogeneity. Furthermore, future research that empirically examines the effects of digital technology adoption on farm productivity and economic performance remains essential to inform evidence-based policymaking and investment decisions.

The United States emerged as the country with the highest number of studies analyzed in this literature review, a result likely attributable to its well-established databases for specific grain crops. In contrast, although Brazil is a major global actor in grain production, particularly in the soybean sector, no studies originating from the country were selected. This absence may be partially explained by the exclusion of non-English publications and the persistent challenges associated with accessing primary microdata from Brazilian rural producers. Furthermore, the diffusion of digital agricultural technologies in Brazilian soybean production appears to encounter substantial barriers, suggesting a need for targeted policy and research efforts to address these limitations.

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3. What drives the adoption of digital technology? An empirical assessment of multiple technology adoption by Brazilian soybean farmers[2]

3.1. Introduction

The diffusion of digital technologies has been increasing in several agricultural activities across different countries (Barnes et al., 2019; Klerkx et al., 2019; Bolfe et al., 2020). Digital agriculture technologies refer to the use of different tools, management practices, and data-driven solutions to enhance the efficiency, productivity, and sustainability of agricultural practices (Balasundram et al., 2023). These technologies encompass a wide range of innovations, including precision agriculture[3], drones, sensors, data analytics, intelligent systems, robotics, internet of things, and blockchain, which collectively might optimize the use of resources in the entire agri-food value chain (Balafoutis et al., 2017; Moreno et al., 2024). Digital Farming Technologies encompass a wide array of tools, ranging from user-friendly mobile apps for decision support to in-field sensors and remote sensing systems for data collection and advanced drones and robots for automating production processes (Shang et al., 2021).

The adoption of these technologies has been driven by the need for agricultural systems to adapt to the growing food demand while optimizing yields, minimizing resource use (mainly land, water, and chemicals), and preserving the environment (Blasch et al., 2022; Carrer et al., 2022). Farm-level studies on digital agriculture technology adoption have been published in recent years (Carrer et al., 2017; Caffaro & Cavallo, 2019; Drewry et al., 2019; Pivoto et al., 2019; Michels et al., 2020; Mozambani et al., 2023; Mendes et al., 2024). Literature reviews have also been conducted to systematize studies on the determinants of adoption of digital technologies in China (Cui & Wang, 2023), the United States (Yeo & Keske, 2024), and Europe (Gabriel & Gandorfer, 2023). In Brazil, there are no systematic literature reviews on the factors that might affect the adoption of DAT. However, there are specific empirical studies on the adoption of digital technologies in sugarcane (Mozambani et al., 2023), citrus (Carrer et al., 2017), beef cattle (Mendes et al., 2024), and grain production (Pivoto et al., 2019).

Nonetheless, the literature lacks an empirical assessment of multiple digital technology adoption by soybean farmers in Brazil, due to the difficulty in finding consolidated databases with primary microdata, such as the Agricultural Resource Management Survey (ARMS)/USDA (McFadden et al., 2023). Many of these technologies – such as georeferenced soil sampling, variable-rate input application, and yield mapping – have complementarities, increasing the relevance of studies that examine the adoption of multiple digital technologies. Furthermore, an integrative empirical approach that considers the effects of personal and behavioral characteristics, farmers' technology

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[2] This manuscript is currently undergoing peer review for potential publication in Precision Agriculture.

[3] Precision agriculture represents a sophisticated management approach that entails the systematic collection, processing, and analysis of temporal, spatial, and individual farm data. This integrated process combines the gathered information with additional relevant datasets to enhance decision-making and optimize the utilization of agricultural production resources (BALAFOUTIS et al., 2017; ISPA, 2021). In the context of this study, precision agriculture technologies are identified as a subset within the broader category of digital technologies.

perceptions, farm management aspects, farm structure, and institutional factors is not commonly adopted in empirical studies.

This paper aims to identify the factors determining soybean farmers' decisions on the adoption and intensity of use of various digital technologies. A structured questionnaire (Appendix A) was applied to 150 soybean farmers of the state of São Paulo (Brazil) to collect primary micro data of the 2023/24 crop year. Econometric models of qualitative choice and count data were used to estimate the factors that affect the probability of adoption and the intensity of use of digital agriculture technologies.

The adoption of DAT can be an important mechanism to increase efficiency in the use of inputs with a positive impact on grain productivity (Kroupová et al., 2025). The area under soybean cultivation has increased significantly in the last decade in the state of São Paulo, rising from 495,833 ha in 2010 to 1,360,285 ha in 2023 (IBGE, 2023). In 2023, the soybean production chain generated a production value of 12.4 billion BRL (2.48 billion USD[4]), ranking third among the agro-industrial chains with the highest production value in the state of São Paulo (Monteiro et al., 2023). The continued growth of soybean production in sustainable and economically viable ways depends on the adoption of technological innovations that increase the productivity of inputs.

This paper is distinguished by its comprehensive analysis of the factors influencing the adoption of eight DAT, namely, autopilot system, georeferenced soil sampling, yield monitor, yield map, variable rate input application, variable rate seeding, farm management software, and drones. Furthermore, this study examines the factors that influence the intensity of technology adoption. Data for this analysis were collected from a sample that included farmers who had not adopted any DAT, as well as those who had adopted one or more of the eight technologies under investigation, thereby accounting for potential complementarities among these innovations.

Additionally, the determinants include six categories: personal and behavioral farmers' characteristics, perception of the technology, management features, farm structure, and institutional factors.

The article is structured as follows. Section 2 contains a literature review on the adoption of DAT. Section 3 provides a detailed characterization of the soybean farmer sample and outlines the variables incorporated into econometric models for hypothesis testing. The fourth section presents and discusses the results. Section 5 contains final remarks.

3.2. Literature Review

The adoption of DAT for optimizing input applications in the production process, such as autopilot systems for tractors and harvesters, georeferenced soil sampling, and variable-rate input application, has been investigated in recent empirical studies (Barnes et al., 2019; Carrer et al., 2022; Blasch et al., 2022; Mozambani et al., 2023). There are also literature reviews addressing this topic (Shang et al., 2021; Mühl & Oliveira, 2022;

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[4] The exchange rate, 4.99 BRL/USD, represented the mean value for the 2023 calendar year, as reported by the BCB (2024).

Moreno et al., 2024; Papadopoulos et al., 2024), as well as reviews on specific technologies, such as farm management information systems (Tummers et al., 2019) and mobile-based technologies (Aparo et al., 2022).

The literature presents classifications for the drivers of technology adoption. For example, Souza Filho et al. (2011) identified four key categories of factors related to technology adoption: socioeconomic factors, farm characteristics, technology attributes, and systemic factors. Shang et al. (2021) highlighted psychological factors, technology attributes, interaction between different technologies, institutional factors, as well as operator and farm characteristics as important drivers of technology adoption. Aparo et al. (2022) categorized the factors influencing farmers' adoption decisions into: socio- demographic variables, technological factors, mobile usage-related attributes, psychological/behavioral factors, constraints, institutional factors, and biophysical factors.

Generally, the empirical studies used farm-level data and applied qualitative choice regression models (e.g., logit and probit), censored variables regression models (e.g., tobit), or count data models (e.g., Poisson, double hurdle models, etc.) to identify the variables that affect the adoption and intensity of use of several digital technologies by farmers in different countries. Table 5 presents a summary of the literature review.

Table 5. Summary of literature review on determinants of Digital Agriculture Technologies adoption

REFERENCE	**DAT ANALYZED**	**DRIVERS OF ADOPTION**	**SAMPLE**	**METHODS**
Barnes et al. (2019)	Machine guidance systems; variable rate nitrogen application; controlled traffic farming; variable rate irrigation; variable rate pesticide application; variable rate seeding/planting; precision physical weeding	Level of education (+) training of staff (+), use of advisors (+)	971 European farmers (cross-country survey of technology intentions among European arable farmers)	Count regression modelling approach
D'Antoni et al. (2012)	Auto-steer GPS guidance system	Farmers' perceptions of importance of precision agricultural technologies (+), perception of potential input cost savings (+), farm size (+), age (-), computers use for farm management (+)	469 cotton farmers in the USA (2009 Southern Cotton Precision Farming Survey)	Multinomial logit (MNL) model
Larson et al. (2008)	Remote sensing for variable-rate input application, such as plant growth regulators	Age (-), level of education (+), irrigated cotton area (+), use of portable computers in fields (+)	941 cotton farmers in 11 southern USA states	Binomial logit model

Paxton et al. (2011)	Yield monitor, grid soil sampling, aerial photos, satellite images, soil survey maps, (viii) handheld GPS/PDA devices	Farmer's age (-), operator's age (-), Formal education of farm operator (+), computer use for management (+), farm location as dummy variables (+)	892 cotton farmers in the southeastern part of the USA	Poisson and negative binomial model
Torbett et al. (2007)	Variable rate application technologies for: N, P, and K, lime, seeds, growth regulator, defoliant, fungicide, herbicide, insecticide, and irrigation	Age (+), perceptions of the importance of Precision Farming technologies (+); land ownership (+); computer use for management (+)	1131 cotton farmers in 6 USA states	Ordered logit analysis
Walton et al. (2010)	Grid soil sampling	Age (-), cotton area (+), land ownership (+), planted other cultures (+), computer use for management (+)	827 cotton farmers in 11 USA states	Separate Probit regression
Watcharaanantapong et al. (2014)	Grid soil sampling, yield monitoring, and remote sensing	Land ownership (+), farmer age (-), information from consultants (+), potential for improved environmental quality (+)	1088 cotton farmers in 12 USA states (Cotton Incorporated Southern PA Survey)	Multivariate censored regression - trivariate Tobit methods
Blasch et al. (2022)	Precision farming technologies	Social influence (+); environmental awareness (+)	250 farmers in the Plain of Tarquinia in Central Italy	Mixed multinomial logit (MMNL) models and latent class logit models
Carrer et al. (2017)	Use of computers and farm management information systems	Experience (-), overconfidence in management (+), technical assistance (+), contract adjustments (-)	98 citrus farmers from the state of São Paulo, Brazil	Logit and count data (Poisson regression) models
Carrer et al. (2022)	GNSS and images for planting row orientation, automatic guidance system, georeferenced grids for soil sampling, images (satellite or drone) for mapping pests and yields, variable-rate applicators of fertilizers and pesticides	Experience (-), schooling (+), farm size (+), technical assistance (+)	131 Brazilian sugarcane farmers (São Paulo state)	Stochastic Production Frontiers (SPFs) and metafrontier - probit selection model

Mozambani et al. (2023)	GNSS and images for planting row orientation, automatic guidance system, georeferenced grids for soil sampling, images (satellite or drone) for mapping pests and yields, variable-rate applicators of fertilizers and pesticides	Agricultural advisor (+), agricultural event (+), experience (+), credit (+), yield perception (+)	131 Brazilian sugarcane farmers (São Paulo state)	Count data model (Poisson regression)

Note: The signs (+) and (-) show the direction of the effect of each variable on the probability of adopting digital technologies.

3.3. Methods

The empirical modelling strategy proposed in this study consists in applying econometric models to assess the impact of a range of factors on the probability of adoption of a set of digital technologies by Brazilian soybean farmers. The econometric models used for empirical analysis are based on the random utility framework as proposed in McFadden (1974). This framework posits that an individual derives utility from selecting a technological alternative. The utility is assumed to be a function of a set of explanatory variables X, which describe the decision-maker *n* and the alternative i. Therefore, individual preferences are evaluated based on observed choices and a random utility function that is usually specified as an additive combination of a deterministic component and a stochastic term (Walker & Ben-Akiva, 2002; Blasch et al., 2022). The decision to adopt a new technology occurs when the expected utility of adoption (Ua) exceeds the expected utility of non-adoption (Un), i.e., Ua > Un (Carrer et al., 2017).

The logit model, with a dependent variable of 0 (non-adoption) or 1 (adoption), was applied to identify the effects of the explanatory variables (x_i) on the probability of adopting each of eight different digital technologies. The count data model, with a dependent variable representing the number of adopted digital technologies (the variable ranges from 0 to 8, where 0 is non-adoption and 8 is the joint adoption of all analyzed technologies), was applied to identify the factors determining the intensity of use of digital technologies by farmers.

3.3.1. Logit model

The farmer's standard behavior observed in the adoption of a technology can be represented by a dummy variable (yi), where:

$yi = 1$ if $Ua > Un$

$yi = 0$ if not. (1)

The likelihood of technology adoption can be defined as follows:

$$P[y_i = 1] = P(e_i > -X_i\beta) = 1 - F(-X_i\beta) = F(X_i\beta) \tag{2}$$

where F is a function of the cumulative distribution and β are the parameters to be estimated through maximum likelihood procedures. The qualitative choice models, frequently used in technological adoption empirical studies (logit and probit), differ only in the choice of the cumulative distribution function (F). The logit model assumes a logistic functional form, while the probit model assumes a standard normal distribution. The results of both models tend to converge, and the choice can be made on a case-by-case basis (Greene, 2003). The logit model was applied to investigate the factors affecting the probability of adoption of DAT by soybean farmers in Brazil. The logit model can be expressed as (Greene, 2003):

$$P_i = P[y_i = 1] = \frac{e^{x_i\beta}}{1+e^{x_i\beta}} \tag{3}$$

After estimating the β parameters, which only show the effect (positive or negative) of the x_i variables on the adoption of each specific digital technology, the marginal effects of each variable on the likelihood of adoption can also be calculated. That is, the effect of minor changes (usually interpreted as unitary changes) in a specific x_i variable on the likelihood of adoption of a specific technology, *ceteris paribus*:

$$\frac{\Delta p_i}{\Delta x_i} = \frac{\partial p_i}{\partial x_i} = \beta_i \frac{1}{1+e^{-x_i\beta}} \times \frac{e^{-x_i\beta}}{1+e^{x_i\beta}} \tag{4}$$

3.3.2. Data count model

In addition to examining the adoption of each single digital technology, the present study investigates the determinants of the intensity of use of digital technologies by soybean farmers. Data count models have been applied in previous studies to examine the adoption of technology packages by farmers (Isgin et al., 2008; Carrer et al., 2017; Mozambani et al., 2023; Mendes et al., 2024). The dependent variable (y) measures the total number of digital technologies adopted by a farmer. Therefore, a Poisson probability distribution is more appropriate than a normal or logistic distribution (Greene, 2003). With Y for the random Poisson variable, the probability density function is expressed as follows:

$$f(y_i \mid x_i) = P(Y_i = y_i) = \frac{e^{\lambda}\lambda^{y}}{y!}, \qquad y = 0,1,2,\ldots \tag{5}$$

where y_i is the number of digital technologies adopted by farmer i and x_i represent the variables that determine the intensity of use of these technologies. The expected mean parameter (λ) of this probability function is defined as:

$$E(y_i|x_i) = \lambda_i = \exp(x'_i\beta) \tag{6}$$

Equation (6) represents the Poisson data count regression model, where the β parameters can be estimated through maximum likelihood procedures. This procedure is done by maximizing the following logarithmic likelihood function:

$$lnL(\beta) = \ln\left[\frac{e^{\lambda}\lambda^{y}}{y!}\right] = -\lambda + y_i\ln(\lambda) - \ln(y_i!) = -\exp(x'_i\beta) + y_i(x'_i\beta) - \ln(y_i!) \tag{7}$$

The Poisson model assumes that the data exhibit equidispersion, i.e., the mean and variance of the dependent variable are equal: $E(y_i) = var(y_i) = \lambda$.

3.3.3. Sample

The empirical analysis is based on cross-sectional primary microdata collected from 150 soybean farmers for the 2023/24 crop year. A structured questionnaire was applied to farmers during on-farm visits. The questionnaire was structured into eight parts: farm characteristics, characteristics of soybean production in the 2023/2024 crop year, adoption of digital technologies, management characteristics, institutional factors, personal farmers' characteristics, a section on behavioral farmers' characteristics, and perceptions of technology (Appendix A)

There is no available list that includes the names of all soybean farmers in the state of São Paulo, such that a random sample could be selected. Therefore, to access the farmers, the researchers requested support from agricultural cooperatives, rural extension service, technical assistance companies, and input suppliers. These organizations maintain lists of farmers, allowing for the random selection of a sample. The data collection was carried out between May and October 2024. Figure 7 shows the distribution of sampled farms at 55 municipalities in the state of São Paulo.

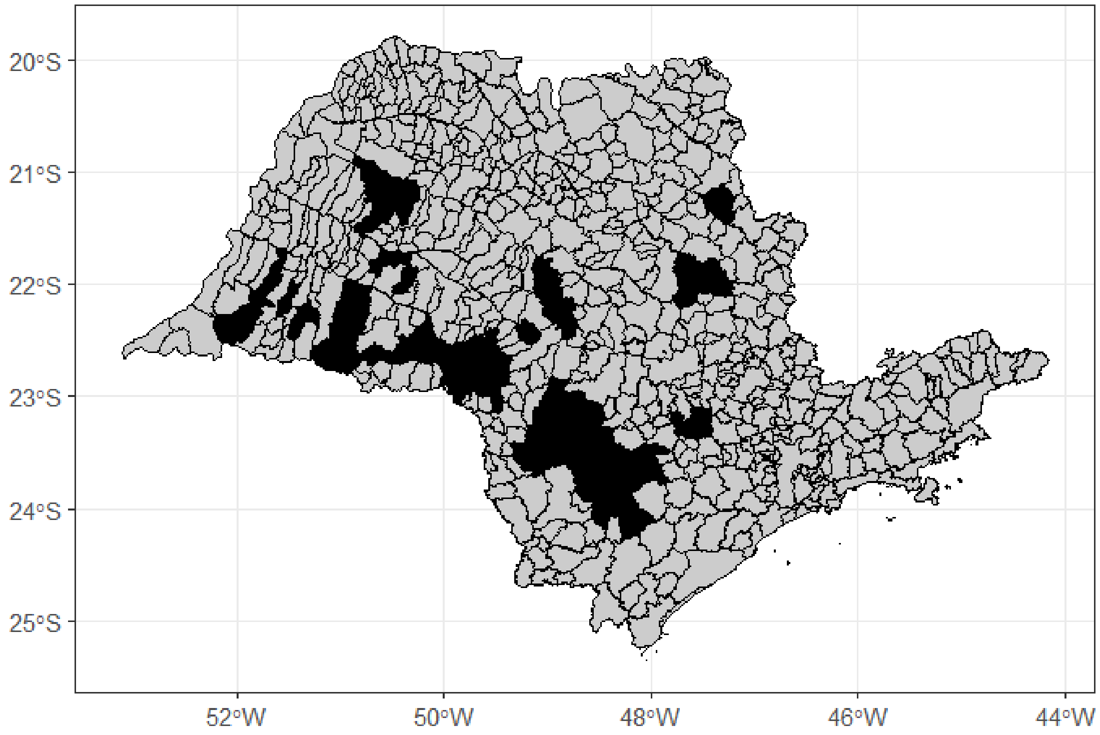

Figure 7. Spatial distribution of sampled farms.

3.3.4. Variables and empirical hypotheses

The factors determining the adoption of digital technologies were grouped into six categories: (i) personal farmers' characteristics; (ii) behavioral farmers' characteristics; (iii) perceptions of technology; (iv) management characteristics; (v) farm characteristics;

(vi) institutional factors (Souza Filho et al., 2011; Balafoutis et al., 2017; Carrer et al., 2020; Vinholis et al., 2021; Carrer et al., 2022; Mendes et al., 2024).

3.3.4.1. Personal characteristics

- Experience

Experience has been used as a proxy for the accumulated knowledge and managerial capabilities (Feder et al., 1985; Souza Filho et al., 2021). Farmers with accumulated experience in such farming activities are better able to understand technical changes, perceive lower levels of risk, and feel more confident in adopting innovations (Souza Filho et al., 2021).

The "accumulated knowledge" effect of experience is expected to surpass the "risk-aversion" effect. Consequently, this hypothesis was subject to empirical testing:

H1a: The greater the farmer's experience, the higher the probability of adopting digital technologies.

- Schooling

Formal education is a variable related to human capital that might explain the likelihood of adopting digital technology (Feder et al., 1985; Larson et al., 2008; Paxton et al., 2011). Farmers with higher levels of education have greater ability to understand functionalities and manage new technologies. Specifically, digital technologies require managerial capabilities to interpret a large amount of data and information. (Carrer et al., 2017; Carrer et al., 2022).

Formal education is measured as a continuous variable representing the years of schooling level of farmers. Thus, the second hypothesis related to farmers' characteristics was proposed:

H1b: Farmers with higher levels of education are more likely to adopt digital technologies.

3.3.4.2. Behavioral characteristics

- Innovativeness

Farmer's "innovation" refers to their willingness and ability to adopt new technologies and practices in their agricultural activities. It encompasses openness to change, experimentation, and the implementation of innovative solutions in agricultural management (Shah et al., 2016; Michels et al., 2020; Mendes et al., 2024).

Based on the statement "I like to test new technologies on my farm," a five-point Likert scale variable was created, derived from the farmer's level of agreement. Thus, the hypothesis regarding the farmer's innovative profile was established:

H2a: The more prone to innovation farmers are, the higher the likelihood of adopting digital technologies.

- Risk aversion

Farmer risk-aversion refers to the tendency of farmers to prefer avoiding uncertainty and potential losses rather than taking risks that could lead to higher gains. In other words, risk-averse farmers are more likely to choose options that offer more predictable outcomes, even if those options might have lower potential returns (Carrer et al., 2017; Lien et al., 2023).

A five-point Likert scale variable was derived from the farmer's level of agreement with the following statement: " When it comes to business, I always prefer the safest option, even though I know I may earn less". Therefore, the following hypothesis was formulated:

H2b: Farmers who are more risk-averse have a lower probability of adopting digital technologies.

3.3.4.3. Perception of technology

- Cost perception

The perceived characteristics of digital technology (e.g., cost, relative advantage, and complexity of use) significantly impact farmers' acceptance and, consequently, the likelihood of adoption (Dwivedi et al., 2019). In the agricultural sector, some studies have shown that farmers' ex-ante perceptions of technological characteristics play an significant role in explaining adoption decisions (Watcharaanantapong et al., 2014; Mozambani et al., 2023).

The five-point Likert scale variable to capture the farmer's cost perception was derived from the following statement: "Digital technologies are too expensive for me." Thus, the empirical hypothesis to be tested was formulated:

H3: If the farmer perceives the technology as expensive, the likelihood of its adoption decreases.

3.3.4.4. Management Characteristics

- Private technical assistance

Access to information about the use of new technology is essential to incentivize the adoption by individuals. In the classic Rogers' (1983) diffusion of innovations theory, information plays a crucial role in the diffusion of new ideas among economic agents.

The transfer of information and the assistance provided by specialists during farm visits have played a significant role in informing and helping farmers and their employees about new technologies (Souza Filho et al., 2011; Carrer et al., 2017; Barnes et al., 2019). Considering that, a dummy variable for hiring consulting services (technical/private assistance) was used as a proxy for access to in-depth information about the technology and its customization to the farmer's profile. Thus, the hypothesis to be tested was proposed:

H4: The hiring of consulting services positively affects the likelihood of adopting digital technologies.

3.3.4.5. Farm Characteristics

- Farm size

The production scale is widely used as a factor that affects the likelihood of adopting digital technology (Walton et al., 2010; D'Antoni et al., 2012; Barnes et al., 2019; Mozambani et al., 2023). Farmers with higher production scales tend to have lower budget constraints and input markets, greater capacity to invest in expensive technologies, and higher levels of managerial skills in assessing the benefits of DAT (Isgin et al., 2008; Michels et al., 2020; Carrer et al., 2022). The area is commonly used as a proxy for the production scale.

Therefore, the area planted with soybeans during the 2023/2024 harvest was used as a proxy for production scale, and the hypothesis was defined:

H5a: Farm size positively affects the adoption of digital technologies by farmers.

- Slope of soybean area

Farm topography plays a pivotal role in decisions regarding the adoption of specific agricultural systems and technologies. Crop cultivation typically occurs on terrains with slopes of up to 6%; however, steeper slopes are occasionally utilized (Thomas et al., 2007).

Flat or gently sloping terrain facilitates the use of machinery, thereby reducing production costs. Furthermore, investing in technological solutions is cheaper and poses fewer risks on flat surfaces compared to uneven terrain. (Bello et al., 2024). Therefore, the slope of the farm was measured as a dummy variable if the farmer perceived a flat slope in most of the soybean-planted area. The hypothesis was established:

H5b: The cultivation of soybeans in flat areas positively affects farmers' adoption of digital technologies.

3.3.4.6. Institutional Factors

- Access to rural credit for investment

Access to financial markets has been essential for purchasing new technologies and fixed capital inputs, especially in the agricultural sector (Girma, 2022; Rayhan et al., 2023). The supply of subsidized credit has been the main policy of the Brazilian federal government to accelerate the diffusion of innovations in agriculture. Empirical evidence suggests that access to this policy has been important in determining the adoption of technologies (Carrer et al., 2020).

Access to credit was measured as a dummy variable indicating whether farmers had access to rural credit for investment in the 2023/2024 harvest. The hypothesis to be tested was formulated:

H6a: Access to rural credit for fixed capital investment positively influences the likelihood of adopting digital technology.

- Cooperativism

Agricultural cooperatives play a crucial role by facilitating access to resources, information, and markets for their members (Leite et al., 2021). According to Abnousi et al. (2020) and Mendes et al. (2024), cooperatives promote the adoption of technological innovations by providing a supportive environment for experimentation and knowledge sharing. Moreover, studies have shown that cooperatives enhance farmers' bargaining power with technology suppliers and improve their access to credit and input markets (Carrer et al., 2013; Holgado-Silva & Binotto, 2022).

Farmers' participation in cooperatives was measured as a dummy variable indicating whether the farmer is a member of an agricultural cooperative. The hypothesis to be tested was established:

H6b: Farmers who are members of cooperatives have a higher probability of adopting digital technology.

In logit models, the dependent variable takes values of 0 (non-adoption) or 1 (adoption) for each DAT. In the count data model, the dependent variable ranges from 0 to 8, enabling the identification of the intensity of use of digital technologies: autopilot, soil sampling, yield map, yield monitor, variable rate seeding, variable rate fertilizer application, drone, and management software.

The explanatory variables are categorized into six groups, as explained previously: (i) personal farmers' characteristics: years of soybean farming experience (EXPERIENCE), and level of education (SCHOOL); (ii) behavioral farmers' characteristics: propensity to test new technologies (INNOVATIVE), and degree of risk-aversion (RISKAV); (iii) perceptions of technology: perception of high costs of adopting digital technologies (EXPENSIVE); (iv) management characteristics: use of technical assistance/ private consultancy (CONSULT); (v) farm characteristics: soybean area (AREA), and slope of soybean area (FLAT); (vi) institutional factors: access to rural credit for investment (CREDITINV), and participation in agribusiness cooperatives (COOP). Appendix B presents the correlation matrix of the explanatory variables.

Table 6 presents a description of the variables used in the econometric models and their descriptive statistics. The first part of the table presents the explanatory variables, while the second part contains the DAT assessed as dependent variables used in the logit and Poisson models.

Table 6. Description and descriptive statistics of the variables used in econometric analysis

Variable	Description	Mean	Std.Dev.	Minimum	Maximum
Explanatory variables					
EXPERIENCE	Years of experience in soybean farming	19.33	12.33	1.0	55.0
SCHOOL	Years of formal study of the farmer	14.27	3.78	3.0	22.0

RISKAV	Five-point Likert scale variable derived from the level of agreement of the farmer with the following statement: “When it comes to business, I prefer the safer option, even though I know I may earn less.”	4.27	0.86	1.0	5.0
INNOVATIVE	Five-point Likert scale variable derived from the level of agreement of the farmer with the following statement: “I like to test new technologies on my farm.”	4.32	0.81	1.0	5.0
EXPENSIVE	Five-point Likert scale variable derived from the level of agreement of the farmer with the following statement: “Digital technologies are too expensive for me.”	3.37	1.17	1.0	5.0
CONSULT	Dummy = 1 if the farmer hired technical assistance (private consultancy) in 2023/2024 and 0 otherwise.	0.36	0.48	0.0	1.0
AREA	Soybean total area planted in the 2023/2024 crop year (in hectares)	468.10	668.73	10.5	4912.0
FLAT	Dummy = 1 if the farmer perceived a flat slope of the soybean plot and 0 otherwise	0.29	0.45	0.0	1.0
CREDITINV	Dummy = 1 if the farmer accessed rural credit for investment in the 2023/2024 crop year and 0 otherwise.	0.16	0.37	0.0	1.0
COOP	Dummy = 1 if the farmer was a member of an agribusiness cooperative and 0 otherwise	0.85	0.35	0.0	1.0
	Dependent Variables for Logit and Poisson Models				
AUTOPILOT	Dummy = 1 if the farmer adopted a yield monitor in at least one machine and 0 otherwise	0.56	0.50	0	1
SOILSAMP	Dummy = 1 if the farmer adopted georeferenced soil sampling and 0 otherwise	0.51	0.50	0	1
YIELDMON	Dummy = 1 if the farmer adopted a yield monitor in at least one machine and 0 otherwise	0.43	0.50	0	1
YIELDMAP	Dummy = 1 if a yield map was generated and used in at least one machine, and 0 otherwise	0.25	0.44	0	1
VRSEED	Dummy = 1 if the farmer adopted variable rate seeding and 0 otherwise	0.09	0.28	0	1
VRFERT	Dummy = 1 if the farmer adopted variable rate application of fertilizers and 0 otherwise	0.29	0.46	0	1

SOFTWARE	Dummy = 1 if the farmer adopted any management software and 0 otherwise	0.41	0.49	0	1
DRONE	Dummy = 1 if the farmer has at least one drone for monitoring the field or applying inputs, and 0 otherwise	0.13	0.33	0	1
DAT	Variable with a value of 0 to 8 that measures the intensity of farmers' adoption of digital agriculture technologies (Number of digital technologies adopted)	2.67	2.28	0	8

Table 7 presents the frequency of adopters of each of the eight digital technologies, as well as the combined adoption of all technologies for count-data econometric modeling.

Table 7. Number of farms that adopted each technology and the intensity of adoption

Technology	**Adopters**	**Number of adopted digital agriculture technologies**								
		0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
AUTOPILOT	84	0	8	16	13	13	11	12	7	4
SOILSAMP	77	0	10	9	13	12	10	12	7	4
YIELDMON	65	0	2	9	11	10	10	12	7	4
YIELDMAP	38	0	0	0	6	5	6	10	7	4
VRSEED	13	0	0	0	1	0	2	1	5	4
VRFERT	44	0	0	1	7	6	9	10	7	4
SOFTWARE	61	0	4	7	11	11	5	12	7	4
DRONE	19	0	2	2	1	3	2	3	2	4
Number of adopters		32	26	22	21	15	11	12	7	4

3.4. Results

Table 8 presents the estimates of the logit and Poisson econometric models. The marginal effects[5] of explanatory variables on adoption and intensity of use of digital technologies are presented in Appendix C. The maximum likelihood ratio test rejects the null hypothesis that the coefficients are statistically equal to zero in all models. Hence, the estimated models are appropriate for identifying the variables that influence the adoption and intensity of use of the technologies under investigation. The confusion matrices and ROC curves of the estimated logit models are presented in Appendix D. In general, the models presented a very satisfactory goodness of fit, indicating reliability in the estimates.

Table 8. Estimates of logit and Poisson models

Variables	**Logit model (coefficients β)**								**Poisson**
	AUTOPILOT	SOILSAMP	YIELDMON	YIELDMAP	VRSEED	VRFERT	SOFTWARE	DRONE	DAT

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[5] The term "marginal effect" denotes the variation in the predicted probability of the occurrence of a dependent event (adoption of one digital technology, e.g.) resulting from a one-unit change in an explanatory variable, with all other variables kept constant. The interpretation of marginal effects can be generalized to encompass each explanatory variable of the estimated econometric models, considering the

specific units of measurement associated with each variable.

Constant	-4.00	-6.55**	-2.33	-2.99	-16.57**	-6.19*	-0.86	-4.22	-0.55
Experience	0.003	0.03*	0.04**	0.02	0.06	0.02	-0.01	0.04	0.01***
School	0.14*	0.11	0.13*	0.04	0.01	0.15*	0.05	0.06	0.05**
Riskav	0.10	-0.31	0.05	0.34	-0.53	-0.27	-0.06	-0.76***	-0.06
Innovative	-0.13	1.08***	-0.34	0.20	1.92*	0.63	0.35	1.00*	0.23***
Expensive	-0.10	-0.43*	-0.28	-0.86***	0.30	-0.56**	-0.73***	-0.55**	-0.18***
Consult	0.30	2.27***	0.22	0.38	0.86	1.32**	-0.28	-0.12	0.23**
Area	0.01***	0.001**	0.004***	0.002***	0.003***	0.002***	0.002***	0.0004	0.0004***
CreditInv	1.12	-0.94	1.80***	1.67**	-0.45	0.51	0.51	-2.08*	0.21*
Coop	0.25	1.17	-0.56	-0.84	2.30	0.74	0.07	1.10	-0.05
Flat	-0.16	0.98**	1.07**	1.51***	0.50	0.68	0.29	-0.15	0.31***
Log-likelihood function	-59.47	-64.69	-63.48	-51.62	-21.96	-54.30	-73.79	-42.79	-261.48
Chi squared (10 d.f.)	86.85	78.46	78.31	66.55	44.51	72.93	55.10	28.41	158.92
Significance level	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00155	0.00000
R^2 McFadden	0.4220	0.3775	0.3815	0.3919	0.5033	0.4018	0.2718	0.2492	0.2331

* Statistically significant at 10%, ** statistically significant at 5%, *** statistically significant at 1%.

The estimates of the Poisson model are consistent with the overall findings of the logit models, showing both convergence and robustness of the empirical results. Variables such as experience, innovativeness, and cultivated area presented a positive influence on the intensity of digital technology use, each statistically significant at the 1% level. The perception of technology costs was also significant at the 1% level and presented a negative influence on the intensity of use, indicating that the perception of high cost is associated with low intensity of digital technologies adoption. Furthermore, years of formal education and the use of private consultancy services positively influenced the intensity of adoption of digital technology, both at the 10% significance level. Thus, the empirical results showed that more intensive adopters of digital technologies are more innovative and experienced, have higher levels of schooling, manage large farms, the slope of soybean area is flat, hire consultancy services, and have a lower perception of digital technology costs.

Table 9 shows whether the hypotheses were supported based on the estimates from the eight logit models and the count data (Poisson) model.

Table 9. Summary of the hypotheses tested and econometric results

Hypothesis	**Variable used to test**	**Which logit models provided evidence supporting the hypothesis?**	**Has the hypothesis been supported by the Poisson model?**
H1a: The greater the farmer's experience, the higher the probability of adopting digital technologies	EXPERIENCE	Soil sampling, yield monitor	Yes
H1b: Farmers with higher levels of education are more likely to adopt digital technologies	EDUCATION	Autopilot, yield monitor, variable rate inputs	Yes

H2a: The more prone to innovation farmers are, the higher the likelihood of adopting digital technologies	INNOVATIVE	Soil sampling, variable rate seed, drone	Yes
H2b: Farmers who are more risk-averse have a lower probability of adopting digital technologies	RISKAV	Drone	No
H3: If the farmer perceives the technology as expensive, the likelihood of its adoption decreases	EXPENSIVE	Soil sampling, yield map, variable rate inputs, software, drone	Yes
H4: The hiring of consulting services positively affects the likelihood of adopting digital technologies	CONSULT	Soil sampling, variable rate inputs,	Yes
H5a: Farm size positively affects the adoption of digital technologies by farmers	AREA	Autopilot, soil sampling, yield monitor, yield map, variable rate seed, variable rate inputs, software	Yes
H5b: The cultivation of soybeans in flat areas positively affects farmers' adoption of digital technologies	FLAT	Soil sampling, yield monitor, yield map	Yes
H6a: Access to rural credit for fixed capital investment positively influences the likelihood of adopting digital technology	CREDITINV	Yield monitor, yield map, drone*	Yes
H6b: Farmers who are members of cooperatives have a higher probability of adopting digital technology	COOP	No	No

Note: *Access to rural credit for investment is negatively related to drone adoption

3.5. Discussion

The drivers that affect the adoption of DAT identified in the logistic regression model were: soybean area, perception of technology cost, experience in soybean production, level of education, innovative profile, hiring of private consultancy, degree of risk aversion, access to rural credit for investment and slope of the soybean plot.

The variable AREA (proxy for production scale) was statistically significant at the 1% level in six out of the eight logit estimated models and 5% level in one of them. This variable was positively associated with the adoption of autopilot, soil sampling, yield monitor, yield map, variable rate seeding, variable rate fertilizer, and software. The result corroborates hypothesis 5a, highlighting the great importance of production scale in explaining the adoption of DAT. Larger farms are more likely to adopt these technologies because some of them require high initial investments in machinery. For example, autopilot and yield monitors have been integrated into modern (and expensive) tractors and harvesters. Agricultural machinery equipped with variable rate technology, such as tractors, sprayers, and planters, also requires a high initial investment. In both cases, high fixed costs require high production over large areas to reduce unit cost. Therefore, large farms can invest in production automation, which can reduce their costs.

The monitoring and coordination of production processes is more complex on large farms, which increases the need for data-driven technologies, including yield monitoring systems, geospatial mapping tools, and specialized software solutions. Large farms can also have greater bargaining power with technology suppliers and more flexibility to test technologies before full-scale adoption.

D'Antoni et al. (2012) identified a positive relationship between farm size and the adoption of auto-steer GPS guidance systems, while Walton et al. (2010) demonstrated that area cultivated with cotton was positively associated with the adoption of grid soil sampling practices in the United States. Carrer et al. (2022) and Mozambani et al. (2023) found similar results when examining the adoption of precision agriculture technologies by sugarcane farmers in Brazil.

The variable EXPENSIVE, which measures farmers' cost perceptions of digital technology, was significant at the 1% level and had a negative impact on the likelihood of adopting software and yield map technologies. Additionally, this variable estimate was significant at the 5% level for the adoption of variable-rate fertilizer and drone, and a 10% level of significance for soil sampling. It shows that if farmers realize that the technology is too expensive for them, the probability of adopting a certain technology decreases. These farmers outweigh the expected investment and marginal cost of the technologies, thereby reducing the expected utility of adoption. The findings highlight the critical role of farmers' perceptions in shaping their technology adoption decisions.

Farmer EXPERIENCE had a positive effect on the likelihood of adopting grid soil sampling (at the 10% level) and yield monitor (at the 5% level). The marginal effect shows that each additional year of experience in soybean farming increases the probability of adopting a yield monitor by 0.53 percentage point, assuming all other variables remain unchanged (Appendix C). Farmers with more experience in soybean production may see benefits in adopting digital technologies, as well as being able to better manage them. The variable was not significant for autopilot, yield map, variable rate seeding, variable rate fertilizer, and software adoption.

Farming experience is a widely utilized variable in studies examining technology adoption. Paustian and Theuvsen (2017) identified a positive relationship between years of farming experience and the adoption of precision agriculture technologies, aligning with the findings presented in this study. In contrast, Carrer et al. (2017) reported a negative association between farming experience and the likelihood of adopting computers, attributing this outcome to the tendency of more experienced farmers to be older and less proficient in the use of computers and software management systems.

The level of education (SCHOOL) of the farmer positively affected the likelihood of adopting both autopilot, yield monitor, and variable rate application of inputs at the 10% level of significance. The education level of the farmer is a relevant proxy for human capital, indicating greater capacity to use the information generated by digital technologies in the decision-making process (Kroupová et al., 2025). The marginal effect of this variable is relatively greater when compared to the farmer's experience, since each year of formal education of the farmer increases the probability of adopting autopilot by 1.8 percentage points. This finding aligns with the results reported by Larson et al. (2008), Paxton et al. (2011), Carrer et al. (2017), Barnes et al. (2019), and Carrer et al. (2022).

The estimates of the variable INNOVATIVE presented positive and statistically significant effects on the probability of adoption of soil sampling (1% significance level), variable-rate seeding, and drone (10% significance level). The result of these two last technologies is particularly interesting. These technologies are in early stages of diffusion in Brazilian crop production. According to the categories of technology adopters proposed by Rogers (1983), its adopters can be classified as innovators.

The estimates of private technical assistance (CONSULT) were positively and statistically significant for the adoption of soil sampling and variable-rate fertilizer technologies. These findings corroborate the importance of access to relevant information to increase the adoption of digital technologies (Kroupová et al., 2025). Private consultancy, or another source of technical assistance, is important for the diffusion of qualified information about digital technologies, as well as for helping with their implementation and management. Specialists have significantly assisted crop farmers in analyzing soil data and making appropriate variable rate application recommendations. This assistance improves both the management and the confidence of farmers in the adoption of precision technologies. Watcharaanantapong et al. (2014) identified a positive relationship between information obtained from consultants and the adoption of grid soil sampling, yield monitors, and remote sensing technologies among cotton farmers in the United States.

The estimates of risk aversion (RISKAV) were statistically significant at the 1% level only for drone adoption. Drones are among the least frequently adopted technological innovations in the sample. The observed negative coefficient supports the hypothesis that investment in drones is predominantly carried out by risk-taking farmers.

Rural credit for investment (CREDITINV) was statistically significant and positively associated with the adoption of a yield map and a yield monitor at significance levels of 1% and 5%, respectively. These technologies are incorporated into machinery, such as harvesters, or integrated into specialized equipment. The acquisition of these devices is supported by Brazil's subsidized rural credit policy (e.g., the Moderfrota program), reinforcing the positive impact of credit on technology adoption. However, investment credit was negatively associated with the adoption of drones.

The role of topography was examined by the FLAT variable, which presented a positive influence on the adoption of georeferenced soil sampling, yield monitors (statistically significant at the 5% level), and yield maps (significant at the 1% level). The integration of yield monitors into harvesters may account for their higher adoption rates in regions characterized by relatively flat topography, where these machines function with enhanced operational efficiency and precision. Georeferenced soil sampling and yield map are complementary technologies to yield monitoring, which can explain the relevance of flat terrain as a facilitating factor for their adoption. The efficiency of these devices increases in flat topography, where they are more likely to be adopted. Furthermore, steep terrains imply higher equipment maintenance costs, reducing the likelihood of technology adoption compared to flatter terrains.

The variable membership in a cooperative (COOP) was not statistically significant at the 10% level in any of the estimated econometric logit models. Thus, it can be assumed that this variable did not influence the adoption of DAT by sampled farmers.

3.6. Conclusions

This study aimed to investigate the determinants of adoption and intensity of use of digital technologies by Brazilian soybean farmers. It is proposed an integrative empirical framework to assess the adoption of eight DAT. Autopilot and georeferenced soil sampling are among the most widespread technologies, with 84 and 77 adopters, respectively. In contrast, drone and variable rate seeding exhibit the lowest adoption rates, with only 19 and 13 users, respectively.

The findings indicated that farm size, experience, farmer's innovativeness, farmer's risk aversion, schooling, technology cost perception, flat slope of the plot, and use of private technical assistance were statistically significant associated with the adoption of at least one of the eight DAT. The factors that positively influenced the intensity of adoption of digital technologies included farm size, experience, farmer's education level, and private consultancy. Conversely, farmers' cost perception of technologies negatively impacted the intensity of adoption.

The findings present significant practical implications. Production scale was identified as a significant barrier to the adoption of DAT. To address this barrier, several strategies may be developed. These strategies involve fostering farmer engagement in collective actions, such as formal or informal associations, that facilitate shared access to expensive digital technologies, significantly lowering adoption costs per farmer. Additionally, public policies designed to support medium and small-scale farmers, such as providing them with access to credit for investments in equipment and machinery, could help overcome scale barriers. Moreover, training programs for both small/medium farmers and public extension agents are essential to effectively disseminate knowledge and promote the adoption of digital technologies.

Access to information is another significant obstacle to the adoption of digital technologies. This challenge is evidenced by factors such as the level of formal education, years of experience in soybean farming, and reliance on private consultancy services. Given these factors, digital transformation in agriculture should be accompanied by training and qualification programs focused on technologies and management. Formal higher education has become essential for decision-makers as agricultural digitalization continues to grow. The integration, comprehension, and management of sensors, big data, drones, and predictive software with artificial intelligence require specific skills and capabilities. Public policies and the private sector should consider these issues. In this context, farmers who perceive digital technologies as excessively expensive are less likely to adopt them. The perception of high costs may be a consequence of the lack of comprehensive information regarding the potential benefits of adopting and utilizing these technologies.

Furthermore, farmers' behavioral characteristics influence the likelihood of adopting digital technologies, especially those in the early stages of diffusion, such as variable rate seeding and drone utilization. Farmers with an innovative mindset and a lower degree of risk aversion are more inclined to embrace these technologies. These findings might be useful to technology developers.

Finally, the article has limitations. The sample is restricted to the state of São Paulo. Expanding the dataset to include farms from other regions and multiple crop seasons could enhance the scope of the empirical analysis. Additionally, incorporating time-sensitive variables, such as output and input prices, as well as climatic conditions, into a panel data framework would provide deeper insights. Future research could explore these aspects further.

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4. Final Remarks

The central aim of this dissertation was to investigate the determinants influencing both the adoption and the intensity of use of DAT among soybean farmers in the state of São Paulo, Brazil. To address this objective, a structured survey questionnaire was employed to gather micro-level data from a representative sample of 150 soybean farms across 55 municipalities within the state. The collected data were analyzed using quantitative techniques grounded in statistical and econometric methodologies, specifically logistic regression and count data models, in order to examine the factors associated with the binary decision to adopt DAT as well as the degree to which such technologies were adopted.

The empirical analysis demonstrated that a range of factors exert a positive and statistically significant influence on both the probability of adoption and the intensity of use of DAT among soybean farmers. Notably, these include the total cultivated soybean area, the presence of flat terrain, access to rural credit for investment, engagement with private consultancy services, the producer's degree of innovativeness, years of experience in soybean farming, and level of formal education attained. Conversely, elevated perceived implementation costs emerged as a principal barrier to both the adoption and extent of utilization of DAT. In addition, specific operational constraints intrinsic to certain digital tools were also identified as deterrents to broader technological uptake

These findings advance the understanding of the underlying mechanisms that shape the adoption of digital technologies in the agricultural sector. Furthermore, it generates actionable insights for consultants, extension professionals, and other key stakeholders, facilitating the identification of principal constraints and enablers associated with the broader diffusion of these technologies. Such insights are particularly relevant given the demonstrated potential of digital tools to enhance agricultural productivity and optimize the efficient allocation and utilization of production inputs.

Conversely, the dependence on cross-sectional data limited to a single harvest year constitutes a methodological limitation, as it restricts the capacity to analyze temporal dynamics and track longitudinal changes in technological adoption within agricultural systems. This constraint impedes a more comprehensive understanding of the evolving nature and long-term effects of DAT over time.

Furthermore, empirical evidence gathered during fieldwork in the 2023/2024 harvest season indicated suboptimal soybean productivity levels, which respondents predominantly attributed to adverse climatic conditions. This finding underscores the importance of integrating climate-related variables into future research designs, as such inclusion may provide deeper insights into the environmental determinants of technological adoption and their associated impacts on agricultural performance.

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APPENDIX A – Questionnaire

EMPRESA BRASILEIRA DE PESQUISA AGROPECUÁRIA - EMBRAPA
UNIVERSIDADE FEDERAL DE SÃO CARLOS - UFSCar
DEPARTAMENTO DE ENGENHARIA DE PRODUÇÃO – DEP

IDENTIFICAÇÃO DO QUESTIONÁRIO
1. Número do questionário: (______) Aplicante ____________________

DATA DA ENTREVISTA
2. Data: ______/______/________

DADOS CADASTRAIS
Entrevistar o responsável pelas decisões estratégicas da empresa. No caso de produtor rural, entrevistar o dono da propriedade. No caso de grupo empresarial, entrevistar o gestor tomador de decisão (verificar a estrutura organizacional no site da empresa ou contato).
3. Nome do entrevistado:____
4. Nome da propriedade:____
5. Localização da propriedade (município/UF):__________________________________
6. Telefone para contato:____
7. E-mail de contato:____

PARTE A – CARACTERÍSTICAS DA PROPRIEDADE RURAL

Possui quantas fazendas/ matrículas? (________)
Considerar a propriedade com maior produção de soja em São Paulo (em caso de vários CNPJs vizinhos em que a gestão é única, considerar como uma fazenda)

8. Estrutura gerencial da fazenda
( ) Grupo comercial/empresa Nome:_________________________________
( ) Pessoa física, mas gestão por meio de administrador
( ) Gestão do proprietário ou arrendatário da fazenda
( ) Outra ____

9. O sr. faz ou já fez a rotação anual de soja com o pasto (sistema integração lavoura-pecuária, não é reforma de pasto apenas quando o pasto está degradado)?
( ) Nunca fiz; ( ) Sim, faço atualmente; ( ) Sim, já fiz, mas parei ( ) ILP sem soja

10. Se faz, em que ano fez a rotação de soja/lavoura com o pasto pela primeira vez?____________
11. Se faz atualmente, o sr. tem o planejamento de rotação para os próximos 3 anos? ( ) Não; ( ) Sim
12. Se faz atualmente, por que começou a fazer? ____________________________________

13. Se faz atualmente, quais as principais dificuldades na implementação do ILP? ________________
____
____

14. Por quê não faz (ou parou de fazer)? ____
____
____

15. Área total dedicada ao sistema ILP (ha):____________________

Rotação: ____________________/_________________/_________________/_____________________

DISTRIBUIÇÃO DO USO DA TERRA NO ANO SAFRA 2023/24 (Set 23-Ago 24)

Atividade	**Área (ha)**	**Textura de solo predominante** (1-Arenosa; 2–Média; 3- Argilosa >35%argila)	**Relevo predominante** (1 -Plano<3º ; 2-Suave ondulado 3-8º; 3- Ondulada 8-20º ; 4- declivosa>20º)	**Produção** (soja – sc/ha e pasto – UA/ha)
16. Área Total da fazenda (própria e arrendada):				
17. Área própria				
18. Área arrendada				
Lavoura temporária (Safra principal/verão):				
19. Soja na reforma da cana				
20. Soja solteira (rotação com milho ou outras culturas)				
21. Soja no ILP (rotação com pasto)				
22. Milho				
23. Outro:				
Lavoura temporária (Segunda safra):				
24. Milho				
25. Sorgo				
26. Pasto safrinha no ILP				
27. Outro:				
28. Outro				
Lavoura permanente:				
29. Cana				
30. Outro				
31. Outro				
32. Pastagem perene no ILP				
33. Pastagem fora do ILP				
34. Outra (granja, tanque criação):				

35. Qual foi a produção de soja na safra 2022/23? (sc/ha ou sc/alq):_________________

36. Faz Plantio Direto na soja? ( ) Não; ( ) Sim

37. Área irrigada com soja (ha) ____

38. Em que ano plantou soja pela primeira vez? __________________________

PARTE B – CARACTERÍSTICAS DA PRODUÇÃO DE SOJA

USO DOS FATORES DE PRODUÇÃO NA SOJA NA SAFRA 2023/24

39. Qual o Tipo de semente? ( ) transgênica; ( ) convencional; ( ) ambas

40. Faz manejo integrado de pragas? ( ) Não; ( ) Sim

41. Usa inoculante? ( ) Não; ( ) Sim

42. Faz uso de outro produto biológico no controle de pragas ? ( ) Não; ( ) Sim

SEMENTE	**SOJA SOLTEIRA (ou na reforma da cana)**	**SOJA EM ILP**	**TOTAL**
43. Quantidade total de semente de soja plantada (kg):			
44. Custo total com semente de soja (R$)			

45. Custo total com inoculante na semente de soja (R$)			
46. Custo total com enraizador na soja (R$)			
DEFENSIVOS	**Aplicações**	**Doses**	**Custo (total ou por dose)**
Dessecação/ Herbicidas			
Fungicidas/ Inseticidas/ Acaricidas/Foliar /Produtos biológicos			

**Se não souber as quantidades e custos totais, anotar a informação que o produtor souber com a unidade de medida, para padronizarmos posteriormente.*

<table>
<tr><th colspan="2">CORRETIVO</th><th>SOJA na reforma da cana</th><th>SOJA SOLTEIRA (milho/outro)</th><th>SOJA EM ILP (rotação com pasto)</th><th>TOTAL</th></tr>
<tr><td colspan="2">47. (   ) Mistura calcário e gesso - especificar a proporção (____________)
(   ) Apenas calcário
(   ) Apenas gesso
(quantidade total: kg ou t)</td><td></td><td></td><td></td><td></td></tr>
<tr><td colspan="2">48. (custo total - R$)</td><td></td><td></td><td></td><td></td></tr>
<tr><td>FERTILIZANTE</td><td>Tipo ou Formulação</td><td>SOJA na reforma da cana</td><td>SOJA SOLTEIRA</td><td>SOJA EM ILP</td><td>TOTAL</td></tr>
<tr><td>49. Fertilizante NPK (quantidade total: kg ou t)</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>50. Fertilizante NPK (custo total: R$)</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>51. Fertilizante NPK (quantidade total: kg ou t)</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>52. Fertilizante NPK (custo total: R$)</td><td></td><td></td><td></td><td></td><td></td></tr>
</table>

53. KCl (cloreto de potássio) (quantidade total: kg ou t)					
54. KCl (cloreto de potássio) (custo total: R$)					
55. Outros fertilizantes Especificar:					

**Se não souber as quantidades e custos totais, anotar a informação que o produtor souber com a unidade de medida, para padronizarmos posteriormente.*

MÃO DE OBRA	**Nº** (funcionários com participação na produção da soja)	**Remuneração média** (Salário mensal (R$)/empregado; R$/diária)	*Se não souber, informar o custo total com mão de obra para soja na safra (R$)*
56. Empregado administrativo/ escritório *(considerar o Nº de empregado e o Valor do salário mensal)*			
57. Empregado permanente no campo *(considerar o Nº de empregado e o Valor do salário mensal)*			
58. Mão de obra temporária/terceirizada *(considerar o Nº de diária e o Valor da diária)*			
59. Mão de obra familiar			

**anotar a informação que o produtor lembrar no momento e especificar no questionário (por exemplo, % de dedicação de tempo dos empregados ou horas/dias/meses de trabalho na soja durante a safra).*

MÁQUINAS próprias usadas na soja	**CV** (se não lembrar para colheitadeira e plantadeira, usar nº de linhas)	**Ano da máquina**	**Consumo de óleo diesel** (l/h)	**Tempo de uso na safra de soja** (total de dias na safra) *
60. Trator 1				
61. Trator 2				
62. Trator 3				
63. Trator 4				
64. Trator 5				
65. Trator 6				
66. Autopropelido				
67. Colhedora 1				
68. Colhedora 2				
69. Drone (VANT)	( ) classe 1 acima de 150kg ( ) classe 2 entre 25 e 150kg ( ) classe 3 abaixo de 25kg ( ) apenas para imagem			

**Anotar a informação que o produtor lembrar no momento e especificar no questionário (por exemplo, núm. de dias, horas, % de tempo na safra, e padronizar após entrevista).*

70. Qual o custo total com óleo diesel na produção de soja? (R$) ________________________________

71. Terceiriza algum serviço de operação agrícola na soja (ex: pulverização ou colheita)? (   ) Não; (   ) Sim
72. Se sim, qual a quantidade de horas máquina contratada na safra 2023/24? ________________________
73. Qual o custo total com o serviço contratado na safra 2023/24 (R$)?______________________________

ENERGIA SOLAR
74. Utiliza energia solar na fazenda? (   ) Não; (   ) Sim

PARTE C – CARACTERÍSTICAS DA COMPRA DE INSUMOS E COMERCIALIZAÇÃO DA SOJA

ARMAZENAMENTO DA PRODUÇÃO

75. Possui estrutura fixa de silo para armazenagem própria (cilíndrico, permanente, metálico, concreto)?
(   ) Não (   ) Sim
76. Qual é a capacidade estática de armazenagem na fazenda (ton):_____________________________
77. Qual é o % de sua necessidade de armazenagem de grãos que essa estrutura está atendendo? _______

RENDA / VENDA DA SOJA EM 2023/24

78. Qual foi o preço médio (por saca) que vendeu a soja em 2023/24 (R$)? (______________)

79. Fez hedge com contratos futuros na bolsa na safra 2023/24? (   ) Não (   ) Sim

Instrumento de comercialização	Quantidade **vendida** (% da safra, sc, ton)	Qual o canal de comercialização? (via cooperativa ou trade)
80. Barter (compra insumo e paga em sc de soja)		
81. Mercado spot, sem contrato e com o preço definido no momento da venda		
82. Contrato de venda antecipada com preço fechado, com ou sem CPR física		
83. Outro, especificar		

CRÉDITO E SEGURO RURAL NA SAFRA 2023/24

84. Fez seguro rural da produção de soja no ano safra 2023/24? (   ) Não (   ) Sim

85. Solicitou crédito rural para soja na safra 2023/24?
(   ) não solicitou; (   ) Sim, mas não obteve aprovação; (   ) Sim e obteve aprovação.

86. Se acessou o crédito na safra 2023/24:

Tipo	**Crédito Rural com juros subsidiados** (R$) – Plano Safra	**Recursos livres dos bancos** (sem subsídio de juros) (R$)
Investimento relacionado a soja		
Custeio para Soja		
Comercialização da soja		
Outro		

87. Acessou algum crédito no programa ABC (Baixo Carbono) na safra 2023/24? (   ) Não; (   ) Sim

88. Acessou algum crédito no programa estadual Integra SP na safra 2023/24? (   ) Não; (   ) Sim

89. Você considera que o volume de crédito rural acessado na safra 2023/24 foi o suficiente para atender suas necessidades na produção de soja? (   ) Não; (   ) Sim

PARTE D – TECNOLOGIAS DIGITAIS

Tecnologias digitais	Adota a tecnologia (marcar com X)	A tecnologia é	Ano de início da adoção
Preparo de solo e tratos culturais			
90. O Sr.(a) usa Drone ou imagem de satélite para fazer curva de nível ou monitoramento da lavoura?		( ) própria; ( ) terceirizada	
91. O Sr.(a) faz amostragem georreferenciada de solo para mapa de fertilidade?		( ) própria; ( ) terceirizada	
92. Se sim, a coleta é manual ou automatizada (com quadriciclo)?			
93. O Sr.(a) faz plantio em taxa variável?		( ) própria; ( ) terceirizada	
94. O Sr.(a) aplica fertilizante/corretivo a taxa variável?		( ) própria; ( ) terceirizada	
Colheita			
95. O Sr.(a) usa monitor de produtividade?		( ) própria; ( ) terceirizada	
96. O Sr.(a) faz mapa de produtividade?		( ) própria; ( ) terceirizada	
Tecnologias complementares			
97. Sr.(a) utiliza GPS nos tratores?			
98. Sr.(a) utiliza piloto automático?			
99. Se sim, em quais operações?			
100. Sr.(a) utiliza controlador de seção? (controla abertura e fechamento dos bicos de pulverização)			
101. Sr.(a) utiliza sistema de telemetria? (coleta dados da operação de máquinas em tempo real)			
102. Sr.(a) utiliza estação meteorológica?		( ) própria; ( ) terceirizada	
103. Sr.(a) utiliza sistemas de irrigação automatizados?			
Gestão			
104. Sr.(a) utiliza planilhas de excel para gestão da fazenda?			
105. Sr.(a) utiliza algum Software de gestão? (ex: ERP, SAP, Aegro, Climate fieldview, etc.)			
106. Sr.(a) utiliza algum aplicativo para controle de alguma operação? (ex: John Deere Operations Center, app de irrigação.)			
107. Outros:			

108. Quais foram as principais dificuldades na adoção das tecnologias digitais ? *(para os adotantes)*

109. Quais as principais dificuldades para você adotar tecnologias digitais ? *(para os não-adotantes)*

PARTE E- CARACTERÍSTICAS DA PRODUÇÃO PECUÁRIA

110. Desde que ano trabalha com pecuária? (___________)

PRÁTICAS/TECNOLOGIAS AGROPECUÁRIAS

Nos últimos 3 anos,

111. Acessou algum crédito para pecuária? (   ) Não; (   ) Sim
112. Se sim, foi do programa ABC ou integra São Paulo (   ) Não; (   ) Sim
113. Fez análise de solo na área de pastagem nos últimos 3 anos? (   ) Não; (   ) Sim; (   ) Sim, na lavoura da rotação
114. Fez correção ou adubação de manutenção da área de pastagem? (   ) Não; (   ) Sim; (   ) Sim, na lavoura da rotação
115. Fez adubação orgânica? (   ) Não; (   ) Sim
116. Fez uso de bioinsumos na área de pastagens (ex: *Metarhizium* no controle de cigarrinha, ou *Azospirillum* na Braquiária)? (   ) Não; (   ) Sim

Na safra atual,

117. Faz manejo de pastagens rotacionado? (   ) Não; (   ) Sim Nº de piquetes_____________
118. Usa identificação eletrônica dos animais? (   ) Não; (   ) Sim
119. Tem certificação SISBOV? (   ) Não; (   ) Sim
120. Como faz o controle dos gastos e receitas (gestão financeira) da pecuária?
   (   ) Não faz (   ) controle manual/caderno, (   ) Planilha de Excel; (   ) Software de gestão
121. Como faz o controle zootécnico do rebanho (anotações de pesagens, vacinas, reprodução, etc)?
   (   ) Não faz (   ) controle manual/caderno, (   ) Planilha de Excel; (   ) Software de gestão

122. Faz uso de alguma outra tecnologia digital na pecuária (ex: estação meteorológica automática, balança de auto-pesagem, uso de imagens por drone ou satélite, etc)? (   ) Não; (   ) Sim
123. Se sim, qual e para qual finalidade? ____

PRODUÇÃO PECUÁRIA NA SAFRA 2023/24 (Set 23 – Ago 24)

124. Marcar quais fases do ciclo pecuário que trabalha?

(   ) Cria
(   ) Recria
(   ) Engorda/terminação - A engorda é a pasto (   ) em confinamento (   ) ou Ambos (   )

125. Composição média do rebanho na safra 2023/24 (nº de cabeças) na área de ILP:

Cria (desmama) ate 7 meses	**Recria (sobreano)**		**Engorda**		**Reprodução**		**Total**
Bezerro/a	Novilho/ garrote		Boi		Touro		
	Novilha/ borrega		Vaca		Matriz		

126. Esse rebanho fica em quantos hectares/alqueires?_________________

127. Taxa de lotação média (cabeca/ha) na safra 2023/24: (calcular) __________

128. Venda de animais na safra 2023/24:

Categoria	**Nº de animais vendidos**	**Valor médio recebido** (R$/und)
Bezerro/a		
Novilho/a		
Boi gordo		
Vaca		
Outro (especificar)		

Se faz engorda, usa Contrato a termo na venda do Gado? ( ) Não; ( ) Sim

USO DOS FATORES DE PRODUÇÃO NA PECUÁRIA NA SAFRA 2023/24

SUPLEMENTAÇÃO ALIMENTAR DO ANIMAL

129. **Tipo**	**Qtd. Fornecida/cabeça/dia** (gr)	**Nº de meses**	**Valor pago/kg** (R$)
Sal mineral			
Sal proteinado			
Outro (ração, feno):			

130. Custo total com suplementação alimentar (sal mineral+ sal proteinado+ outros alimentos (R$ /ano): ________________________ (*se não preencher no quadro acima*)

SANIDADE ANIMAL

131. Custo total com vacinas e medicamentos na safra 2023/24 (R$): ________________________
(se não souber o valor total, anotar o custo por cabeça no ano)

Sanidade Animal	**Aplicações**	**Número de animais**	**Custo (por aplicação ou total)**
Vacina aftosa			
Carbúnculo			
Botulismo			
Vermifugação			
Carrapato			
Mosca			
Outros (medicamentos colocados no sal)			

INSEMINAÇÃO ARTIFICIAL *(apenas se fizer cria)*

132. Custo total com inseminação artificial (R$)? __________________________
(se não souber o valor total, anotar o custo por cabeça)

MÃO DE OBRA

133. TIPO	**Nº de empregado** ou % de dedicação de empregado	**Salário mensal** (R$/empregado)	Custo total com mão de obra na pecuária (R$) (*se não souber informação anterior*)
Permanente			
Familiar			
	Nº de diárias no ano	**Valor da diária** (R$/diária)	
Temporária/terceirizada			

**anotar a informação que o produtor lembrar no momento e especificar no questionário (por exemplo, % de dedicação de tempo dos empregados permanentes ou horas/dias/meses de trabalho no pasto durante a safra). Anotar a unidade.*

SEMENTE DE PASTO NA ÁREA DE ILP *(se utilizou no ano agrícola 2023/24)*

134. Qual é a espécie de pasto predominante (braquiária decumbens, Mombaça, etc)?________________

135. Custo total com semente do pasto que você formou (R$):_________________________
(*se não souber informação anterior*, anotar Quantidade de semente de pasto plantada/há:______________________e valor pago por kg de semente (R$):_______________________________)

CORRETIVO E FERTILIZANTE NO PASTO

Produto	**Especificar o tipo**	**Quant aplicada/ha de pasto**	**Valor pago/ton (R$)**
136. Mistura (calcário e gesso)			
137. Calcário			
138. Gesso			
139. Fertilizante 1			
140. Fertilizante 2			
141. Outros:			

142. Custo total com corretivo e fertilizante de pasto (R$) (incluir esterco, etc): _____________
(Se não preencher quadro acima)

DEFENSIVOS AGRÍCOLAS NO PASTO *(se utilizou na safra 2023/24)*
143. Custo total com defensivos químicos (herbicidas, inseticidas e outros) no pasto (R$): _________________________
144. Custo total com bioinsumos no pasto (R$): ______________________

MÁQUINAS

Máquinas próprias usadas na pecuária	**CV**	**Ano do trator**	**Tempo estimado do uso na pecuária no ano** (em horas, dias, etc)*
145. Trator 1			
146. Trator 2			
147. Outro (ex: drone)			

**Anotar a informação que o produtor lembrar no momento e especificar no questionário (por exemplo, hora máquina utilizada por dia, % de tempo de uso da máquina no dia, número de dias em que utiliza a máquina por mês, etc).*

148. Contratou algum serviço terceirizado na pecuária em 2023/24? ( ) Não ( ) Sim
149. Se sim, qual o serviço? ________________________________
150. Nº total de horas contratado?____________________________
151. Valor total do serviço contratado na safra 2023/24 (R$)? _____________________

152. Possui **curral de manejo**? ( ) Não ( ) Sim
153. Qual a capacidade em cabeças do curral de manejo? _________________________

PARTE F – CARACTERÍSTICAS DO TOMADOR DE DECISÃO

REDE SOCIAL/ ACESSO A INFORMAÇÃO

Grupos formalmente organizados:

154. É associado/cooperado?	155. Frequência de participação nas reuniões
Associação de produtores ( ) sim ( ) não	( ) nunca participo; ( ) vou em algumas reuniões (ocasionalmente); ( ) vou em quase todas as reuniões
Sindicato Rural ( ) sim ( ) não	( ) nunca participo; ( ) vou em algumas reuniões (ocasionalmente); ( ) vou em quase todas as reuniões
Cooperativa ( ) sim ( ) não	( ) nunca participo; ( ) vou em algumas reuniões (ocasionalmente); ( ) vou em quase todas as reuniões

156. Recebeu assistência técnica em 2023/24? De quais organizações?	
Extensão governamental	( ) Não ( ) Sim
Fornecedor de insumos	( ) Não ( ) Sim
Associação/cooperativa	( ) Não ( ) Sim
Consultoria contratada	( ) Não ( ) Sim
Comprador de produtos	( ) Não ( ) Sim
Outro:______________	( ) Não ( ) Sim

157. Para as decisões sobre a produção agropecuária, qual a importância o Sr.(a) atribui para os canais de informação abaixo?

Canal de informação	**Frequência**
Mídias tradicionais (TV, rádio, revista, jornal)	( ) não uso; ( ) uso pouco; ( ) uso muito
Aplicativos de **troca de informação** (facebook, whatsApp, telegram)	( ) não uso; ( ) uso pouco; ( ) uso muito
Aplicativos de divulgação de conteúdo digital (podcast, youtube, instagram, tiktok) – **só recebe informação**	( ) não uso; ( ) uso pouco; ( ) uso muito
Sites de internet (blog, portais de notícias especializadas, boletins de preço)	( ) não uso; ( ) uso pouco; ( ) uso muito
Outros produtores, vizinhos, parentes	( ) não uso; ( ) uso pouco; ( ) uso muito
Dia de campo, feiras e eventos do agronegócio	( ) não uso; ( ) uso pouco; ( ) uso muito

158. Participa de quantos grupos virtuais para troca de informação agropecuária (ex: WhatsApp; telegram)? (__________________)

CONHECIMENTO FORMAL E EXPERIÊNCIA

159. Idade (anos): (______)

160. Quantos anos o sr. estudou ?: ____________(anos)

0 – sem instrução
1 – 1ª série fundamental
2 - 2ª série fundamental
3- 3ª série fundamental
4 - 4ª série fundamental
5 – 5ª série fundamental
6 - 6ª série fundamental
7 - 7ª série fundamental
8 - 8ª série fundamental
9 – 9ª série fundamental
10 - 1ª série médio
11 - 2ª série médio
12 - 3ª série médio/curso técnico
13 – superior incompleto
16 – superior completo
17- especialização
18 – mestrado
22 – doutorado

161. Possui outras atividades de renda além da agropecuária? (   ) Não (   ) Sim

PARTE G- COMPORTAMENTO DO PRODUTOR

Assinale, para cada uma das afirmações listadas abaixo, o seu grau de concordância.	**Discordo totalmente**	**Discordo**	**Nem discordo e nem concordo**	**Concordo**	**Concordo totalmente**
162. Eu gosto de testar tecnologias novas na minha fazenda	O	O	O	O	O
163. Confio na minha intuição na hora de tomar decisões na fazenda	O	O	O	O	O
164. Quando se trata de negócios, eu prefiro a opção mais segura, mesmo sabendo que eu possa ganhar menos	O	O	O	O	O
165. Minha capacidade de gestão é superior à média dos produtores da minha região	O	O	O	O	O
166. Quando eu tenho que tomar decisões importantes, eu busco conselhos com outros produtores e técnicos	O	O	O	O	O
Em relação ao uso das tecnologias digitais					
167. As tecnologias são muito caras para mim	O	O	O	O	O
168. As tecnologias são muito difíceis para eu aprender	O	O	O	O	O
169. As tecnologias são muito difíceis para outras pessoas da fazenda aprenderem	O	O	O	O	O
170. Eu não tenho boa internet na fazenda	O	O	O	O	O
171. Minha atividade agrícola é muito pequena para adotar essas tecnologias	O	O	O	O	O
172. Eu não tenho tempo suficiente para aprender sobre essas tecnologias	O	O	O	O	O
173. Eu preciso ver a tecnologia funcionando em outra fazenda para eu adota-la	O	O	O	O	O
174. Eu preciso testar essas tecnologias antes de adota-las	O	O	O	O	O
175. Não tenho certeza se essas tecnologias são adequadas para a minha fazenda	O	O	O	O	O
176. Eu não confio que os dados da minha fazenda estão seguros com essas tecnologias	O	O	O	O	O

TERMO DE CONSENTIMENTO LIVRE E ESCLARECIDO

(Resolução CNS 510/2016)

Prezado(a),

Gostaríamos de convida-lo (a) para participar das pesquisas intituladas “ADOÇÃO DE TECNOLOGIAS DE AGRICULTURA DIGITAL E EFICIÊNCIA TÉCNICA NA PRODUÇÃO AGROPECUÁRIA EM PROPRIEDADES RURAIS DO ESTADO DE

SÃO PAULO**”** (financiada pela Fapesp**,** processo nº 2022/02967-5) e “ADOÇÃO E IMPACTO DA ADOÇÃO DE TECNOLOGIA PARA AGRICULTURA DE BAIXO CARBONO: SISTEMAS DE INTEGRAÇÃO LAVOURA-PECUÁRIA” (financiada pelo CNPq processo nº 404187/2023-4).

Os projetos são coordenados pelo Departamento de Engenharia de Produção da Universidade Federal de São Carlos (UFSCar) e EMBRAPA, respectivamente.

A sua participação é voluntária, portanto, o(a) senhor(a) pode desistir de participar a qualquer momento, sem nenhuma penalização ou prejuízo.

Todas as informações obtidas serão confidenciais e os dados coletados somente serão utilizados para fins científicos.

Declaro que concordo em participar da pesquisa ___________________________

APPENDIX B. Correlation matrix of independent variables

	Experience	*School*	*Riskav*	*Innovative*	*Expensive*	*Private assist*	*Area*	*InvCredit*	*Coop*	*Flat*
Experience	1.00									
School	-0.23	1.00								
Riskav	0.03	-0.29	1.00							
Innovative	-0.03	0.07	-0.07	1.00						
Expensive	0.03	-0.38	0.20	-0.15	1.00					
Consult	0.07	0.28	-0.12	0.01	-0.26	1.00				
Area	0.06	0.10	-0.22	0.08	-0.17	0.28	1.00			
InvCredit	0.11	-0.06	-0.07	0.08	-0.01	0.05	0.13	1.00		
Coop	0.02	-0.07	0.15	0.05	0.00	-0.16	-0.14	0.03	1.00	
Flat	0.22	-0.06	-0.06	0.11	0.03	-0.05	-0.02	-0.04	0.05	1.00

APPENDIX C. Marginal Effects of explanatory variables.

Variables	Partial effects								
	AUTOPILOT	SOILSAMP	YIELDMON	YIELDMAP	VRSEED	VRFERT	SOFTWARE	DRONE	DAT
Experience	0,0005	0,005*	0,005**	0,002	0,003	0,0026	-0,002	0,003	0,03***
School	0,02*	0,02	0,02*	0,004	0,001	0,02*	0,01	0,01	0,12**
Riskav	0,01	-0,04	0,01	0,04	-0,02	-0,03	-0,01	-0,07**	-0,16
Innovative	-0,02	0,15***	-0,05	0,02	0,08*	0,07	0,06	0,09*	0,61***
Expensive	-0,01	-0,06*	-0,04	-0,09***	0,01	-0,06**	-0,12***	-0,05**	-0,49***
Consult	0,04	0,35***	0,03	0,04	0,04	0,17**	-0,05	-0,01	0,62*
Area	0,001***	0,0002**	0,001***	0,0002***	0,0001***	0,0003***	0,0003***	0,36D-04	0,001***
CreditInv	0,15	-0,13	0,27***	0,21**	-0,02	0,06	0,09	-0,12***	0,60
Coop	0,03	0,16	-0,08	-0,10	0,07**	0,08	0,02	0,08	-0,14
Clay	-0,02	0,14**	0,15**	0,18***	0,02	0,08	0,05	-0,01	0,89***

APPENDIX D. Goodness of fit of logit models

Table 10. Confusion matrix of AUTOPILOT logit model

Actual value	**Predicted Probability**		**Prediction Success**	**Sample Size**
	Prob(y=0)	Prob(y=1)		
y=0	46 (30.7%)	19 (12.7%)	46/66= 69.7% (Specificity)	66
y=1	19 (12.7%)	64 (42.7%)	64/84= 76.2% (Sensitivity)	84
Correct predicition of model			(46+64) / 150=73.3%	

Table 11. Confusion matrix of SOILSAMP logit model

Actual value	**Predicted Probability**		**Prediction Success**	**Sample Size**
	Prob(y=0)	Prob(y=1)		
y=0	52 (34.7%)	20 (13.3%)	52/73= 71.2% (Specificity)	73
y=1	20 (13.3%)	56 (37.3%)	56/77= 72.7% (Sensitivity)	77
Correct predicition of model			(52+56) / 150=72.0%	

Table 12. Confusion matrix of YIELDMON logit model

Actual value	**Predicted Probability**		**Prediction Success**	**Sample Size**
	Prob(y=0)	Prob(y=1)		
y=0	64 (42.7%)	20 (13.3%)	64/85= 75.3% (Specificity)	85
y=1	20 (13.3%)	44 (29.3%)	44/65= 67.7% (Sensitivity)	65
Correct predicition of model			(64+44) / 150=72.0%	

Table 13. Confusion matrix of YIELDMAP logit model

Actual value	**Predicted Probability**		**Prediction Success**	**Sample Size**
	Prob(y=0)	Prob(y=1)		
y=0	95 (63.3%)	16 (10.7%)	95/112= 84.8% (Specificity)	112
y=1	16 (10.7%)	21 (14.0%)	21/38= 55.3% (Sensitivity)	38
Correct predicition of model			(95+21) / 150=77.3%	

Table 14. Confusion matrix of VRSEED logit model

Actual value	Predicted Probability		Prediction Success	Sample Size
	Prob(y=0)	Prob(y=1)		
y=0	130 (86.7%)	6 (4.0%)	130/137= 94.9% (Specificity)	137
y=1	6 (4.0%)	6 (4.0%)	6/13=46.2% (Sensitivity)	13
Correct predicition of model			(130+6) / 150=90.7%	

Table 15. Confusion matrix of VRFERT logit model

Actual value	Predicted Probability		Prediction Success	Sample Size
	Prob(y=0)	Prob(y=1)		
y=0	88 (58.7%)	17 (11.3%)	88/106= 83.0% (Specificity)	106
y=1	17 (11.3%)	26 (17.3%)	26/44= 59.1% (Sensitivity)	44
Correct predicition of model			(88+26) / 150=76.0%	

Table 16. Confusion matrix of SOFTWARE logit model

Actual value	Predicted Probability		Prediction Success	Sample Size
	Prob(y=0)	Prob(y=1)		
y=0	64 (42.7%)	24 (16.0%)	64/89= 71.9% (Specificity)	89
y=1	24 (16.0%)	36 (24.0%)	36/61= 59.0% (Sensitivity)	61
Correct predicition of model			(64+36) / 150=66.7%	

Table 17. Confusion matrix of DRONE logit model

Actual value	Predicted Probability		Prediction Success	Sample Size
	Prob(y=0)	Prob(y=1)		
y=0	117 (78.0%)	13 (8.7%)	117/131=89.3% (Specificity)	131
y=1	13 (8.7%)	5 (3.3%)	5/19=26.3% (Sensitivity)	19
Correct predicition of model			(117+5) / 150=81.3%	

Figure 8. ROC curve for AUTOPILOT logit model

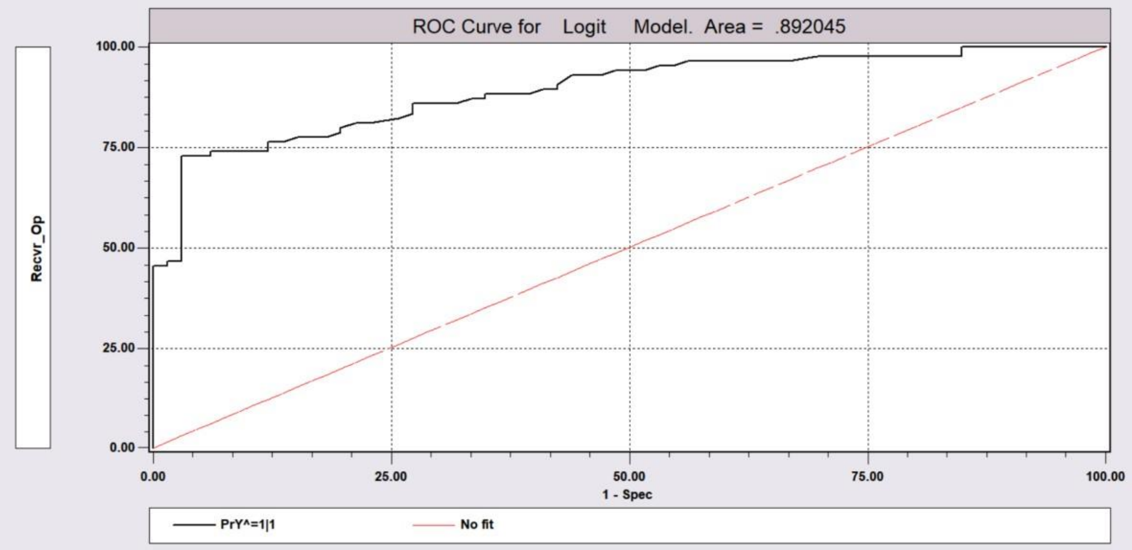

Figure 9. ROC curve for SOILSAMP logit model

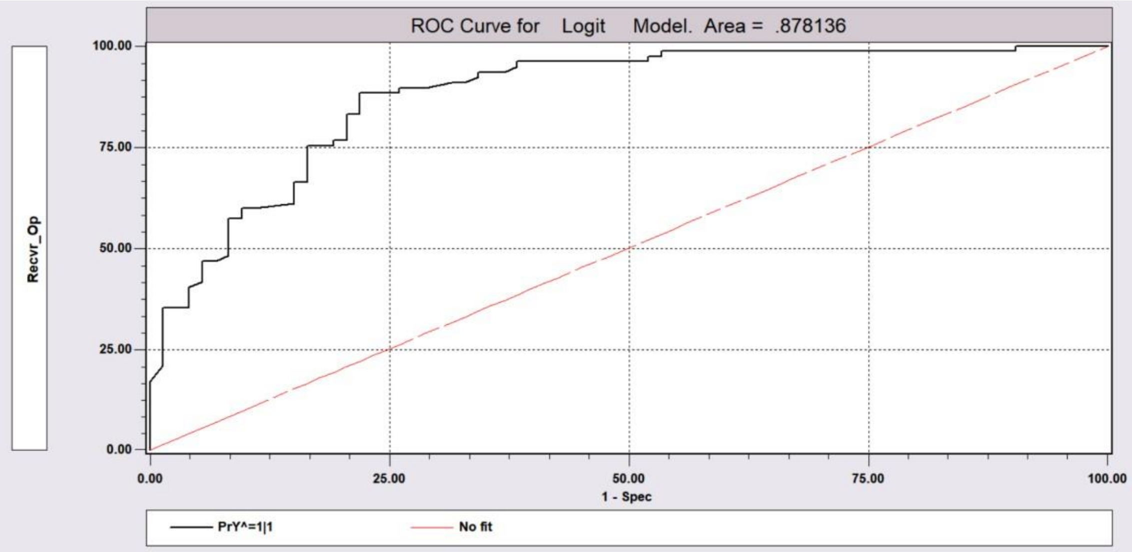

Figure 10. ROC curve for YIELDMON logit model

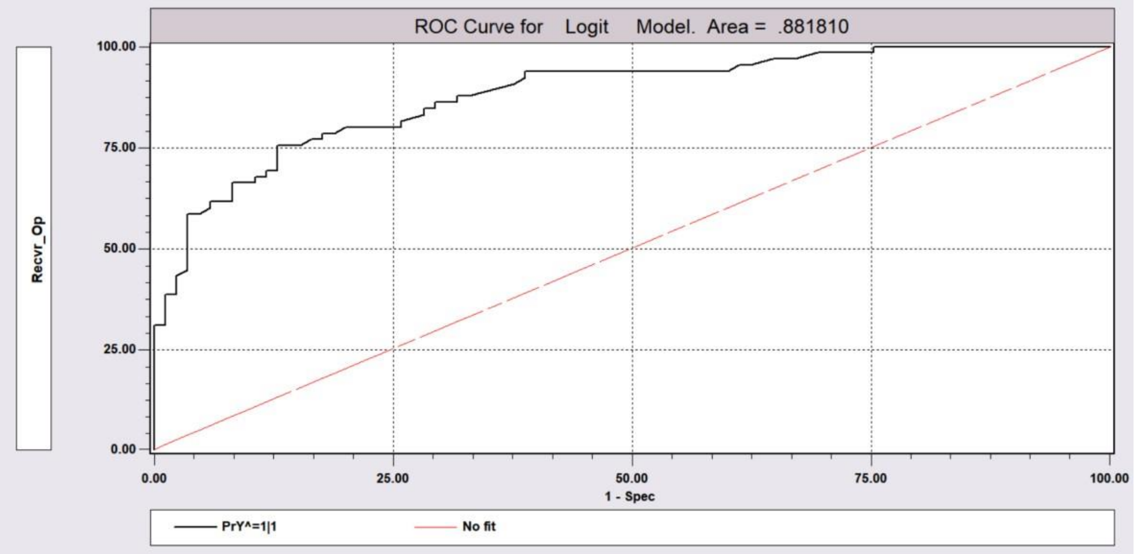

Figure 11. ROC curve for YIELDMAP logit model

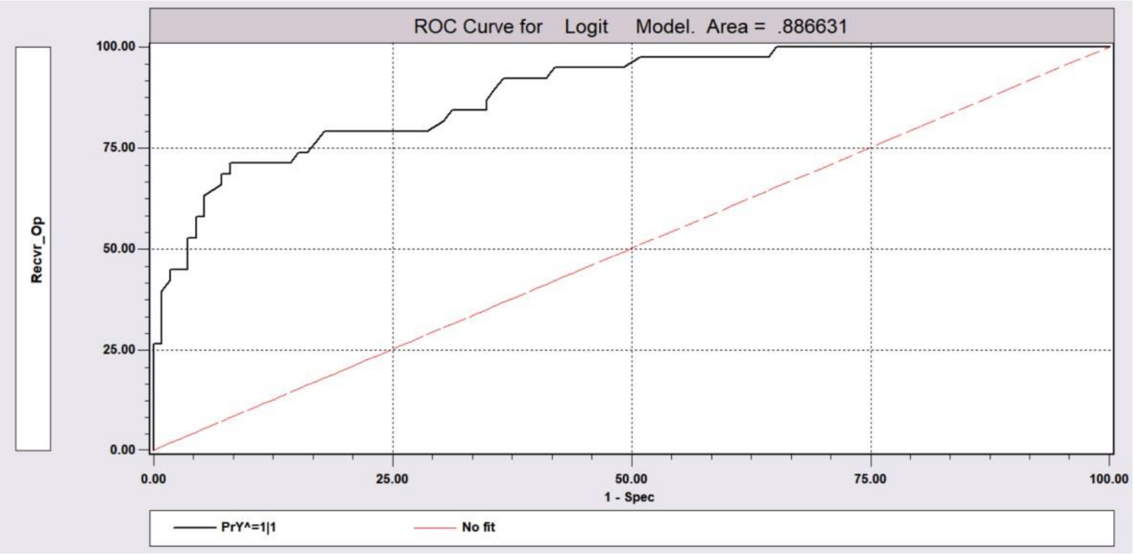

Figure 12. ROC curve for VRSEED logit model

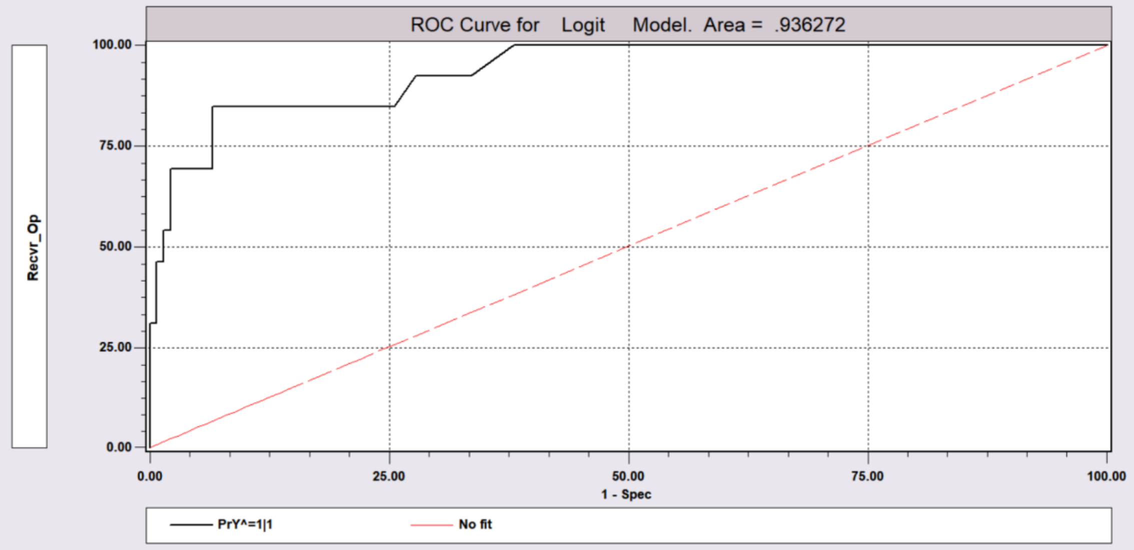

Figure 13. ROC curve for VRFERT logit model

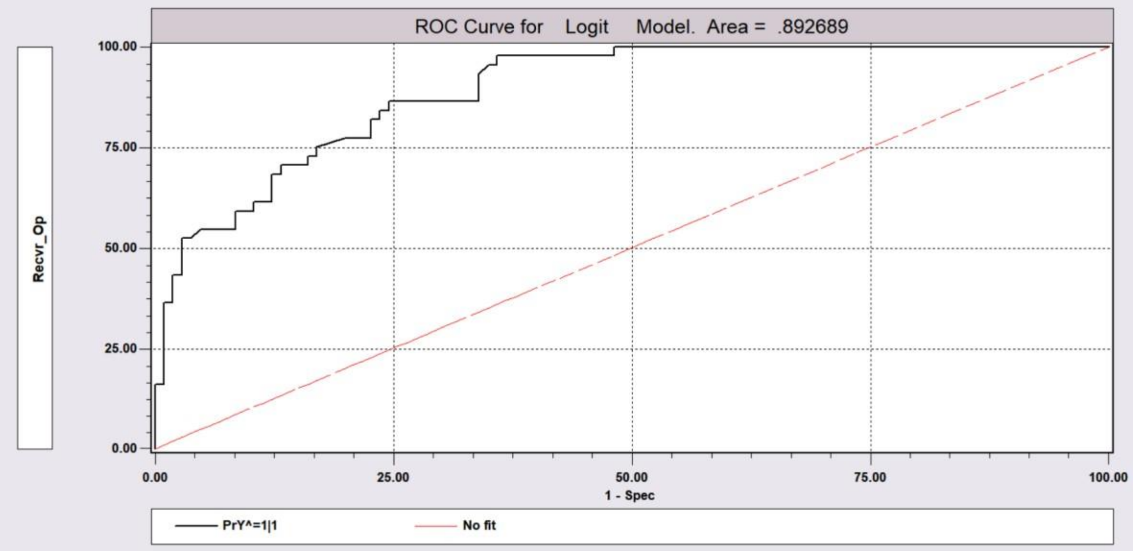

Figure 14. ROC curve for SOFTWARE logit model

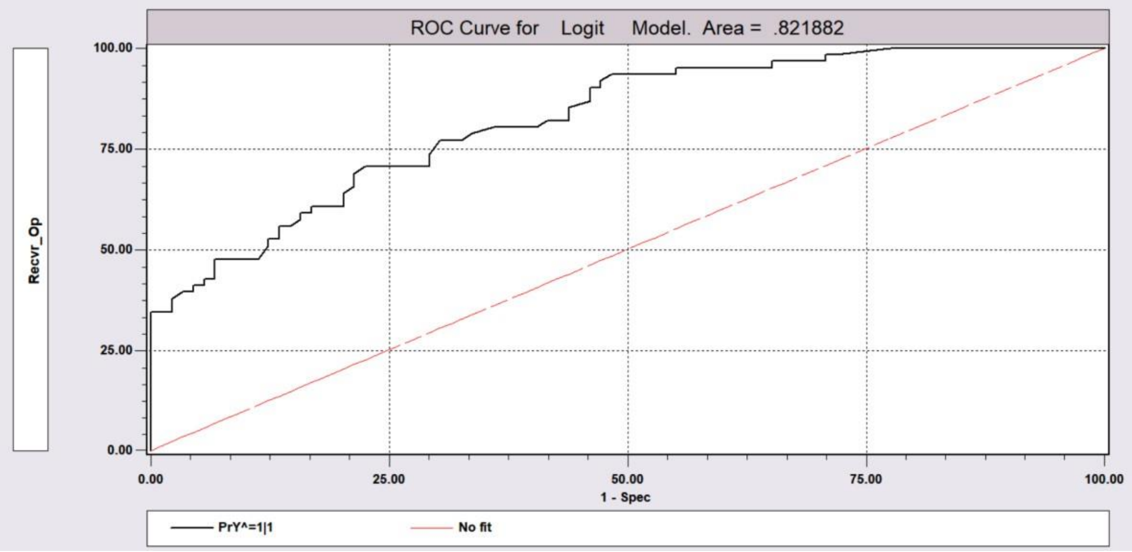

Figure 15. ROC curve for DRONE logit model