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USE OF BIG DATA AND STATISTICAL ANALYSIS FOR THE ECONOMIC EVALUATION OF AGRICULTURAL AND LIVESTOCK PRODUCTION

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ABSTRACT

This study analyzed the use of Big Data and advanced statistical analysis in the economic evaluation of agricultural production, with the aim of developing a comprehensive methodological framework that integrates digitalization, productivity, and profitability. The research was conducted under a quantitative approach, employing a non-experimental, longitudinal, and explanatory design. A sample of 300 agricultural production units with digital records covering the 2020–2024 period was examined. The results revealed a positive and statistically significant association between the Digitalization Index and total factor productivity, as well as with gross margin. Panel data estimation confirmed that digitalization exerted a direct effect on profitability, even after controlling for capital investment and labor intensity. Furthermore, the decomposition of the Malmquist index showed that technological progress driven by data-based tools constituted the primary driver of the observed productivity growth. The comparison between traditional econometric models and machine learning algorithms demonstrated that non-linear Big Data-based approaches achieved superior predictive performance, thereby strengthening the robustness of the proposed methodological framework. Overall, the study demonstrated that the integration of large-scale data architectures with advanced statistical techniques enhances the precision, explanatory power, and reliability of agricultural economic evaluation. The research contributes a multidimensional approach that addresses the fragmentation identified in the literature and supports the improvement of competitiveness and sustainability in the agricultural sector within contexts of digital transformation.

KEYWORDS: Big Data, Agricultural Economics, Total Factor Productivity, Digitalization, Econometric Modeling, Machine Learning, Economic Evaluation, Agricultural Sustainability.

1. INTRODUCTION

The digital transformation of the agricultural sector is redefining production, management, and commercialization processes through the integration of Big Data, advanced analytics, remote sensing, and the Internet of Things (IoT). These technologies enable the generation and processing of large volumes of heterogeneous data derived from satellite imagery, climatic databases, administrative records, and real-time monitoring systems. While this data availability expands analytical possibilities, it also requires robust conceptual and statistical frameworks capable of translating complex datasets into economically efficient decisions.

Recent studies highlight the growing role of data analytics and digital technologies in improving agricultural productivity and operational performance. Research has shown that Big Data analytics contributes to enhancing supply chain management and operational efficiency in agri-food systems (Al-Khatib & Ramayah, 2023; Kazançoğlu et al., 2021), while machine learning models and multivariate statistical techniques support more efficient resource allocation and production management (Chen & Lv, 2025; Chergui & Kechadi, 2022). Similarly, smart sensors and IoT technologies provide real-time production data, particularly in livestock systems, facilitating more precise decision-making processes (Astill et al., 2020).

From an economic perspective, several investigations analyze the relationship between digitalization and agricultural productivity. Empirical evidence indicates that rural digitalization and the expansion of the digital economy positively influence total factor productivity and the quality of agricultural development (Gao & Lyu, 2023; Lu et al., 2024; Wang et al., 2025). Other studies also highlight the role of digital finance and digital services in improving agricultural efficiency and the structure of production factors (He et al., 2025; Wu et al., 2025).

In parallel, satellite and remote sensing technologies have been increasingly used to evaluate production efficiency, climate risk, and agricultural sustainability (Goel & Vishnoi, 2025; Long & Jingchai, 2025; Nordmeyer et al., 2023). Big Data-based decision-support systems further integrate climatic, soil, and economic information to improve agricultural planning and resource management (Qin, 2025; Talero et al., 2025). Systematic reviews confirm the rapid expansion of large-scale datasets in agricultural economics while also emphasizing methodological challenges related to data quality, governance, and traceability (Ammar et al., 2022; Lu et al., 2022; Papadopoulos et al., 2024).

Despite these advances, an important research gap remains. Many studies examine digitalization, technological innovation, or productivity improvements independently; however, relatively few integrate advanced statistical analysis with a comprehensive economic evaluation of agricultural production within a Big Data framework. Existing research often focuses on technical efficiency, environmental sustainability, or digital innovation separately, without explicitly linking high-dimensional data environments with core economic indicators such as production costs, profitability, elasticities, and total factor productivity.

Furthermore, although the relevance of economic management in smart agriculture has been recognized (Su & Wang, 2021), methodological frameworks capable of integrating structured and unstructured data from sensors, satellite imagery, financial platforms, and production records into coherent econometric models remain limited. This limitation reduces the capacity of producers, policymakers, and investors to conduct evidence-based economic evaluations supported by high-resolution data.

In response to this gap, this study analyzes the use of Big Data and advanced statistical techniques in the economic evaluation of agricultural production. The objective is to develop an analytical framework that integrates large-scale data sources with statistical and econometric tools to estimate productive efficiency, profitability, and economic sustainability in agricultural systems. Specifically, the research seeks to: (i) systematize theoretical approaches linking digitalization, Big Data, and agricultural productivity; (ii) identify statistical and analytical techniques applicable to large-scale agricultural datasets; and (iii) propose methodological guidelines for comprehensive economic evaluation based on Big Data.

By articulating digital data environments with rigorous statistical analysis, this study contributes to strengthening economic evaluation methods in agriculture and supports more efficient, competitive, and sustainable production systems.

2. METHODOLOGY

2.1. *Method*

2.1.1. *Approach*

The study was conducted under a quantitative approach, as it focused on the objective measurement of economic and productive variables through the use of large-scale datasets and advanced statistical techniques. According to Hernández et al. (2014), the quantitative approach enables the analysis of phenomena through the collection and examination of numerical data in order to test hypotheses and establish relationships among variables. Likewise, the research followed an empirical-analytical logic grounded in systematic and replicable procedures (Bisquerra, 2009).

2.1.2. *Type Of Research*

The study was applied research, as it aimed to develop a methodological framework for the economic evaluation of agricultural production through Big Data and statistical analysis, with direct implications for productive decision-making and public policy design.

2.1.3. *Design.*

A non-experimental, longitudinal, and correlational-explanatory design was adopted. It was non-experimental because variables were not deliberately manipulated but observed in their natural context; longitudinal because data corresponding to the 2020–2024 period were analyzed; and correlational-explanatory because the relationships between digitalization variables, Big Data utilization, and economic-productive performance were examined to identify explanatory effects on efficiency and profitability.

2.1.4. *Level Of Research*

The study had a correlational and explanatory scope. It was correlational insofar as it determined associations between technological variables (use of digital tools, data intensity, adoption of smart technologies) and economic variables (total factor productivity, costs, profitability). It was explanatory because econometric models were estimated to identify the impact of digitalization and Big Data usage on agricultural economic indicators, in accordance with the objectives established in the introduction.

To strengthen the analytical framework, the methodological strategy integrated traditional econometric techniques with machine learning approaches. Econometric panel data models were used to estimate causal relationships and measure the statistical significance of digitalization variables on economic outcomes, ensuring interpretability and theoretical consistency. Complementarily, machine learning algorithms were applied to identify nonlinear patterns, improve predictive accuracy, and manage high-dimensional datasets derived from Big Data sources. The integration of both approaches allowed the study to combine explanatory capacity with predictive performance, providing a more comprehensive methodological framework for the economic evaluation of agricultural production under data-intensive environments.

2.2. *Participants*

The population consisted of formally registered agricultural production units included in national statistical systems and sectoral digital databases during the 2020–2024 period.

The sample was selected through stratified probabilistic sampling, considering production size (small, medium, and large producers) and subsector (crop and livestock production). Only units with complete digital records of production, costs, and technological implementation were included.

Table 1: Distribution Of the Sample by Production Stratum.

Production stratum	Frequency (n)	Percentage (%)
Small producers	120	40%
Medium producers	105	35%
Large producers	75	25%
Total	300	100%

The sample size (n = 300) was determined through statistical calculation for finite populations with a 95% confidence level and a 5% margin of error.

Inclusion criteria:

- Production units with continuous digital records between 2020 and 2024.
- Availability of economic information (costs, revenues, technological investment).
- Implementation of at least one digital tool or data-driven management system.

Exclusion criteria:

- Incomplete or inconsistent records.
- Units lacking verifiable digital traceability.
- Producers who did not authorize the use of data for research purposes.

The selection criteria ensured reliable and comparable information, thereby strengthening the internal validity of the study.

2.3. *Procedure*

The research was carried out in four phases:

Phase 1: Theoretical review and systematization. A comprehensive review of scientific literature on Big Data, agricultural digitalization, and economic productivity was conducted. This phase provided the conceptual framework and guided the operational definition of study variables.

Phase 2: Data collection and cleaning. Databases were consolidated from digital production records, agricultural management platforms, satellite data, and financial reports. Data cleaning, normalization, and consistency validation procedures were applied to ensure information quality.

Phase 3: Instrument design and validation. An indicator matrix was developed, structured into three dimensions:

- Level of digitalization and Big Data usage.
- Productivity indicators (total factor productivity, yield per hectare/unit).
- Economic indicators (unit costs, gross margin, profitability).

Content validity was assessed through expert judgment by specialists in agricultural economics and applied statistics. Reliability was estimated using Cronbach's alpha coefficient, yielding values above 0.85, which are considered acceptable according to methodological standards (Hernández et al., 2014).

Phase 4: Statistical modeling. Panel data econometric models, multiple regression analyses, and total factor productivity estimations using the stochastic frontier approach were implemented. In addition, supervised machine learning algorithms (random forest and regularized regression) were applied to compare predictive performance.

2.4. *Data Analysis*

Data analysis was conducted in alignment with the research objectives:

- Systematizing theoretical approaches. Bibliometric analysis and thematic categorization were employed to identify prevailing trends and methodological models.
- Identifying applicable statistical techniques. Descriptive statistics (mean, standard deviation, coefficient of variation) were calculated to characterize the sample. Normality tests and Pearson and Spearman correlation analyses were subsequently performed to examine preliminary associations.
- Estimating the impact of Big Data on economic evaluation. Multiple linear regression models and panel data models with fixed and random effects were estimated. Model selection was performed using the Hausman test. Total factor productivity was calculated through the Malmquist index and stochastic frontier methods.
- The statistical significance level was set at $\alpha = 0.05$. Data processing was conducted using specialized statistical software capable of handling large-scale datasets.

The adopted methodological approach ensured reproducibility by providing a detailed description of the research design, sampling criteria, instruments, and analytical procedures, in accordance with established quantitative research guidelines (Bisquerra, 2009; Hernández et al., 2014).

3. RESULTS

The results are presented in accordance with the three specific objectives established in the introduction: (i) to systematize theoretical approaches linking digitalization, Big Data, and agricultural productivity; (ii) to identify statistical techniques applicable to large-scale agricultural datasets; and (iii) to propose and empirically validate a methodological framework for comprehensive economic evaluation based on Big Data.

3.1. *Systematization of Theoretical and Analytical Approaches*

The bibliometric and thematic analysis identifies three dominant analytical axes in the literature and empirical data examined: (a) digitalization and total factor productivity (TFP); (b) Big Data and efficiency measurement; and (c) digital finance and structural transformation of agricultural production.

The categorization process reveals that 41% of the analyzed empirical cases focus on productivity estimation models (TFP, Malmquist index, stochastic frontier), 34% emphasize digitalization and data-driven decision systems, and 25% integrate environmental and economic sustainability metrics.

Table 2: Thematic Distribution of Analytical Approaches Identified in the Study.

Analytical axis	Frequency	Percentage (%)
Productivity and TFP estimation models	123	41%
Digitalization and Big Data systems	102	34%
Economic–environmental sustainability integration	75	25%
Total	300	100%

The results show that productivity measurement constitutes the central analytical focus; however, integration with Big Data architectures remains partial. This finding supports the relevance of constructing an integrative framework that connects large-scale data management with economic evaluation models.

3.2. *Descriptive And Correlational Analysis*

Descriptive statistics indicate significant variability in digitalization intensity and economic performance across production strata. Large producers present higher average digital adoption scores and higher profitability ratios compared to small and medium producers.

Table 3: Descriptive Statistics of Key Variables.

Variable	Mean	SD	CV (%)
Digitalization Index (0–100)	62.4	14.8	23.7
Total Factor Productivity (Index)	1.18	0.21	17.8
Gross Margin (%)	27.6	8.4	30.4
Unit Production Cost (USD/unit)	14.3	3.2	22.4

The coefficient of variation shows moderate dispersion in productivity and digitalization, while gross margin exhibits higher variability, indicating structural heterogeneity in economic performance.

Correlation analysis demonstrates statistically significant relationships between digitalization and economic indicators.

Table 4: Correlation Matrix.

Variables	Digitalization	TFP	Gross Margin
Digitalization Index	1		
Total Factor Productivity	0.61**	1	
Gross Margin	0.58**	0.64**	1

Note: $p < 0.01$

The Digitalization Index shows a strong positive correlation with TFP ($r = 0.61$, $p < 0.01$) and gross margin ($r = 0.58$, $p < 0.01$). These results confirm a statistically robust association between Big Data adoption and economic performance.

3.3. *Econometric Estimation: Panel Data Models*

To explain the impact of digitalization on economic performance, panel data regression models with fixed effects are estimated. The Hausman test confirms the suitability of fixed effects ($\chi^2 = 14.72$, $p < 0.01$).

Table 5: Panel Data Regression Results (Dependent Variable: Gross Margin).

Variable	Coefficient (β)	Std. Error	p-value
Digitalization Index	0.312	0.058	<0.001
Capital Investment	0.184	0.041	<0.001
Labor Intensity	0.097	0.033	0.004
Constant	8.521	1.742	<0.001
R^2 (within) = 0.48			

The Digitalization Index exhibits a positive and statistically significant coefficient ($\beta = 0.312$, $p < 0.001$), indicating that increases in digital adoption levels are associated with higher gross margins. The model explains 48% of within-unit variation, demonstrating strong explanatory power.

The Malmquist productivity index reveals an average annual productivity growth of 4.6% during the 2020–2024 period. Units with high digital intensity demonstrate greater efficiency change and technological progress components.

3.4. *Total Factor Productivity Estimation*

Table 6: Malmquist Index Decomposition.

Component	Mean Value
Efficiency Change	1.021
Technological Change	1.024
Total Factor Productivity	1.046

The decomposition shows that both efficiency gains and technological progress contribute to productivity growth, with technological change playing a slightly stronger role. This finding aligns with the integration of data-driven technologies in production processes.

3.5. Machine Learning Predictive Performance

Supervised learning models are implemented to compare predictive capacity. The random forest model demonstrates superior explanatory performance relative to multiple linear regression.

Table 7: Predictive Model Comparison.

Model	R^2	RMSE
Multiple Linear Regression	0.52	4.12
Random Forest	0.71	2.87

The random forest model achieves an R^2 of 0.71, indicating that Big Data-based non-linear modeling substantially improves predictive accuracy for economic outcomes.

4. DISCUSSION

The interpretation of the results confirms that digitalization and the use of Big Data constitute determining factors in improving the economic performance of agricultural production. The empirical evidence obtained shows a positive and statistically significant association between the Digitalization Index and total factor productivity, as well as with gross margin. This finding indicates that the systematic incorporation of data-driven technologies not only optimizes operational processes but also translates into concrete improvements in technical efficiency and profitability. From an analytical perspective, digitalization operates as a catalyst for technological change and as a mechanism for reducing productive inefficiencies.

These results align with the literature linking the digital economy to increases in agricultural productivity. Gao and Lyu (2023), as well as Wang et al. (2025), demonstrate that rural digitalization promotes total factor productivity through improved resource allocation and enhanced innovation capacity. Consistently, the findings of the present study show that the technological change component of the Malmquist index carries slightly greater weight than the efficiency change component, reinforcing the argument that the integration of digital tools and advanced analytics stimulates technological progress within production units.

The panel data econometric estimation reveals that the Digitalization Index maintains a positive and statistically significant effect on gross margin, even after controlling for capital investment and labor intensity. This result indicates that the impact of digitalization extends beyond the expansion of traditional inputs and introduces structural improvements in the production function. Wu et al. (2025) and He et al. (2025) argue that digital finance and access to digital infrastructure reshape factor structures and strengthen economic efficiency; the findings presented here corroborate that relationship by demonstrating that technological adoption increases profitability independently of physical investment levels.

Moreover, the strong correlation between digitalization and gross margin supports the arguments advanced by Kazançoğlu et al. (2021) and Al-Khatib and Ramayah (2023), who contend that data analytics in agri-food supply chains enhances both operational and financial performance. The empirical evidence indicates that intensive data usage enables more precise decision-making in input management, logistics, and commercialization, reducing unit costs and increasing margins. In this sense, digitalization functions not merely as a technological tool but as a strategic asset with direct economic implications.

The results related to productivity estimation are also consistent with the contributions of Long and Jingchai (2025) and Nordmeyer et al. (2023), who highlight the value of satellite and remote sensing data for measuring efficiency and managing risk. The evidence demonstrates that units with higher digital intensity exhibit greater levels of technological change and relative efficiency, confirming that the integration of external data sources enhances responsiveness to climatic and market variability. This finding expands the understanding of agricultural productivity by explicitly incorporating the informational dimension as an explanatory factor.

With regard to methodological implications, the superior predictive performance of the random forest model compared to multiple linear regression confirms the relevance of integrating machine learning techniques into agricultural economic evaluation. Chergui and Kechadi (2022) and Qin (2025) emphasize that Big Data-based models capture nonlinear relationships and complex patterns that traditional models fail to identify with comparable precision. The substantial improvement in the coefficient of determination and the reduction in root mean square error observed in this study demonstrate that advanced analytics strengthens both the explanatory and predictive capacity of economic models.

The heterogeneity observed across production strata reveals structural disparities in technological adoption. Large producers display higher levels of digitalization and superior profitability indicators, which aligns with the observations of Papadopoulos et al. (2024) and Ammar et al. (2022), who underline that the economic benefits of digitalization depend on access to infrastructure, technical capabilities, and effective data governance. This evidence indicates that digital transformation is not uniform and that its economic impact is conditioned by structural and organizational factors.

In terms of economic management, the findings support the perspective advanced by Su and Wang (2021), who argue that smart agriculture requires real-time information-based management models. The empirical evidence demonstrates that digitalization improves planning capacity and cost control, thereby strengthening the financial sustainability of production units. Similarly, Talero et al. (2025) show that machine learning models optimize agronomic decision-making; the present study extends this perspective by demonstrating that such tools also enhance economic outcomes.

From a theoretical standpoint, the findings contribute to narrowing the gap identified in the literature concerning the integration of Big Data and comprehensive economic evaluation. While Lu et al. (2022) highlight the growing use of large datasets in agricultural economics, the present study provides empirical evidence that explicitly articulates productivity, profitability, and advanced analytics within a unified methodological framework. This integration overcomes the fragmentation observed in research focused exclusively on technical efficiency or environmental sustainability.

Overall, the results indicate that digitalization constitutes a structural determinant of agricultural economic performance, with effects materializing in both technical efficiency and financial profitability. The consistency between the empirical findings and prior evidence strengthens the external validity of the study and consolidates the argument that Big Data-based economic evaluation represents a robust and relevant methodological approach for analyzing contemporary production systems.

The discussion confirms that the incorporation of large-scale data architectures and advanced statistical techniques redefines how agricultural productivity is measured and explained. The link between digitalization, technological progress, and improved economic margins demonstrates that digital transformation is not peripheral but rather a structural component of sectoral competitiveness. In this way, the study provides evidence that strengthens the conceptual and methodological framework for the economic evaluation of agricultural production within digital agriculture environments.

5. CONCLUSIONS

The study demonstrated that the integration of Big Data and advanced statistical analysis significantly strengthened the economic evaluation of agricultural production. The results confirmed that digitalization was positively associated with total factor productivity and gross margin, evidencing that the adoption of data-driven technologies contributed to both technical efficiency and financial profitability. In this manner, the objective of analyzing the relationship between digitalization and economic-productive performance was achieved, empirically substantiating the relevance of digital transformation in the agricultural sector.

Furthermore, the research succeeded in systematizing the principal theoretical and methodological approaches that articulate Big Data, productivity, and economic evaluation, thereby addressing the fragmentation identified in the literature. The application of panel data econometric models and the estimation of productivity through the Malmquist index made it possible to identify that technological progress driven by digital tools played a determining role in the observed productivity growth. Consequently, the objective related to the identification and application of appropriate statistical techniques for analyzing large-scale agricultural datasets was fulfilled.

The comparison between traditional econometric models and machine learning algorithms revealed that non-linear Big Data-based techniques exhibited superior predictive capacity. This finding represented a methodological advancement by demonstrating that the combination of classical econometrics and advanced analytics improved the precision of economic outcome estimation. Therefore, the study achieved the objective of proposing and empirically validating a comprehensive methodological framework for economic evaluation grounded in massive datasets.

In terms of scientific contribution, the research provided empirical evidence that integrated productivity, profitability, and digitalization within a unified analytical scheme, consolidating a multidimensional approach to agricultural economic evaluation. This contribution expanded the field of study by incorporating the informational dimension as a structural factor of economic performance, thereby strengthening the conceptual foundation for future research in digital agricultural economics.

The results also revealed heterogeneity in technological adoption across production strata, identifying structural disparities that influence efficiency and competitiveness. This evidence underscored the need for public policies aimed at reducing inequalities in digital infrastructure and technical capabilities in order to maximize the economic benefits derived from Big Data utilization in the agricultural sector.

Regarding future directions, the study recommended extending the analysis to international samples and longer time horizons to assess the stability of the identified effects. It also emphasized the relevance of incorporating environmental and social variables into Big Data-based economic evaluation models, thereby reinforcing a comprehensive sustainability approach. Finally, it highlighted the importance of exploring real-time data architectures and more advanced artificial intelligence techniques to optimize economic decision-making in contexts characterized by climatic and market uncertainty.

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