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Digital Revolution in Agriculture: Using Predictive Models to Enhance Agricultural Performance Through Digital Technology

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Abstract: Digital innovation in agriculture has become a powerful force in the modern world as it revolutionizes the agricultural sector and improves the sustainability and efficacy of farming practices. In this context, the study examines the effects of digital technology, as reflected by the digital economy and society index (DESI), on key agricultural performance metrics, including agricultural output and real labor productivity per person. The paper develops a strong analytical method for quantifying these associations using predictive models, such as exponential smoothing, ARIMA, and artificial neural networks. The method fully illustrates how economic and technological components interact, including labor productivity, agricultural output, and GDP per capita. The results demonstrate that digital technologies significantly impact agricultural output and labor productivity. These findings illustrate the importance of digital transformation in modernizing and improving agriculture's overall efficacy. The study's conclusion highlights the necessity of integrating digital technology into agricultural policy to address productivity problems and nurture sustainable growth in the sector.

Keywords: digital technologies; productivity; agricultural output; digital economy and society index; digital agriculture

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1. Introduction

The digital agricultural revolution is a transformative phenomenon with extensive implications for agricultural practices. Estimates suggest that the global population will reach nearly 10 billion by 2050 [1]. This demographic surge will significantly increase the demand for essential resources, particularly food, requiring higher quantity and improved quality. Global food production must increase by approximately 60–70% to meet the needs of a growing population [2,3].

Meeting this demand poses challenges, including climate changes that will exacerbate existing risks and introduce new ones, compounded by the complex interplay between environmental and socio-economic factors [4]. Climate change amplifies the vulnerability of traditional agricultural systems, directly impacting crop productivity, soil health, and the availability of critical resources such as water. Addressing these challenges requires adopting innovative solutions, such as advanced digital technologies, sustainable farming practices, and international collaboration to manage food resources [5]. Agriculture can only evolve to meet present and future global demands through an integrated approach driven by collaboration and innovation.

Expanding agricultural production sustainably hinges mainly on advances in technology and innovation research [6]. Digital technologies offer a promising strategy to enhance agricultural growth by increasing agricultural production processes' scale, efficiency, and effectiveness. Precision agriculture, for instance, utilizes technologies such as artificial intelligence (AI), advanced sensors, and data-driven management systems to optimize inputs like water, fertilizers, and pesticides according to specific crop needs [7].

Moreover, drones and remote sensing technologies provide detailed insights into crop conditions and environmental factors, enabling quick and informed decision-making. This approach improves agricultural yields and addresses soil erosion and biodiversity loss. Thus, digital agriculture becomes essential for modernizing the sector and ensuring a sustainable future that responsibly and efficiently addresses demographic and climate challenges.

This research aims to develop a robust analytical framework to evaluate the relationship between digitalization and agricultural efficiency while offering perspectives for integrating digital technologies into agricultural development strategies. The research deepens the understanding of interactions between economic and technological variables, including the DESI, labor productivity, agricultural output, and GDP per capita, by employing predictive models such as artificial neural networks, ARIMA, and exponential smoothing. This analysis provides a solid foundation to demonstrate the significant impact of digitalization on agriculture and underscores the urgency of adapting swiftly to new technological realities.

While the impact of digital technologies on other economic sectors is well-documented, agriculture still needs to be explored. Key challenges include the need for standardized methodologies for quantifying these technologies' effects and the complexity of adapting them to the agricultural sector's unique characteristics, such as high variability and dependence on natural factors. Furthermore, only some studies predictively analyze the influence of digitalization on agricultural production and productivity to ensure the food system's sustainability. The originality of this study lies in integrating advanced predictive models to examine the influence of the DESI on agricultural output and productivity. The findings contribute significantly to the literature by highlighting the importance of digital transformation for modernizing agriculture.

The paper has six sections: introduction, literature review and hypothesis formulation, materials and methods, results, discussions, and conclusions. Together, these sections provide a comprehensive perspective on the influence of digital technologies on agriculture.

2. Literature Review and Hypotheses

2.1. The Influence of Digitalization on Total Production and Agricultural Productivity

Numerous strategies shape agriculture within the European Union. The European Green Deal is a set of policy initiatives to make Europe the first climate-neutral continent by 2050, relying on a sustainable growth strategy integrating all economic sectors [8]. The "Farm to Fork" strategy has revolutionized agri-food systems and sped up the shift to a clean, circular economy [9]. These programs highlight how important it is for citizens, businesses, and governments to work together to guarantee a smooth transition.

Digital agriculture incorporates advances and digital technologies into food systems, value chains, and agricultural production [10]. It includes ideas like precision agriculture [11] and smart farming [12], which use data and cutting-edge technologies to maximize agricultural operations [13].

Digital agriculture, formally introduced in 1997, uses information and GIS technologies to improve agricultural productivity, farmer incomes, and product competitiveness [14]. With the addition of detecting technologies like remote and proximity sensors, it has developed into precision agriculture [15–17] and is becoming increasingly compatible with digital governance and mobile connectivity. Agricultural data management, accurate component distribution, and production tool control are the main areas of research in developed nations [10]. Sensors and other Internet of Things (IoT) devices help farmers by enhancing production management through interconnected networks. Planting schedules could be established by farmers using technological devices [18]. Despite the lack of agreement on digitalized agriculture, research is concentrated on evaluating agricultural informatization and creating digital infrastructures [14,19–25]. These innovative methods enhance farm competitiveness by increasing agricultural production sustainably and resource-efficiently [26], allowing farmers to achieve higher profits while reducing environmental impacts, aligning with global sustainability and environmental protection goals [23,24,27].

Implementing precision agriculture involves a more detailed and personalized approach than conventional farming practices. It enables farmers to apply the right amounts of fertilizers, water, or pesticides required for each section of land based on specific soil and crop conditions [28]. This approach boosts productivity and protects the environment by reducing the risks of pollution and resource depletion. Furthermore, by leveraging these technologies, farmers can achieve higher yields of superior quality and more accurately anticipate market demands, fostering conditions for long-term sustainable and competitive agriculture [29].

Precision farming emphasizes leveraging advanced technologies to integrate relevant data into decision-making processes, aiming to optimize production and address the complex challenges of the global agricultural sector [30]. Its impact transcends crop production, extending to fields such as water management in viticulture [31,32], horticulture [33,34], livestock production [35,36], and pasture management [37,38]. These applications highlight its versatility and relevance across various contemporary agricultural domains [13,39]. More than just a collection of technologies, precision farming represents an integrated system that transforms resource management practices, nurturing more sustainable, competitive agriculture adaptable to current socio-economic and environmental demands.

Digital agriculture relies on sensors, smart machinery, drones, and satellites to collect and analyze vast datasets. These include information on location, weather conditions, crop or livestock behaviors, plant health, resource consumption, energy use, market prices, and economic indicators [10]. The objective is to enhance efficiency, reduce costs, and minimize environmental impact. By adopting these technological solutions, agriculture evolves into a more sustainable practice, addressing challenges such as climate change, global population growth, and food security needs. Simultaneously, it facilitates greater product traceability and transparency across supply chains, strengthening consumer trust [11–13].

Data collected through digital technologies optimize agricultural production systems, tackle societal concerns, and ensure better monitoring of controversies within agricultural chains and sectors [40]. Innovative concepts like precision agriculture and precision farming, emerging in the 1990s [41], use diverse sensors, drones, and monitoring devices to gather detailed crop data [42]. These technologies improve agricultural yield and sustainability while reducing waste in resources such as water and chemical fertilizers. Precision farming also enables custom-made interventions, adapting practices to the specific needs of individual plots, enhancing efficiency, and minimizing environmental impact [13,43].

Integrating advanced digital technologies at every stage of agricultural processes, from planning and planting to harvesting and distribution, marks the onset of the digital agricultural revolution or Agriculture 4.0 [44]. Agriculture 4.0 reshapes traditional practices by providing integrated solutions to global challenges such as rising food demand, climate change, and limited natural resources. This approach relies on widespread technologies like the IoT, AI, big data, and robotics, enabling precise and efficient agricultural resource management [45–48].

Through data exchange and technological solutions, farmers worldwide may access innovations that improve production, lessen environmental impact, and promote sustainability. Consequently, Agriculture 4.0 changes how food is produced and reinterprets how technology, the environment, and society interact [49,50]. A highly flexible production model based on digitization and customization is the goal of the so-called "Industry 4.0" [46,47,50–52], which parallels this fourth agricultural revolution and allows for real-time interactions between people, products, and devices across production processes [53]. With cutting-edge technologies like IoT, drones, robotics, and artificial intelligence, adopting Industry 4.0 paradigms significantly changes agriculture [54–56].

Alongside Industry 4.0, Agriculture 4.0 is developing and embracing new digital technologies [5,46–52]. Resilience, innovation, and sustainability are encouraged when comparable concepts and technology are applied to agricultural systems. The parallels between these two revolutions underscore the importance of technological innovation and convergence in transforming the agricultural and industrial sectors. Both Industry 4.0 and Agriculture 4.0 have the potential to transform how resources are used, increasing resilience and sustainability in a world that is changing quickly [53].

Although AI has enormous potential in many domains, including agriculture, its use in reducing crop loss risks is still in its infancy. AI contributes by monitoring and analyzing data from diverse sources (sensors, drones, satellite imagery), providing farmers with precise insights into crop conditions and forecasting potential risks like pest infestations or extreme weather events [29,57].

The adoption of digital tools in agriculture has been widely studied through the lens of the technology acceptance model (TAM) and the diffusion of innovations theory, which emphasize the role of perceived usefulness and ease of use in fostering technology adoption. Recent studies have applied these models to precision agriculture, demonstrating how farmers' attitudes and external factors like access to resources shape the uptake of innovative solutions [58–60]. Innovation network theory highlights the collaborative dynamics among farmers, technology providers, and researchers, which are pivotal in promoting knowledge exchange and resource sharing, facilitating the effective implementation of advanced technologies in agriculture [61,62].

Moreover, the socio-technical perspective provides an integrated view by addressing the interaction between technical innovations and social dimensions, such as farmer education, infrastructure development, and supportive policies. Socio-technical systems theory suggests that the successful adoption of digital solutions is contingent on addressing these interconnected factors, corroborated by recent findings on the barriers and facilitators of digital transformation in agriculture [63–65].

This study is grounded in the resource-based view (RBV), which provides a robust theoretical framework for understanding how strategic resources, such as digital technologies, contribute to enhanced agricultural performance. Empirical evidence underscores how these technologies contribute to improved productivity and cost reduction, framing them as indispensable tools for modern agrarian systems [66,67]. By framing digital technologies as valuable, rare, inimitable, and non-substitutable resources, the RBV underscores their role in driving agriculture productivity, efficiency, and sustainability. This perspective enables the analysis to highlight how integrating digital solutions can create a competitive advantage for farms, facilitating resilience and adaptability in the face of economic and environmental challenges.

The first hypothesis suggests that digitalization indicators significantly influence overall production and agricultural productivity, emphasizing the importance of implementing digital technologies in the agricultural sector to ensure the food system's sustainability.

Hypothesis H1. *The evolution of digitalization levels, measured using the DESI, significantly influences agricultural output and productivity.*

2.2. The Impact of Digitalization on Future Trends in Agricultural Output and Productivity Evolutions

Digital agriculture incorporates advanced technologies to optimize resource use, enhance efficiency, and reduce costs in farming while improving management across the agricultural sector [10,68–70]. By integrating emerging tools like the IoT, big data analytics, and AI, digital agriculture fosters a more sustainable agro-industrial system. These technologies enable real-time monitoring and precise adaptation of agricultural processes, supporting both productivity and rural transformation. Farmers gain new opportunities through innovative solutions to achieve higher profits and contribute to the local economy [58].

Investments in technological research contribute to developing sustainable solutions within the agricultural sector, which is increasingly needed in addressing global challenges such as population growth, climate change, and limited natural resources [5]. Agriculture 4.0 introduces an innovative paradigm that integrates advanced technology across all aspects of agricultural production. Advanced sensors allow real-time monitoring of soil and plant conditions, facilitating informed decision-making to reduce waste and optimize resource use [71]. Simultaneously, AI and big data enable predictive analyses of risks such as drought or crop diseases, offering proactive solutions to minimize losses [48].

Robotics advances automation in agricultural processes like harvesting, reducing reliance on manual labor and enhancing operational efficiency. Cloud computing technologies ensure seamless storage and access to complex data, promoting global collaboration in research and the swift implementation of innovations [44]. These technological advancements drive productivity growth and mitigate environmental impact, promoting sustainable agricultural practices.

Enhancing productivity, alongside environmental and sustainability motivations, remains an important driver of digital agriculture adoption [72]. By increasing productivity, agriculture can meet the demands of a growing population without exceeding ecosystems' natural limits. Researchers employ various econometric and statistical methods to measure productivity in agriculture, analyzing diverse temporal and spatial contexts [14,73–76]. These approaches provide detailed insights into shifts in technological efficiency and agricultural progress, forming a robust foundation for comparing performance across regions and economic contexts. Furthermore, these methods guide policymakers in crafting effective public policies to support the transition toward more sustainable and environmentally responsible agriculture.

Technological progress is central to productivity improvement in agriculture [77]. Environmental regulations significantly influence agricultural practices by shaping how natural resources are managed, with appropriate legal frameworks encouraging the adoption of greener technologies [78]. Furthermore, human capital and urbanization are essential in accelerating agricultural modernization as young workers migrate to urban centers and research and education hubs emerge to equip farmers with innovative solutions [79,80]. Internal agricultural sector restructuring, including administrative modernization and adaptation to new economic and ecological conditions, is fundamental for enhancing process efficiency and competitiveness [81].

Technical efficiency and optimal resource allocation are decisive for achieving desired yields within the constraints of finite agricultural resources [82,83]. Financial support, especially regarding farm size and access to credit, is instrumental in ensuring balanced sectoral development [84,85]. Emerging digital technologies, including AI, machine learning [86], and IoT devices [87–91], improve agricultural precision and sustainability while reducing environmental impact and increasing output. Better data integration in agricultural operations is made possible by these technologies, which support data-driven decision-making and encourage a modern strategy that satisfies the ecological and economic objectives of the 21st century.

The enormous collection of agriculture data raises serious concerns about data privacy. This data must be protected from breaches and unauthorized access [13,92,93]. Creating strong legislative frameworks to handle data security and privacy concerns is important. To foster confidence between farmers and consumers regarding digital technology in agriculture, protecting data entails avoiding illegal access and maintaining openness. Regulations must change quickly to handle new issues with storing, processing, and sharing sensitive data as digital technologies proliferate. Industries must adopt safe technology and invest in state-of-the-art security solutions to fully realize the potential of digital agriculture and pave the way for a more sustainable and effective agricultural future [94].

The second hypothesis states that digitalization indicators can influence patterns in agricultural output and productivity trends, highlighting the necessity of integrating digital technologies in the agricultural sector.

Hypothesis H2. *As measured using the DESI, the evolution of digitalization levels significantly positively influences future trends in total agricultural output and productivity.*

The following section outlines the research design and methodologies employed to examine the impact of digital technologies on agricultural productivity based on the insights gathered from the literature.

3. Materials and Methods

3.1. Research Design

The research design began with the establishment of its objectives. The primary aim was to explore how digital technologies, quantified using the digital economy and society index (DESI), influence key agricultural performance indicators, such as real labor productivity per person and agricultural output. The analysis explores dynamic temporal relationships between digitalization and agricultural performance metrics. This methodological choice enables the study to capture trends and immediate effects over time, providing actionable insights relevant to the specific context of agricultural digital transformations.

Once the objectives were defined, the next step involved a comprehensive review of the specialized literature. This review aimed to situate the study within the broader context of digital transformations shaping modern agriculture. Prior studies were analyzed to identify knowledge gaps and construct a solid theoretical foundation.

Based on the literature and stated objectives, research hypotheses were formulated to examine the direct impact of the DESI on labor productivity and agricultural output. The research employed robust predictive models, including artificial neural networks, ARIMA, and exponential smoothing, enabling temporal analysis and future trend estimation. The selection of the ARIMA model is grounded in its suitability for analyzing direct temporal relationships and capturing dynamic interactions between digitalization indicators and agricultural performance metrics. The rigorous validation process associated with the ARIMA model (including applying Akaike and Bayesian criteria) ensures its predictions' reliability and practical relevance. This level of precision supports its integration into agricultural planning processes, enabling informed decision-making driven by insights into digital trends.

Furthermore, the ARIMA model adapts seamlessly to specific data characteristics, avoiding unnecessary analytical complications often associated with latent-factor models. The ARIMA model maintains a thoughtful balance between detail and interpretability by leveraging the DESI, a composite index that encapsulates complex digitalization data. The model's robustness in contexts with relatively short time series enhances its applicability in rapidly evolving fields such as digitalization, where extensive historical panel data were unavailable.

The results were presented clearly and coherently, using graphical visualizations and statistical interpretations to highlight identified relationships. The discussion and conclusions extensively interpreted the results, contextualizing them within agricultural development practices and strategies.

3.2. Selected Variables

The study analyzed the relationship between the digital economy and agricultural sector performance by integrating essential variables, offering insights into economic and social dynamics. The digital economy indicator selected was the DESI, a weighted score from 0 to 100 provided by the European Commission. The DESI synthesizes the level of digitalization across European economies, analyzing domains such as connectivity, human capital, digital public services, and digital technology integration [95]. This index is well-known for its ability to reflect digitalization progress and impact on economic sectors.

The research included the variable agricultural output (AGROUT), which represents the value of agricultural output at basic prices [96]. Data provided by Eurostat for this indicator enabled a detailed analysis of agriculture's contribution to the overall economy, highlighting production dynamics and sector adaptability facing economic and technological changes.

The study employed the variable real GDP per capita (RGDPpc), expressed in euros per capita and adjusted to chain-linked volumes with the reference year 2010 [97]. Also sourced from Eurostat, this indicator evaluates living standards and overall economic performance, serving as a central element in understanding digitalization's influence on various economic sectors, including agriculture.

Lastly, the analysis incorporated the real labor productivity per person (RLPpp), measured as an index with a 2015 base of 100 [98]. This indicator reflects the real productivity of labor per employed person, offering valuable insights into resource efficiency across sectors, including agriculture. Productivity data provide evidence of digitalization's impact on labor efficiency, a vital aspect of an innovation and sustainability-driven economy.

Table 1 presents variables used in empirical research.

Table 1. Research variables.

Variable	Dataset	Measures	References
DESI	Digital economy and society index	Weighted score (0 to 100)	[95]
AGROUT	Agricultural output	Production value at basic price—million euro	[96]
RGDPpc	Real GDP per capita	Chain linked volumes (2010), euro per capita	[97]
RLPpp	Real labor productivity per person	Index, 2015 = 100	[98]

Source: author's design based on [95–98].

The research aims to highlight the complex links between digital transformation and economic performance in the agricultural sector. Integrating digital technologies into agriculture may significantly impact productivity and long-term sustainability.

3.3. Research Methods

Artificial neural networks (ANNs) analysis represents an innovative approach for analyzing complex relationships between variables, successfully applied across various economic and social domains. In this study, ANNs were used to assess the influence of digitalization, measured using the DESI, and economic growth, represented by real GDP per capita (RGDPpc), on agricultural output (AGROUT) and real labor productivity per person (RLPpp). This method effectively interprets subtle and nonlinear interdependencies that traditional approaches might miss [99].

By employing ANNs, the study offers a fresh perspective on digitalization's impact and economic growth, providing a foundation for informed decision-making in public policies and economic and social development strategies. This approach delivers predictions and enhances understanding of variable dynamics, paving the way for more efficient agriculture and higher labor productivity.

The multilayer perceptron (MLP) model was chosen to determine these influences (1):

$$y = \left(\sum_{i=1}^{n} w_i x_i + b\right) = \varphi\left(W^T X + b\right) \tag{1}$$

w, x—vectors of weights and inputs;
b—bias;
i—cases;
φ—activation functions.
As activation functions, we used a hyperbolic tangent function (2):

$$f(n) = \frac{1}{1 + e^{-n}} \tag{2}$$

n—input variables;
$f(n)$—output variables.

The autoregressive integrated moving average (ARIMA) model is one of the most robust and widely applied methods for time series analysis. Its effectiveness lies in capturing complex relationships among variables over time and delivering accurate short- and medium-term forecasts. Initially developed by Box and Jenkins [100], the model integrates three fundamental components, granting flexibility and applicability across various fields.

Implementing the ARIMA model follows a well-defined process that includes parameter identification, estimation, and validation [101]. Analyzing autocorrelation and partial autocorrelation plots during the identification phase helps determine the optimal values for the parameters. Subsequently, parameter estimation involves specialized algorithms, while model validation employs statistical criteria such as the Akaike Information Criterion (AIC) and tests for residual autocorrelation [102]. This rigorous process ensures the development of robust models capable of reliable forecasts [103]. The general formula of the ARIMA model (3) reflects this comprehensive approach.

$$\left(1 - \sum_{i=1}^{p} \varphi_i L^i\right)(1 - L)^d X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right)\varepsilon_t \tag{3}$$

X_t—data series
L—lag operator
φ_i—parameters of the autoregressive part of the model
θ_i—parameters of the moving average part
ε_t—error

In parallel with the ARIMA model, exponential smoothing methods offer another valuable approach to time series forecasting. Developed by Brown [104], an exponential smoothing model relies on a simple yet powerful methodology that assigns greater weight to recent values, effectively capturing current trends and seasonality. It is particularly advantageous for long-time series characterized by cyclical variations, seasonality, or abrupt changes.

Successful application of this method requires precise parameterization. The coefficients α (level), β (trend), and F_{t+m} (forecast for the next step) are iteratively calibrated to minimize forecast errors (4)–(6).

$$S_t = \alpha y_t + (1-\alpha)(S_{t-1} + b_{t-1}) \quad (4)$$

$$b_t = \beta(S_t - S_{t-1}) + (1-\beta)b_{t-1} \quad (5)$$

$$F_{t+m} = S_t + mb_t \quad (6)$$

y_t—the observed value at time t;
S_t—the smoothed value for the level at time t;
b_t—the estimated trend at time t;
α—the smoothing parameter for the level;
β—the smoothing parameter for the trend;
F_{t+m}—the forecasted value for m steps ahead of time t.

By fine-tuning these parameters, the method adapts to changes in the time series, delivering accurate and relevant predictions.

The ARIMA and Brown's exponential smoothing models are reliable tools for time series analysis, each with strengths custom-made to specific contexts. While the ARIMA model is particularly effective when capturing recent data trends is decisive, exponential smoothing models long-term relationships. Both methods find applications across various domains, supporting informed decision-making based on rigorous forecasts.

The following section presents the results derived from the applied models and hypotheses investigations, providing a deeper understanding of the influence of digitalization on agricultural performance.

4. Results

Examining hypothesis H1 involved leveraging artificial neural network analysis to establish relationships among the model variables. The input layer comprises independent variables that feed into the model: DESI (digital economy and society index) and RGDPpc (real gross domestic product per capita). These variables connect to the hidden layer units through weights adjusted during training. The input layer also includes a bias term, enabling the network to capture more complex relationships.

The hidden layer contains two units (neurons): H(1:1) and H(1:2). These units are responsible for capturing nonlinear relationships between inputs and outputs. H(1:1) may represent the direct effects of digitalization on labor productivity and agricultural output, while H(1:2) might reflect indirect influences, such as improved agricultural infrastructure. The output layer features two dependent variables: RLPpp (real labor productivity per person) and AGROUT (agricultural output). The model summary shows that the training and testing phases of MLP exhibit robust performance (Table 2).

Table 2. Model Summary.

Phase	Indicators		Values
Training	Sum of squares error		0.058
	Average overall relative error		0.021
	Relative error for scale	RLPpp	0.024
	Dependents	AGROUT	0.019
	Stopping rule used		Training error ratio criterion (0.001) achieved
	Training time		0:00:00.00

Table 2. *Cont.*

Phase	Indicators		Values
Testing	Sum of squares error		0.018
	Average overall relative error		0.009
	Relative error for scale Dependents	RLPpp	0.008
		AGROUT	0.010

Source: author's design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

Figure 1 illustrates the relationships within the MLP model, while Table 3 presents the estimated parameters of the model.

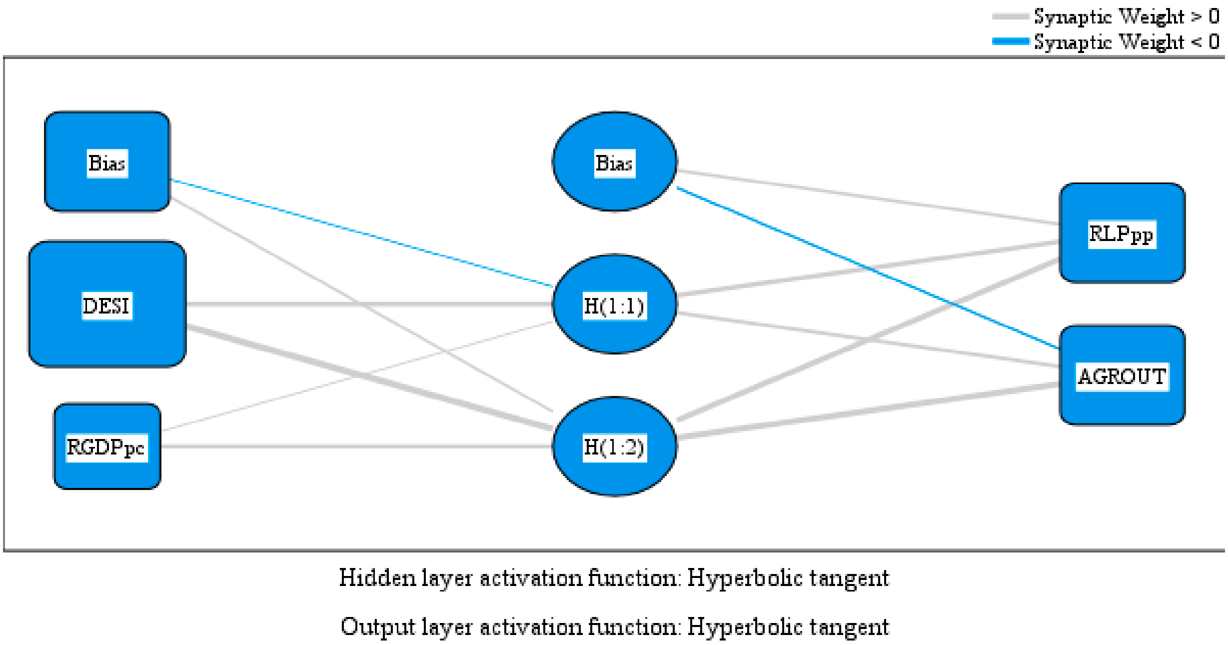

Figure 1. MLP model. Source: author's design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

Table 3. Parameter estimates.

Predictor		Predicted			
		Hidden Layer 1		Output Layer	
		H(1:1)	H(1:2)	RLPpp	AGROUT
Input layer	(Bias)	−0.175	0.671		
	DESI	1.353	2.136		
	RGDPpc	0.323	0.856		
Hidden layer 1	(Bias)			0.723	−0.506
	H(1:1)			1.100	0.784
	H(1:2)			1.715	1.730

Source: author's design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

Input terms with weights of 1.353 influence the H(1:1) unit for the DESI and 0.323 for RGDPpc and a bias contribution of −0.175. Similarly, H(1:2) receives inputs weighted at 2.136 for the DESI and 0.856 for RGDPpc, with a bias of 0.671. RLPpp is affected by the hidden units with weights of 1.100 for H(1:1) and 1.715 for H(1:2), accompanied by a bias of 0.723. These values indicate that both hidden units play a significant role in determining labor productivity. AGROUT is similarly influenced by H(1:1) and H(1:2), with weights of

0.784 and 1.730, respectively, and a bias of −0.506. These values underscore the significant contribution of the hidden layer to estimating agricultural output.

The model structure reveals how the complex relationships among digitalization, economic growth, labor productivity, and agricultural output are captured and processed within the neural network layers. The results highlight a positive relationship between the DESI and the output variables AGROUT and RLPpp, suggesting that digitalization drives productivity and agricultural output. Farmers can more effectively monitor crops, optimize resource use, and reduce losses by adopting AI, IoT, agricultural drones, and crop management software. Furthermore, economic growth, measured through RGDPpc, facilitates access to these technologies, creating a conducive environment for sustainable agricultural development.

Hypothesis H1 asserts that the evolution of digitalization, as measured using the DESI, exerts a significant positive influence on the future trajectory of agricultural output. Validating this hypothesis carries important implications for both research and public policy. On the one hand, it emphasizes how important digitalization is for promoting sustainable agriculture and economic prosperity, setting the stage for more research into the precise mechanisms in which it works. However, to optimize the benefits of digitization for agriculture, it highlights the necessity of funding rural digital infrastructure and enhancing farmers' digital literacy.

Investigating hypothesis H2 required the application of predictive models (Brown and ARIMA) to forecast trends in the study variables over future periods. The first step involved identifying variable trends based on past developments.

The predictive models using Brown's exponential smoothing approach revealed a consistent upward trend for RGDPpc and RLPpp. This analysis used historical data from 2001 to 2022 and provided projections for 2023–2028, highlighting economic growth stability and sustained productivity improvements.

For RLPpp, the smoothing coefficient Alpha (0.461) was statistically significant ($p < 0.001$), demonstrating that the model balanced the influence of recent and older data points. Similarly, the Alpha coefficient for RGDPpc (0.427) was also statistically significant ($p < 0.001$), reflecting an equally distributed impact of historical and recent trends on the forecasted trajectory. The fit statistics underline the robustness and reliability of the Brown model in capturing trends and providing accurate predictions for the variables analyzed (Table 4).

Both the stationary R-squared and R-squared values average of 0.930 indicate high explanatory power and a strong ability of the model to capture the variation in the data. The RMSE (root mean square error) and MAE (mean absolute error) values highlight the precision of the model's predictions, with relatively low average error measures. The MAPE (mean absolute percentage error) value of 2.013% confirms the model's accuracy in predicting outcomes, reflecting minimal deviation from actual values. While MaxAPE and MaxAE values show some higher extremes, these are likely outliers and do not diminish the overall model reliability. The normalized BIC value suggests that the model balances fit quality and complexity well.

RLPpp forecasts indicate steady growth from 116.96 in 2023 to 125.10 in 2028, signaling continuous improvements in labor productivity. Technological advancements, enhanced human resource efficiency, and modernized economic practices will likely drive these improvements. This upward dynamic suggests a favorable framework for long-term economic growth.

Table 4. Brown models parameters for RGDPpc and RLPpp depending on the previous annual evolution.

Model			Estimate	SE	t	Sig.
RLPpp-Model_1	No transformation	Alpha (level and trend)	0.461	0.093	4.979	0.000
RGDPpc-Model_2	No transformation	Alpha (level and trend)	0.427	0.090	4.742	0.000

Model fit

Fit statistic	Mean	SE	Min	Max	Percentile						
					5	10	25	50	75	90	95
Stationary R-squared	0.930	0.066	0.883	0.977	0.883	0.883	0.883	0.930	0.977	0.977	0.977
R-squared	0.930	0.066	0.883	0.977	0.883	0.883	0.883	0.930	0.977	0.977	0.977
RMSE	307.906	431.740	2.620	613.192	2.620	2.620	2.620	307.906	613.192	613.192	613.192
MAPE	2.013	0.247	1.839	2.188	1.839	1.839	1.839	2.013	2.188	2.188	2.188
MaxAPE	6.520	3.301	4.186	8.854	4.186	4.186	4.186	6.520	8.854	8.854	8.854
MAE	241.548	338.958	1.869	481.227	1.869	1.869	1.869	241.548	481.227	481.227	481.227
MaxAE	562.975	786.323	6.961	1118.989	6.961	6.961	6.961	562.975	1118.989	1118.989	1118.989
Normalized BIC	7.663	7.715	2.207	13.118	2.207	2.207	2.207	7.663	13.118	13.118	13.118

Source: author's design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

Projections for RGDPpc demonstrate consistent growth, from 29452 euro per capita in 2023 to 31605 euro per capita in 2028. These values reflect sustained economic expansion, implying a robust macroeconomic environment with strong adaptability to evolving factors. RGDPpc growth underscores a macroeconomic context where investments and public policies support steady development.

Figure 2 and Table A1 in Appendix A present detailed projections for RGDPpc and RLPpp using exponential smoothing.

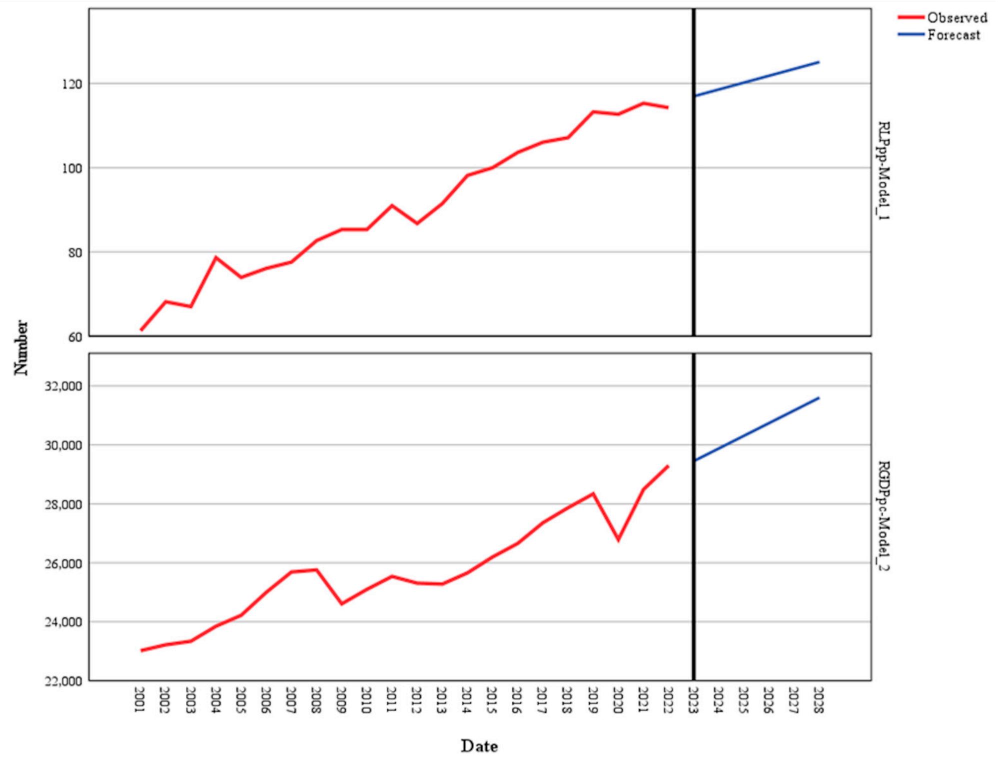

Figure 2. The forecasts of RGDPpc and RLPpp depending on the previous annual evolution using the Brown model. Source: author's design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

These forecasts emphasize the ongoing importance of investing in technology and human capital development as key drivers of economic performance and productivity. Furthermore, they highlight the necessity of balancing stability with innovation to support sustainable and competitive growth.

The ARIMA models for the DESI and AGROUT variables, based on data from 2017 to 2022, provided significant insights into digitalization and agricultural performance over the 2023–2028 forecast period. For the DESI, the model suggested an average annual growth of approximately 3.62, supported by statistically significant trends, reflecting the steady progress of digitalization. The model's negative constant (−7266.648) is an adjusted starting point, with the year coefficient indicating an upward trajectory.

AGROUT forecasts based on the ARIMA model showed an average annual growth of approximately €23,038 million, supported by statistically significant year coefficients. Although the model's negative constant (−46,079,931.086) might appear counterintuitive, the positive long-term trend is far more relevant. The ARIMA models provide reliable results, effectively capturing temporal patterns and offering meaningful predictions for the DESI and AGROUT depending on the previous annual evolution. (Table 5).

Table 5. ARIMA models parameters for DESI and AGROUT depending on the previous annual evolution.

Model					Estimate	SE	t	Sig.
DESI-Model_1	DESI	No transformation	Constant		−7266.648	719.199	−10.104	0.001
	Year	No transformation	Numerator	Lag 0	3.619	719.199	−10.104	0.001
AGROUT-Model_2	AGROUT	No transformation	Constant		−46,079,931.086	15,748,772.572	−2.926	0.043
	Year	No transformation	Numerator	Lag 0	23,037.691	7798.482	2.954	0.042

Model Fit

Fit statistic	Mean	SE	Min	Max	Percentile						
					5	10	25	50	75	90	95
Stationary R-squared	0.824	0.196	0.686	0.963	0.686	0.686	0.686	0.824	0.963	0.963	0.963
R-squared	0.824	0.196	0.686	0.963	0.686	0.686	0.686	0.824	0.963	0.963	0.963
RMSE	16,312.229	23,066.869	1.490	32,622.969	1.490	1.490	1.490	16,312.229	32,622.969	32,622.969	32,622.969
MAPE	3.742	1.705	2.536	4.948	2.536	2.536	2.536	3.742	4.948	4.948	4.948
MaxAPE	6.294	3.199	4.032	8.555	4.032	4.032	4.032	6.294	8.555	8.555	8.555
MAE	11,327.328	16,017.760	1.061	22,653.595	1.061	1.061	1.061	11,327.328	22,653.595	22,653.595	22,653.595
MaxAE	21,581.467	30,518.222	1.825	43,161.108	1.825	1.825	1.825	21,581.467	43,161.108	43,161.108	43,161.108
Normalized BIC	11.389	14.134	1.395	21.383	1.395	1.395	1.395	11.389	21.383	21.383	21.383

Source: author's design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

The ARIMA model fit statistics indicate a solid performance in capturing the data dynamics. The stationary R-squared and R-squared values average 0.824, demonstrating a substantial ability to explain variability within the dataset. The RMSE and MAE values show the model's predictive precision, although higher than in some other models, reflecting variability in the data.

The MAPE value of 3.742% suggests that the ARIMA model maintains a reasonable level of accuracy in predictions, with deviations remaining within acceptable limits.

The DESI is projected to increase from 54.07 in 2023 to 72.16 in 2028, indicating accelerated digital transformation with potentially significant impacts across economic sectors, including agriculture. AGROUT forecasts predict growth from 525317 million euros in 2023 to 640506 million euros in 2028, reflecting gradual improvements in agricultural output. This growth may stem from modernized agricultural technologies and direct digitalization effects.

Figure 3 and Table A1 in Appendix A illustrate RGDPpc and RLPpp projections using ARIMA models.

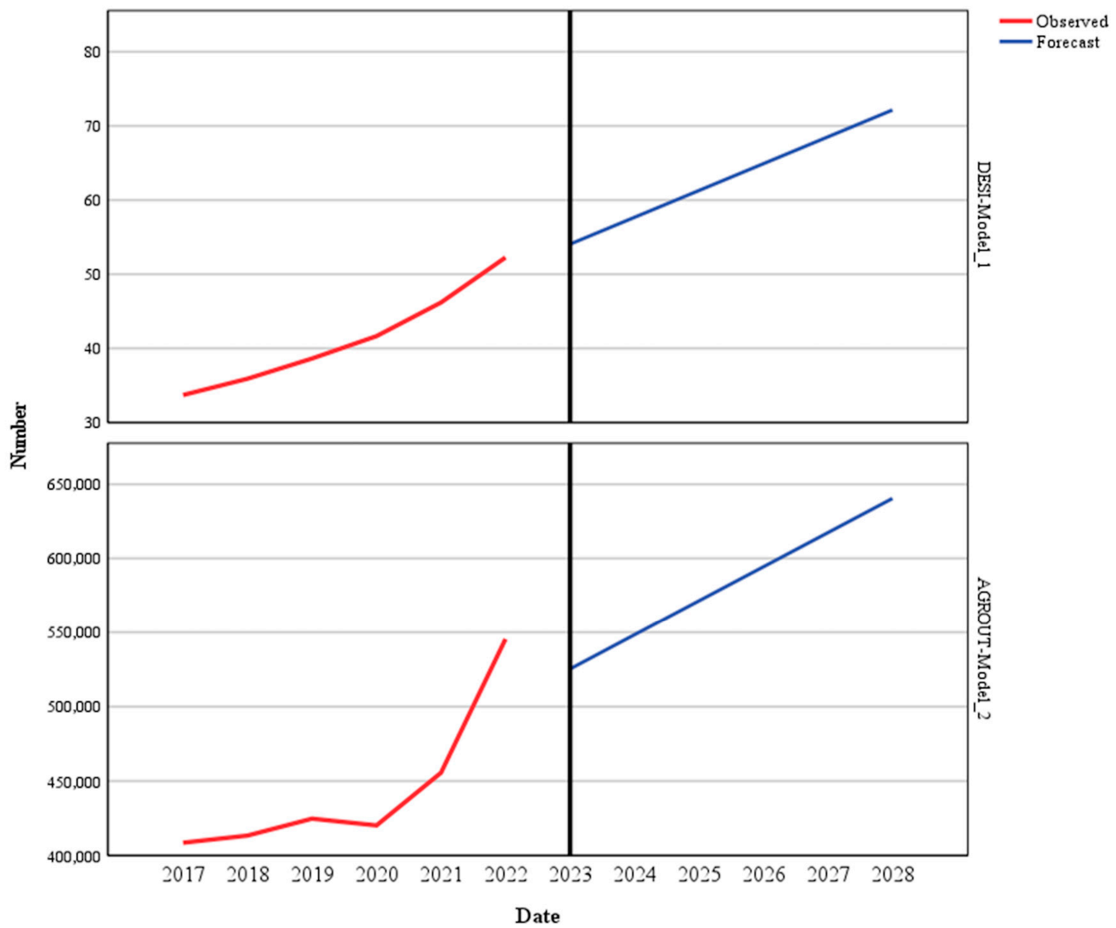

Figure 3. The forecasts of RGDPpc and RLPpp depending on the previous annual evolution using the ARIMA model. Source: author's design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

The DESI's growth indicates widespread adoption of digital technologies, which optimize agricultural processes, reduce operational costs and improve yields.

ARIMA models exploring the influence of the DESI on AGROUT and RLPpp reveal positive impacts of digitalization on agricultural performance and labor productivity for the 2023–2028 forecast period. For AGROUT, the DESI coefficient (6911.650), statistically significant (p = 0.010), shows that each additional DESI unit correlates with an approximate

6912 million euros increase in agricultural output. These values underscore the substantial role of digital transformation in agriculture. The model constant (158,519.754) reflects a baseline level of agricultural output, adjusted for other variables.

For RLPpp, the DESI coefficient (0.460) indicates a statistically significant positive relationship ($p = 0.047$), with each DESI unit contributing approximately 0.46 to RLPpp. This finding highlights how digitalization enhances economic activities and labor productivity in agriculture and related sectors. The constant (92.403) denotes the adjusted baseline for labor productivity. The ARIMA models provide reliable results, effectively capturing temporal patterns and offering meaningful predictions for AGROUT and RLPpp depending on the DESI's evolution. (Table 6).

Table 6. ARIMA models parameters for AGROUT and RLPpp depending on the DESI's evolution.

Model					Estimate	SE	t	Sig.
AGROUT-Model_1	AGROUT	No transformation	Constant		158,519.754	63,269.269	2.505	0.066
	DESI	No transformation	Numerator	Lag 0	6911.650	1510.735	4.575	0.010
RLPpp-Model_2	RLPpp	No transformation	Constant		92.403	6.777	13.634	0.000
	DESI	No transformation	Numerator	Lag 0	0.460	0.162	2.842	0.047

Model Fit

Fit statistic	Mean	SE	Min	Max	Percentile						
					5	10	25	50	75	90	95
Stationary R-squared	0.754	0.121	0.669	0.840	0.669	0.669	0.669	0.754	0.840	0.840	0.840
R-squared	0.754	0.121	0.669	0.840	0.669	0.669	0.669	0.754	0.840	0.840	0.840
RMSE	11,655.607	16,479.987	2.497	23,308.718	2.497	2.497	2.497	11,655.607	23,308.718	23,308.718	23,308.718
MAPE	2.690	1.331	1.749	3.632	1.749	1.749	1.749	2.690	3.632	3.632	3.632
MaxAPE	4.480	2.496	2.715	6.245	2.715	2.715	2.715	4.480	6.245	6.245	6.245
MAE	8216.568	11,617.224	1.950	16,431.186	1.950	1.950	1.950	8216.568	16,431.186	16,431.186	16,431.186
MaxAE	13,123.967	18,555.744	3.075	26,244.860	3.075	3.075	3.075	13,123.967	26,244.860	26,244.860	26,244.860
Normalized BIC	11.569	12.928	2.427	20.710	2.427	2.427	2.427	11.569	20.710	20.710	20.710

Source: author's design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

The ARIMA model fit summary indicates a strong ability to capture data variability, as evidenced by the stationary R-squared and R-squared values averaging 0.754. These values reflect a high level of explanatory power and consistency across predictions. The RMSE and MAE values highlight the model's accuracy, with moderate deviations in absolute terms, while the MAPE of 2.69% suggests that the model maintains a reliable degree of predictive precision relative to the magnitude of the data. The MaxAPE and MaxAE values point to occasional more significant deviations, which could arise from specific anomalies or high-variability observations. The normalized BIC score suggests a reasonable trade-off between model complexity and goodness-of-fit.

AGROUT forecasts show steady growth from approximately 532,226 million euros in 2023 to 657,283 million euros in 2028. This upward trend reflects ongoing improvements in agricultural output, mainly attributable to digital technology adoption. Digitalization improves production efficiency, optimizes resource use, and reduces losses, enabling the agricultural sector to meet market demands better.

For RLPpp, the forecasts show gradual growth in labor productivity, from 117.27 in 2023 to 125.59 in 2028. This trend reflects consistent progress supported by increasing levels of digitalization. Implementing digital technologies facilitates better use of labor and resources, enhancing efficiency and reducing the time required for various operations.

Figure 4 and Table A1 in Appendix A present projections for RGDPpc and RLPpp using ARIMA models.

The findings illustrate that digitalization, measured using the DESI, is fundamental in determining agricultural output and labor productivity. The DESI's growth signals not just technological modernization but also the creation of a more competitive and sustainable agricultural environment.

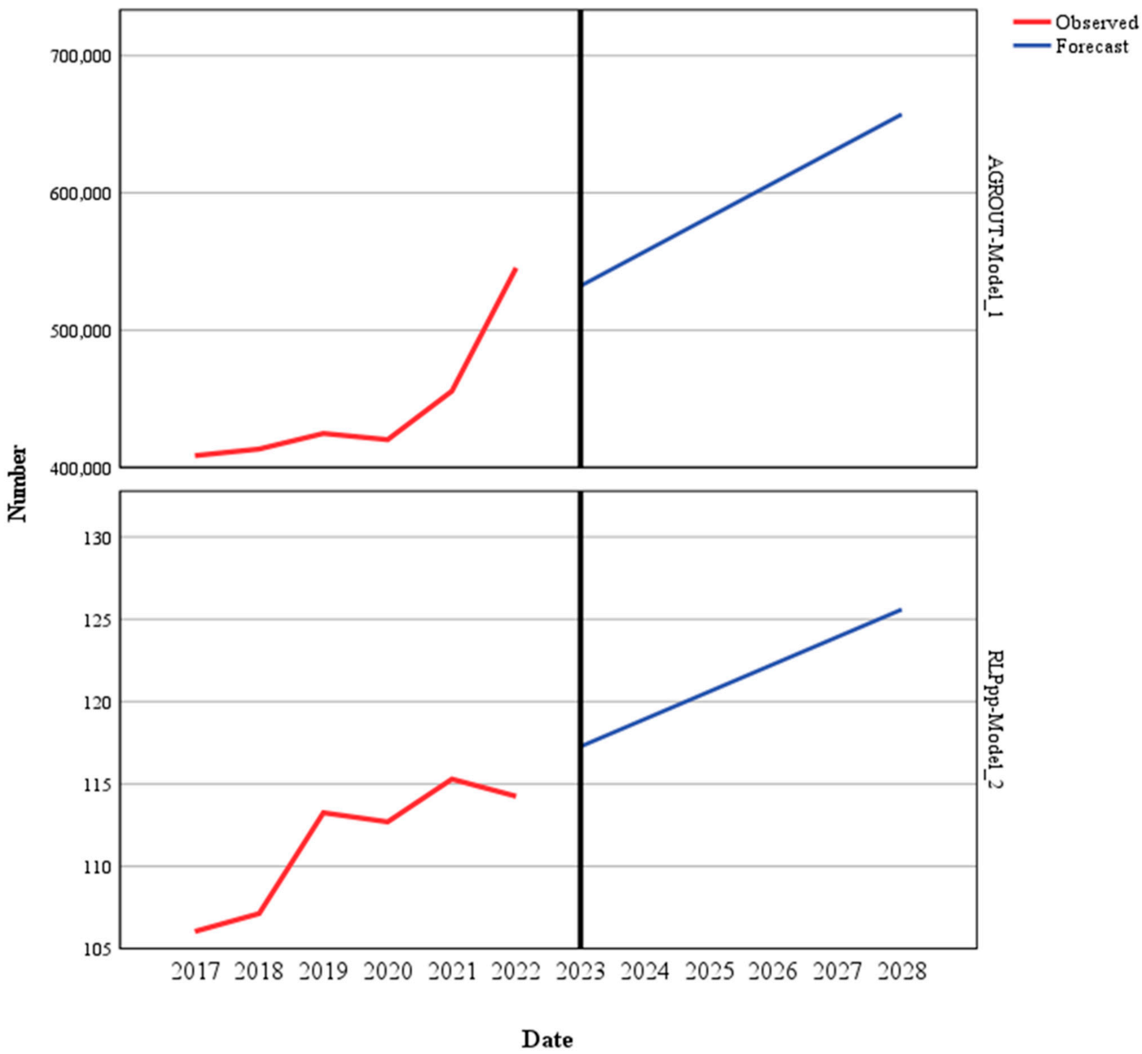

Figure 4. The forecasts of AGROUT and RLPpp depending on the DESI's evolution using the ARIMA model. Source: author's design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

For the 2023–2028 period, agriculture and labor productivity are expected to show positive dynamics as digitalization continues to expand and transform traditional operational models. These results highlight the importance of policies supporting digital technology adoption, particularly in rural areas, to fully capitalize on their potential to drive economic development and agricultural sustainability.

ARIMA models based on RGDPpc as an independent variable reveal trends and demonstrate how economic growth influences agricultural output and labor productivity during the 2023–2028 forecast period.

For AGROUT-Model_1, the RGDPpc coefficient is positive (0.034) and marginally significant ($p = 0.051$). These values suggest a modest relationship between overall economic growth and agricultural output, indicating that improvements in per capita GDP contribute positively but not decisively to agricultural progress. The negative constant (−299.408) is insignificant.

RLPpp-Model_2's RGDPpc coefficient is not statistically significant ($p = 0.311$), suggesting a weaker link between GDP per capita and labor productivity. However, the constant (7.631) is significant ($p = 0.039$), indicating an underlying influence on labor productivity potentially driven by additional unmodeled factors. ARIMA models provide a functional but not highly precise representation of the data, making it a suitable tool for capturing general patterns (Table 7).

The ARIMA model fit summary reflects a moderate level of predictive accuracy. The stationary R-squared and R-squared values, averaging around 0.45, indicate that the model captures nearly half of the variability in the data, suggesting room for improvement in explanatory power. The MAPE value of 3.876% demonstrates acceptable predictive accuracy, while the MaxAPE and MaxAE highlight occasional more significant deviations, likely reflecting outliers or high variability within specific data points. The normalized BIC values suggest that the model maintains a balance between complexity and fit, though they imply that simpler models may also be explored.

For AGROUT, forecasts predict steady growth from approximately 512,020 million euros in 2023 to 623,569 million euros in 2028. This upward trend reflects the gradual consolidation of agricultural output, facilitated by digital technology integration and GDP per capita growth. RLPpp forecasts indicate slow but steady labor productivity growth, from 114.62 in 2023 to 119.48 in 2028. This modest increase likely stems from technological advancements and overall economic conditions.

Figure 5 and Table A1 in Appendix A present projections for RGDPpc and RLPpp using ARIMA models.

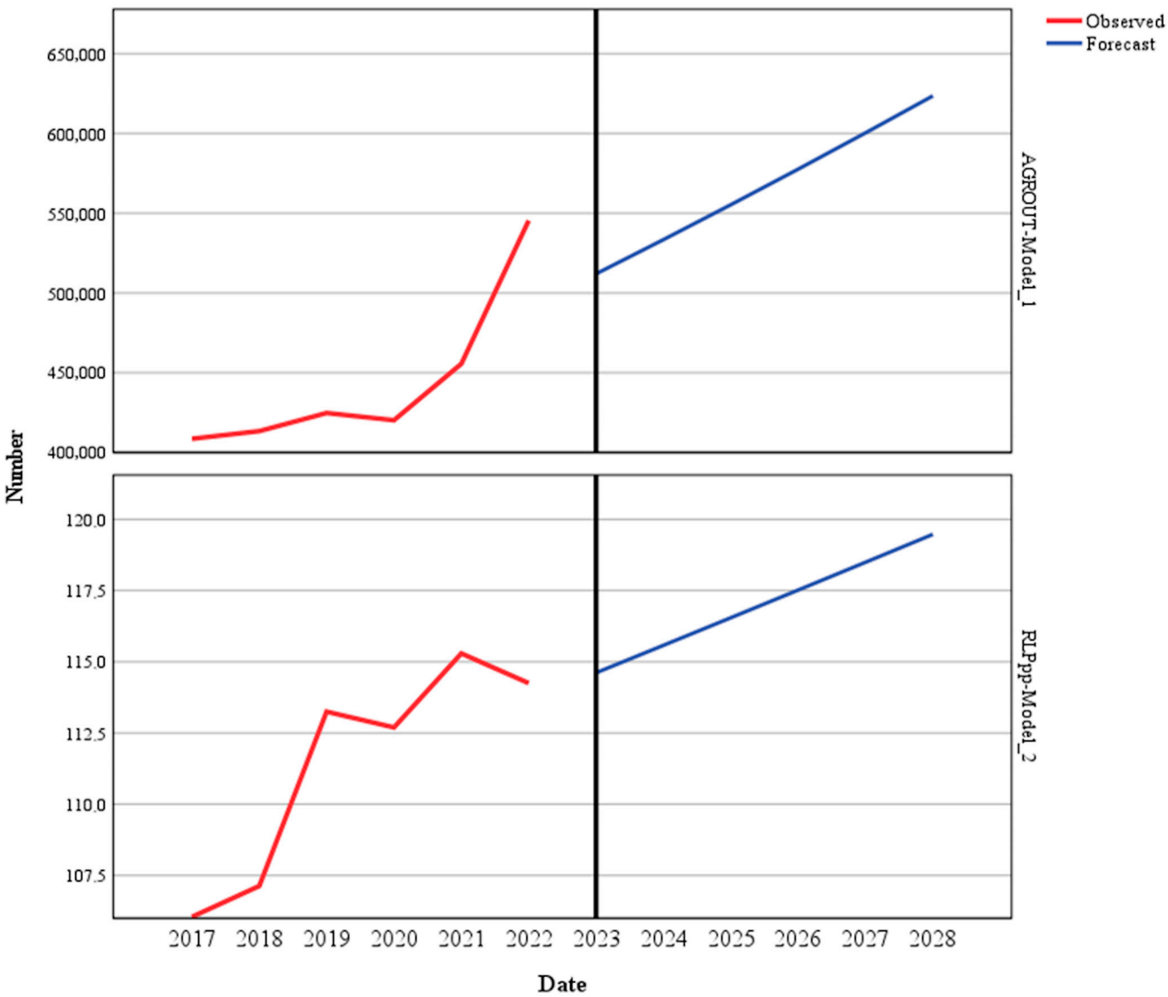

Figure 5. The forecasts of AGROUT and RLPpp depending on the RGDPpc's evolution using the ARIMA model. Source: author's design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

Table 7. ARIMA models parameters for AGROUT and RLPpp depending on the RGDPpc.

Model					**Estimate**	**SE**	**t**	**Sig.**
AGROUT-Model_1	AGROUT	Square root	Constant		−299.408	349.314	−0.857	0.440
	RGDPpc	No transformation	Numerator	Lag 0	0.034	0.012	2.765	0.051
RLPpp-Model_2	RLPpp	Square root	Constant		7.631	2.526	3.021	0.039
	RGDPpc	No transformation	Numerator	Lag 0	0.000	0.00009	1.158	0.311

Model Fit

Fit statistic	**Mean**	**SE**	**Min**	**Max**	**Percentile**						
					5	**10**	**25**	**50**	**75**	**90**	**95**
Stationary R-squared	0.454	0.287	0.251	0.656	0.251	0.251	0.251	0.454	0.656	0.656	0.656
R-squared	0.462	0.294	0.254	0.670	0.254	0.254	0.254	0.462	0.670	0.670	0.670
RMSE	16,721.637	23,642.667	3.747	33,439.527	3.747	3.747	3.747	16,721.637	33,439.527	33,439.527	33,439.527
MAPE	3.876	2.092	2.397	5.355	2.397	2.397	2.397	3.876	5.355	5.355	5.355
MaxAPE	5.851	3.016	3.718	7.983	3.718	3.718	3.718	5.851	7.983	7.983	7.983
MAE	12,085.466	17,087.700	2.637	24,168.295	2.637	2.637	2.637	12,085.466	24,168.295	24,168.295	24,168.295
MaxAE	20,453.780	28,920.389	3.977	40,903.583	3.977	3.977	3.977	20,453.780	40,903.583	40,903.583	40,903.583
Normalized BIC	12.336	12.864	3.239	21.432	3.239	3.239	3.239	12.336	21.432	21.432	21.432

Source: author's design using SPSS v.27 (IBM Corporation, Armonk, NY, USA).

Overall, the results suggest that GDP per capita plays a moderate role in influencing agricultural output, while its impact on labor productivity is less pronounced. For the 2023–2028 period, stable agricultural expansion and modest labor productivity growth are anticipated. These trends reveal untapped potential that could be unlocked through more targeted policies and increased investment in digitalization.

The analysis of RLPpp and AGROUT forecasts across three scenarios based on annual evolution, RGDPpc, and DESI trends reveals significant differences among these predictive models. These differences provide insights into the determinants and allow evaluation of hypothesis H2's validity.

For RLPpp, consistent growth across all scenarios is evident (Figure 6).

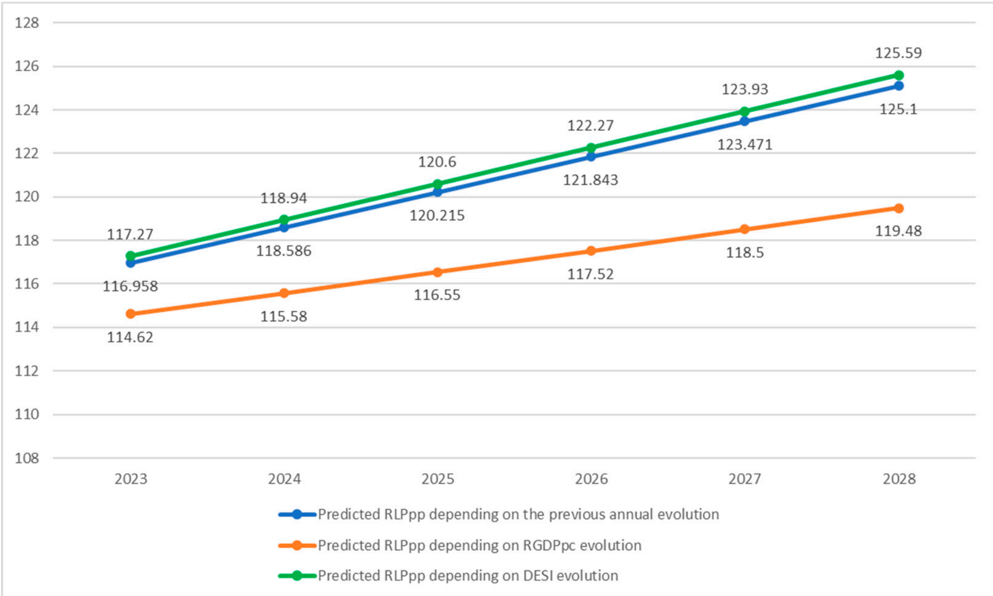

Figure 6. The forecasts of RLPpp depend on the previous annual evolution and the RGDPpc's and the DESI's evolution. Source: author's design based on computed data.

However, DESI-based projections systematically exceed those derived from RGDPpc or annual trends. For instance, in 2023, labor productivity per person projected using the DESI is 117.27, compared to 114.62 based on RGDPpc. This gap widens by 2028, with the DESI forecasting a productivity level of 125.59 versus 119.48 from the RGDPpc model. This discrepancy suggests that digitalization is central to enhancing labor productivity, supporting the hypothesis that the DESI has a significant positive influence.

For AGROUT, scenario differences are even more pronounced (Figure 7).

DESI-driven projections indicate significantly higher total agricultural output than those based on RGDPpc or annual trends. For example, in 2023, the DESI-based projection estimates 532,225.79 million euros compared to 512,020.3 million euros using RGDPpc. By 2028, the DESI-based projection estimates agricultural output at 657,283.23 million euros, over 33,000 million euros higher than the RGDPpc-based projection.

These findings highlight digitalization's more substantial and direct influence on agricultural performance. Comparing the two variables, digitalization's impact is more pronounced for total agricultural output than labor productivity. Nonetheless, the DESI consistently demonstrates a significant positive effect, confirming that technological progress and digital integration yield substantial benefits.

This analysis validates hypothesis H2, reinforcing that digitalization stimulates production growth and enhances agricultural resource use efficiency. The results suggest that digitalization, as captured by the DESI, is a key catalyst for agricultural development, positively impacting output and productivity. In a context where sustainability and efficiency are increasingly indispensable, adopting digital technologies emerges as a fundamental strategy for the future of agriculture.

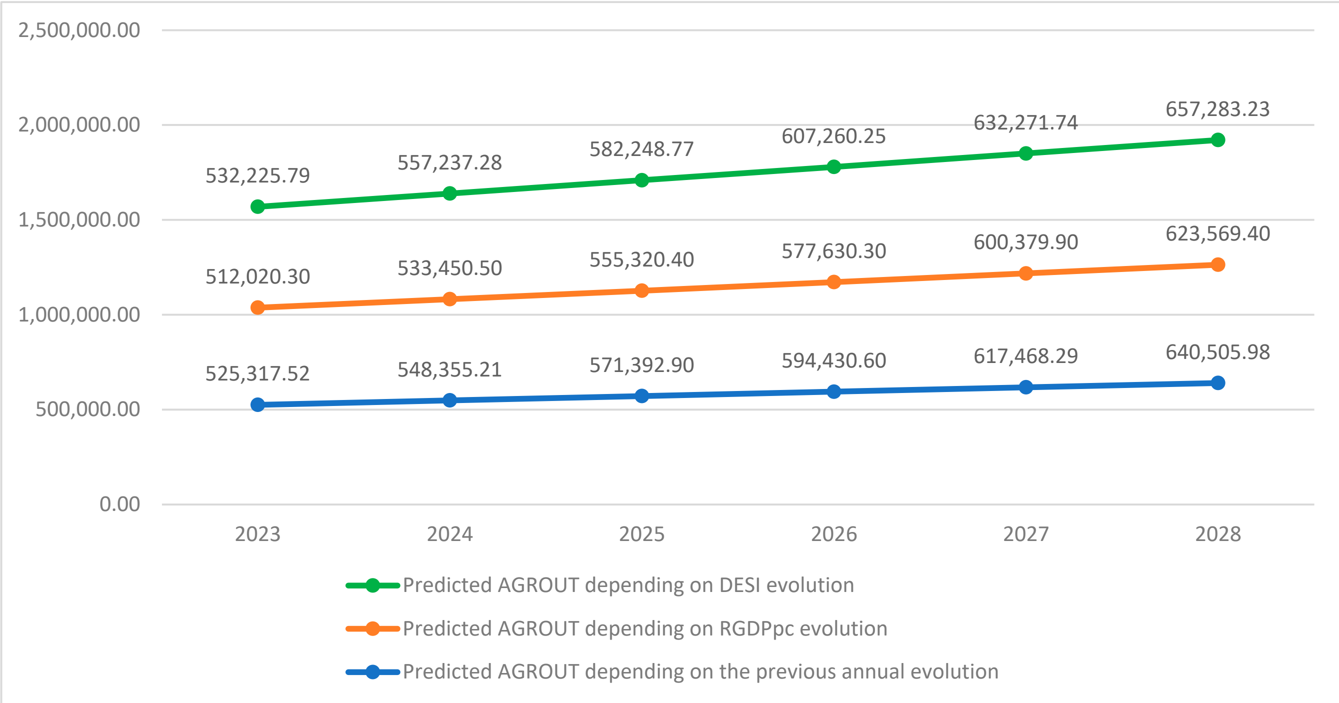

Figure 7. The forecasts of AGROUT depending on on the previous annual evolution, the RGDPpc's and the DESI's evolution. Source: author's design based on computed data.

5. Discussion

Digital agriculture has emerged as a transformative approach to agricultural production, leveraging advanced technologies to optimize farming practices and enhance sustainability. By fostering knowledge sharing and promoting the exchange of best practices among farmers, digital agriculture addresses critical societal concerns such as ensuring food security, reducing inequalities in access to technology, and enhancing resource efficiency. This transformative potential, underpinned by integrating technologies like sensors, drones, and artificial intelligence (AI), redefines agricultural processes.

Research has extensively explored the role of data-driven decision-making and big data analytics in precision agriculture. These tools enable farmers to make informed and efficient choices, underpinned by the continuous monitoring and analysis of critical data on soil, climate, crop health, and resource use [105–109]. Technologies like soil and air sensors allow real-time tracking of crop health and environmental conditions, enabling timely interventions. Concurrently, AI-driven software analyzes vast datasets, providing precise forecasts regarding fertilizer requirements, crop behavior, and water management [110–112]. Such advancements illustrate the practical applications of digital agriculture, such as optimizing irrigation schedules or customizing nutrient applications, which directly enhance productivity and sustainability.

The study's findings confirm hypothesis H1, demonstrating that digitalization significantly and positively impacts agricultural output. The relationships between the digital economy and society index (DESI), RGDPpc, and output variables such as labor productivity (RLPpp) and agricultural output (AGROUT) were explained using artificial neural networks. These findings align with existing literature, underscoring the transformative potential of Agriculture 4.0 in enhancing sustainability and efficiency within the agricultural sector [50,52]. Advanced technologies, including IoT, AI, and robotics, facilitate resource optimization, waste reduction, and improved resilience to climate change [113,114]. For example, IoT-based systems enable farmers to monitor soil moisture levels remotely, reducing water wastage while maintaining optimal crop conditions.

This study also highlights the synergistic effects of digitalization when combined with economic variables such as RGDPpc. These results resonate with other studies that emphasize the necessity of financial and technological resources for the widespread adoption of Agriculture 4.0 [5,61]. However, the literature also identifies significant challenges, including unequal access to technology, high costs, and potential ecological risks [25,115]. Addressing these barriers is crucial to realizing the full potential of digitalization. Implementing well-designed public policies that promote equitable access to digital technologies and prioritize ecological sustainability is essential for ensuring inclusive benefits across different regions and demographics.

The results of this study not only validate hypothesis H1 but also contribute to the broader discourse on leveraging Agriculture 4.0 as a strategic tool for agricultural transformation. Digitalization represents both an opportunity and a responsibility, offering a pathway to a more efficient, resilient, and accountable agricultural sector. For instance, programs like digital extension services can bridge the knowledge gap by providing farmers with customized advice and real-time solutions tailored to their contexts.

The findings related to hypothesis H2 further reinforce the transformative role of digitalization in contemporary agriculture. Recent studies corroborate the increasing influence of digital technologies on agricultural output and labor productivity, highlighting their capacity to optimize processes and deliver substantial economic benefits [116]. These advancements improve operational efficiency and enhance production quality and quantity through minimized losses and more sustainable resource utilization. For example, Chandio [117] illustrates the role of real-time meteorological data in enhancing cereal yields in China, while Weltin et al. [118] and Symeonaki et al. [119] document the economic advantages of digital technologies for farmers, showcasing both immediate and long-term benefits. These findings are consistent with the study's results, which reveal that the impact of digitalization surpasses traditional determinants like economic growth and annual trends.

Nevertheless, the benefits of digitalization are not uniformly distributed. Many technologies are still in developmental stages and face significant challenges in application, particularly in regions with limited digital resources or technological expertise. Trujillo-Barrera et al. [120] and Chinseu et al. [121] emphasize the need for localized adaptations and continuous refinements of emerging technologies to ensure their effectiveness. Furthermore, Visser et al. [122] highlight the risks associated with immature technologies, which may underperform or fail under specific conditions.

Adopting digital solutions also depends on effectively communicating their benefits to farmers. Studies by Murendo et al. [123], Dinesh et al. [124], and Kalfas et al. [29] underscore the importance of efficient information dissemination and ongoing dialogue between farmers and experts. For example, farmer field schools and participatory training programs can enhance the understanding and adoption of digital tools, fostering confidence in their practical utility. Moreover, access to technical support and applicable knowledge facilitates the transition to modern digital practices [125].

The findings related to hypothesis H2 validate the critical role of digitalization as a catalyst for agricultural development while highlighting the complexities involved in its implementation. The successful adoption of digital technologies hinges on factors such as government support, farmer education, and the development of appropriate infrastructure. Addressing these prerequisites is essential for ensuring that the advantages of digitalization are equitably accessible and that its long-term impact on agriculture is maximized. Investments in rural broadband connectivity can significantly reduce the digital divide, enabling farmers in remote areas to benefit from advanced technologies. These insights contribute to a more nuanced understanding of digitalization's role in agriculture, emphasizing the need for a collaborative, inclusive, and forward-looking approach to harness its transformative potential.

The discussion of these results sets the stage for exploring the broader implications, particularly how digital transformation can be leveraged to improve agricultural productivity and sustainability.

6. Implications and Limitations

6.1. Theoretical Implications

This research offers valuable insights into the relationship between digitalization and agricultural performance, building on existing perspectives on the transformation of agricultural systems. By confirming the positive influence of digitalization, as measured using the DESI, on labor productivity and total agricultural output, this study highlights the importance of integrating digital technologies into theoretical models explaining modern agricultural dynamics. This study bridges theoretical constructs with practical applications by including real-world examples, such as the impact of IoT on resource optimization and AI on predictive analytics. This contribution adds a new dimension to the literature, emphasizing digitalization's role as a key driver in creating a more resilient and sustainable agricultural system.

The research supports the European vision of agriculture transformed through digitalization, aligning with the European Green Deal and the Farm to Fork strategy. These political initiatives advocate for harmonizing economic, ecological, and social objectives. The findings demonstrate how digitalization can become a cornerstone in achieving this balance, providing a theoretical lens to understand how technology integration addresses global priorities such as environmental protection, inequality reduction, and food security assurance. This perspective underscores digitalization as a tool and a platform for systemic transformation.

This study also redefines traditional understandings of agricultural productivity and performance by proposing an approach where technological progress acts as a transformative force. By embedding digitalization into theoretical models of agriculture, the research creates an analytical framework that explains not only economic growth but also adaptation processes to climate change and global resource pressures. The theoretical implications extend beyond the conventional economic paradigms, providing an understanding of how digital innovations facilitate a more adaptive and resilient agricultural sector.

Therefore, this research contributes to expanding modern agricultural theory, foregrounding a paradigm where digitalization is both a driver of change and a necessary condition for shaping a sustainable, adaptable, and inclusive agricultural future. It encourages a reconfiguration of theoretical thinking, emphasizing the importance of a global perspective that integrates technology, policy, and sustainability into a unified vision for agricultural development.

6.2. Practical Implications

As the world faces rapid population growth and mounting pressures on natural resources, this paper provides valuable insights into reshaping agricultural practices through digitalization. The research findings underscore the significant influence of digital technologies on agricultural performance, particularly in labor productivity and output growth. These results highlight that digitalization is no longer an optional innovation but a strategic necessity for the future of agriculture.

The study confirms that agricultural digitalization is a cornerstone of Agriculture 4.0, a concept that redefines agricultural production through integrated and sustainable solutions. For instance, real-time meteorological data and AI-based analytics enable farmers to optimize irrigation and fertilizer, leading to substantial productivity gains. This transformation enhances efficiency and productivity and revitalizes rural communities, yielding significant economic and social benefits. Furthermore, digital technologies facilitate better market access, transparency in supply chains, and reduced resource wastage, addressing some of the most pressing challenges in global agriculture.

Overall, engaging in the digitalization of agriculture represents an investment in the future, capable of redefining sustainability and food security globally. This strategic direction is decisive for addressing the growing demands for food production and building an agricultural system capable of withstanding economic and environmental uncertainties while offering sustainable solutions for future generations. Practical steps (expanding rural broadband infrastructure and providing digital education for farmers) are essential to ensure these benefits are accessible to all.

6.3. Limitations and Further Research

Although the results confirm the hypothesis that digitalization significantly influences agricultural performance, this study does not encompass all aspects or fully explain the interdependencies among the analyzed factors.

One limitation pertains to the data used, which, while relevant and current, do not capture the full spectrum of regional and national variability in digitalization levels and agricultural contexts. Each region has unique characteristics regarding available resources, digital infrastructure, and public policies, which can impact how digitalization contributes to agricultural performance. Expanding the analysis to include more regions and a broader range of contextual variables could provide more generalizable conclusions.

Furthermore, the dynamic nature of digital technologies poses methodological challenges. Rapid technological advancements can render some models outdated in a short time frame. The research utilized data available at the time from Eurostat and the European Commission's DESI database.

Another limitation is the difficulty of isolating digitalization's effects from other determinants of agricultural performance, such as agricultural policies, climate change, or global market dynamics. While the methodology attempts to account for these factors by identifying biases, their influences cannot be excluded. Developing more complex models that integrate a wider range of variables and account for their interactions could improve understanding of the mechanisms through which digitalization impacts agriculture.

The research focuses on temporal relationships and does not include a detailed causality test between digitalization, measured using the DESI, and agricultural indicators such as labor productivity or agricultural output. Although the models, such as the ARIMA model and artificial neural networks, allow for trend estimation and predictions, they cannot provide definitive evidence of causal relationships. Future research could benefit from complementary approaches, such as structural econometric models, to further explore the causal mechanisms between digitalization and agricultural performance.

A notable limitation of this study lies in its reliance on time series analysis, which, while effective for capturing temporal dynamics, does not account for potential cross-sectional heterogeneity across regions or countries. This approach may limit the generalizability of the findings to broader contexts, as it focuses solely on temporal relationships without exploring structural variations. Future research could address this limitation by incorporating panel data analysis into the methodological framework. By combining temporal and cross-sectional dimensions, such studies could provide a more nuanced understanding of how digitalization impacts agricultural performance across diverse regions or countries. This multidimensional perspective would enable more robust and comprehensive conclusions, enhancing the relevance and applicability of the results in varied contexts.

The analysis focuses on the general impact of digitalization on the agricultural sector without exploring in detail the effects of digital technologies on different agricultural sub-sectors, such as crop farming, livestock, or aquaculture. Future research can address these sub-sectors in greater detail, exploring the digital transformations across various areas of agriculture and providing a more comprehensive understanding of their impact on the agricultural sector. Furthermore, analyzing the relationship between digitalization and agricultural sustainability could provide significant insights, particularly in transitioning to more environmentally friendly farming practices.

The study emphasizes the need for interdisciplinary approaches that combine economic, technological, and social perspectives to create an integrated understanding of agricultural transformation. Such an approach promises to support the formulation of more effective policies tailored to the agricultural sector's needs.

7. Conclusions

This research addresses current global challenges, including increasing food demand, resource pressures, and the need to modernize agriculture. It highlights the essential role of digitalization in transforming the agricultural sector into a more sustainable, resilient, and future-oriented system. The findings validate the hypothesis that technological progress, measured through the DESI, significantly influences agricultural productivity and labor efficiency.

Digitalization emerges not just as a tool for economic growth but as a strategic factor capable of redefining traditional agricultural practices, making them more adaptable to current challenges. In a global context marked by growing resource pressures, climate change, and stringent market demands, adopting digital technologies in agriculture is no longer an option but a necessity. Through an analysis of DESI effects, this paper highlights the substantial contributions digitalization can make to enhancing economic returns and the sustainability of agriculture.

The study also provides a solid theoretical foundation for understanding the relationship between technology and agriculture, complementing the existing literature with relevant data and conclusions. Only an integrated approach can lead to an effective transition to agriculture that produces more and does so responsibly toward the environment and society, emphasizing the role of digitalization in shaping a sustainable future for agriculture.

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Data Availability Statement: Data are available in a publicly accessible repository. The data presented in this study are openly available: https://digital-decade-desi.digital-strategy.ec.europa.eu/datasets/desi-2022/charts/desi-composite?indicator=desi_sliders&breakdownGroup=desi&period=2017&unit=pc_desi_sliders&desi_dps=5 (accessed on 16 November 2024); https://ec.europa.eu/eurostat/databrowser/view/tag00102/default/table?lang=en&category=t_agr.t_aact; (accessed on 16 November 2024); https://ec.europa.eu/eurostat/databrowser/view/sdg_08_10/default/table?lang=en (accessed on 16 November 2024); https://ec.europa.eu/eurostat/databrowser/view/nama_10_lp_a21/default/table?lang=en (accessed on 16 November 2024).

Conflicts of Interest: The authors declare no conflict of interest.

List of Acronyms

Acronym	Definition
DESI	digital economy and society index
GDP	gross domestic product
AGROUT	agricultural output
RGDPpc	real GDP per capita
RLPpp	real labor productivity per person
IoT	Internet of Things
AI	artificial intelligence
ANN	artificial neural network
ARIMA	autoregressive integrated moving average

Appendix A

Table A1. Historical and future trends.

Historical Trend					Forecasts Depending on the Previous Annual Evolution Using ARIMA		Forecasts Depending on the Previous Annual Evolution Using Brown		Forecasts Depending on RGDPpc and DESI Using ARIMA Model			
Year	**DESI**	**RGDPpc**	**AGROUT**	**RLPpp**	**Predicted DESI**	**Predicted AGROUT**	**Predicted RGDPpc**	**Predicted RLPpp**	**Predicted AGROUT/ RGDPpc**	**Predicted AGROUT/ DESI**	**Predicted RLPpp/ RGDPpc**	**Predicted RLPpp/ DESI**
2001	-	23,020	-	61.282	-	-	-	-	-	-	-	-
2002	-	23,220	-	68.158	-	-	-	-	-	-	-	-
2003	-	23,340	-	67.022	-	-	-	-	-	-	-	-
2004	-	23,850	-	78.623	-	-	-	-	-	-	-	-
2005	-	24,220	-	73.946	-	-	-	-	-	-	-	-
2006	-	25,000	-	76.091	-	-	-	-	-	-	-	-
2007	-	25,690	-	77.587	-	-	-	-	-	-	-	-
2008	-	25,760	-	82.686	-	-	-	-	-	-	-	-
2009	-	24,610	-	85.315	-	-	-	-	-	-	-	-
2010	-	25,100	-	85.325	-	-	-	-	-	-	-	-
2011	-	25,540	-	90.979	-	-	-	-	-	-	-	-
2012	-	25,310	-	86.751	-	-	-	-	-	-	-	-
2013	-	25,280	-	91.477	-	-	-	-	-	-	-	-
2014	33.71595	25,660	385,805.88	98.166	-	-	-	-	-	-	-	-
2015	35.92010	26,200	408,601.05	100.000	-	-	-	-	-	-	-	-
2016	38.64427	26,660	413,419.03	103.635	-	-	-	-	-	-	-	-
2017	41.66519	27,360	424,770.73	106.047	-	-	-	-	-	-	-	-
2018	46.19966	27,870	420,250.13	107.132	-	-	-	-	-	-	-	-
2019	52.27523	28,340	455,631.66	113.252	-	-	-	-	-	-	-	-
2020	33.71595	26,790	545,440.94	112.699	-	-	-	-	-	-	-	-
2021	35.92010	28,490	385,805.88	115.296	-	-	-	-	-	-	-	-
2022	38.64427	29,300	408,601.05	114.253	-	-	-	-	-	-	-	-
2023	-	-	-	-	54.06900	525,317.52	29,452	116.958	512,020.3	532,225.79	114.62	117.27
2024	-	-	-	-	57.68774	548,355.21	29,883	118.586	533,450.5	557,237.28	115.58	118.94
2025	-	-	-	-	61.30649	571,392.90	30,313	120.215	555,320.4	582,248.77	116.55	120.60
2026	-	-	-	-	64.92523	594,430.60	30,744	121.843	577,630.3	607,260.25	117.52	122.27
2027	-	-	-	-	68.54397	617,468.29	31,174	123.471	600,379.9	632,271.74	118.5	123.93
2028	-	-	-	-	72.16272	640,505.98	31,605	125.100	623,569.4	657,283.23	119.48	125.59

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