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MANAGERIAL DECISIONS IN LARGE-SCALE AGRICULTURE THROUGH THE INTEGRATION OF AI

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Abstract: *The adoption of artificial intelligence (AI) in managerial decision-making processes within large-scale agriculture represents a significant advancement in optimizing financial performance, resource allocation, and operational efficiency. This study examines the impact of AI integration by comparing traditional Enterprise Resource Planning (ERP) systems with a conceptual AI-driven model, emphasizing economic efficiency and sustainability. Through a structured analysis, the findings indicate a 13.5% increase in profitability per hectare and a 10% reduction in adjusted operational costs when AI-based automation is employed. The AI model enhances decision-making by incorporating real-time data from multispectral imaging, weather monitoring systems, and financial reports, generating predictive analytics that refine input allocation and risk management strategies. Furthermore, AI contributes to environmental sustainability by minimizing resource inefficiencies and reducing the ecological footprint of agricultural interventions. The results underscore the potential of AI as a transformative tool in agricultural management, advocating for further empirical validation and integration of AI-enhanced decision-making frameworks to improve resilience and long-term competitiveness in the sector.*

Keywords: *artificial intelligence, agricultural management, decision optimization, economic efficiency, sustainability*

JEL Classification: *C53, M11, M15, O33, Q12, Q16*

1. Introduction

Large-scale agriculture is a cornerstone of global food security, providing essential resources for an ever-growing population. However, it faces numerous challenges, including fluctuating market conditions, climate change, and increasing production costs. These pressures highlight the importance of precise accounting and managerial decision-making to optimize resource allocation, improve profitability, and mitigate risks. Traditional processes of the decision making, while established, very often rely on the experience of the manager, which may lead to inefficiencies or errors, particularly in a rapidly changing economic and environmental landscape.

Over the last two decades, the Enterprise Resource Planning systems (ERP) have become a standard tool for managing the economic operations of medium and large farms. These systems centralize financial and operational workflows, streamlining operational and management processes, providing a structured framework for decision making. Despite their utility, ERP systems have clear limitations. They primarily rely on historical data and lack the capacity to deliver real-time predictive analyses or actionable recommendations tailored to specific farm conditions. Moreover, ERP systems often fail to integrate complex datasets, such as those generated by autonomous drones's multispectral sensors or other advanced technologies, such as specialized climate information software.

Artificial intelligence (AI) offers an innovative solution to these challenges by introducing a proactive and predictive approach to decision-making. Unlike ERP systems, AI employs advanced algorithms capable of analyzing multiple variables in real-time—economic, climatic, and operational. This capability enables AI to provide highly specific and context-sensitive recommendations, automate complex processes, and optimize resource usage. For example, AI can integrate data from drones and weather forecasting systems to precisely determine the application of fertilizers or irrigation schedules, thereby reducing costs and improving yields.

This study investigates the transformative potential of integrating artificial intelligence into accounting and managerial decision-making in large-scale agriculture. Through simulations and comparative analyses, we evaluate how AI can address the inherent limitations of traditional ERP systems. The research focuses on demonstrating how automated decision-making processes, powered by AI, can enhance economic efficiency and reduce financial risks for large-scale farms.

This paper makes a significant contribution to the specialized literature by:

- Conducting a comparative analysis of the performance of ERP and AI systems.
- Evaluating the impact of AI usage on sustainability and profitability.
- Proposing an operational model for integrating AI into farm decision-making processes.

2. Literature Review

The integration of artificial intelligence (AI) into large-scale agriculture represents a transformative shift in optimizing productivity, sustainability, and economic efficiency. AI-driven systems enhance farm management by utilizing data analytics, machine learning algorithms, and automation to support precision agriculture. This literature review examines the latest advancements in AI applications within the agricultural sector, focusing on decision-making optimization, predictive analytics, and resource management.

AI technologies have significantly improved efficiency in agricultural operations by leveraging real-time data processing and automation. Recent studies highlight AI's role in optimizing irrigation systems, detecting plant diseases, and predicting crop yields.

AI has been successfully implemented in decision-making frameworks for crop selection, soil management, and fertilization schedules. According to Assimakopoulos et al. (2025), AI, combined with IoT, is enhancing smart farming practices, allowing farmers to make data-driven decisions that increase yield efficiency.

AI-powered sensors and drones are being employed to assess crop health, detect pest infestations, and optimize harvesting schedules. Rajesh Basa (2024) reported that AI models can predict crop yields with 90% accuracy, enabling better financial planning and resource allocation.

Economic and Sustainability Impacts of AI in Agriculture

AI-driven solutions not only increase economic efficiency but also contribute to sustainable farming practices. AI-based automation has led to a reduction in operational costs and waste. A study by Minhajul Islam Mim et al. (2025) demonstrated that AI-powered autonomous farming systems significantly lower labor costs and improve productivity. Additionally, AI-driven irrigation systems have reduced water usage by 30%, as observed in precision agriculture implementations.

AI promotes sustainable agricultural practices through efficient pesticide and fertilizer application. According to Abdul Hussein et al. (2024), AI integrated with IoT ensures optimized energy use in agricultural operations, leading to reduced environmental impact.

Challenges and Ethical Considerations

Despite its benefits, AI integration in agriculture faces challenges such as high implementation costs, data security concerns, and the risk of workforce displacement.

Many farms, particularly in developing countries, face barriers in adopting AI due to high initial costs and lack of access to advanced digital infrastructure. AI adoption in agriculture raises concerns about data privacy, as many AI systems collect vast amounts of farm data without clear ownership agreements. A study by Hampel and Fabulya (2024) highlights potential risks, including algorithmic biases and cybersecurity threats that could impact farmers' decision-making autonomy.

So, AI has emerged as a transformative force in large-scale agriculture, improving efficiency, cost management, and sustainability. However, further research is needed to address economic barriers, ethical considerations, and hybrid AI-ERP model integration. Future studies should explore AI-driven collaborative farming networks and blockchain technology for secure data management.

3. Research Methodology

As part of this study, the analysis was conducted using data collected from a large-scale farm in the South Muntenia region of Romania, which employs an ERP system for managing economic and financial operations. The aim of the study was to compare the performance of the existing ERP system with a theoretical model based on artificial intelligence (AI) that integrates advanced data sources. The information sources used and those proposed for future AI implementations include:

Existing ERP systems - These provide accounting and operational data such as production costs, annual revenues, financial flows, and resource planning. The analyzed ERP system is a traditional one, with functionalities limited to historical data analysis and reactive recommendations.

Drones equipped with multispectral cameras - Drones provide detailed crop maps, using color variation analyses to identify areas affected by nutrient deficiencies, water stress, or diseases. These data are essential for AI, which can optimize agricultural interventions by applying inputs (fertilizers, herbicides) locally, thus reducing waste.

Field sensors and weather stations (including modern software solutions) - In addition to traditional sensors that measure temperature, humidity, and other local conditions, software solutions like INOVAGRIA Meteo, developed by SIVECO Romania in collaboration with the National Meteorological Administration (ANM), can provide precise, real-time meteorological data. These data include information on precipitation, temperature, soil moisture, water reserves, and extreme weather alerts. By integrating such information, AI could make automatic decisions regarding the optimal time for planting, applying phytosanitary treatments, or managing water resources.

Economic and financial data from literature - Theoretical AI simulations were complemented by economic and climatic data from the literature to conceptually validate the proposed benefits of AI compared to ERP.

AI utilization and differences from ERP

The theoretical AI-based model proposed in this study brings significant improvements by integrating these advanced data sources, which are not natively available in ERP systems. Unlike ERP, AI uses data from drones, sensors, and meteorological software to make proactive decisions, such as:

- Reducing costs by optimizing the application of inputs.
- Increasing profitability by prioritizing agricultural interventions.
- Managing climatic risks by adapting strategies in real-time.

Through these functionalities, AI addresses the limitations of ERP systems, which predominantly rely on traditional statistical analyses and historical data.

Model used for simulations

We propose the use of a conceptual artificial intelligence (AI) model based on machine learning to optimize accounting and managerial decisions in large-scale agriculture. The theoretical model relies on the following components:

- *Multi-factorial regression algorithms* - These are suggested for analyzing the complex relationships between economic, operational, and climatic variables.
- *Integration of multispectral data* - Data collected from drones and sensors is proposed to generate crop health indices and other actionable metrics for decision-making.
- *Decision automation* - The conceptual model includes recommendations for the automated generation of operational solutions, such as prioritizing agricultural activities or allocating inputs.

This conceptual model can be implemented in the future using platforms such as *Scikit-learn* or *TensorFlow* for training and validating the algorithms. *Scikit-learn* is an open-source Python library designed for machine learning. It is widely used due to its accessibility and variety of algorithms, including classification, regression, and clustering. Ideal for predictive analysis and optimization, Scikit-learn is recognized for its ease of integration and its advanced tools for data preprocessing and evaluation. *TensorFlow*, developed by Google, is a flexible and powerful framework for deep learning. Designed to handle complex neural networks, TensorFlow offers support for distributed processing and GPU acceleration, making it ideal for advanced artificial intelligence projects. Its popularity stems from its ability to create robust models and its vast ecosystem of tools and extensions.

The AI system will be built on a multi-factorial regression algorithm, leveraging the collected data to generate predictions related to:

- Profitability per hectare (P/Ha).
- Operational costs adjusted for climatic factors.
- The impact of financial decisions on net profitability.

Popular libraries such as Scikit-learn and TensorFlow are suggested for implementing and validating the AI model, given their flexibility and capability to handle large datasets and complex relationships. Furthermore, the theoretical performance of AI could be compared to that of traditional ERP systems, which rely on descriptive statistical methods for data analysis. This comparison would highlight the advantages of AI in managing real-time variables and generating predictive insights.

Simulation parameters

Table 1 summarizes the key parameters analyzed and used in the simulation process. These parameters provide the basis for the comparative analysis of the study between the ERP system and the proposed AI-based model. The data include operational, economic and climatic variables, which are crucial for assessing the impact of automating operational and managerial decisions within the farm.

Table 1. Parameters used in the simulations

Parameter	Description	Value
Total number of farms	Number of farms analyzed	1
Farm size	Farm area in hectares	300
Time frame	Period analyzed	2019–2023
Average cost per hectare	Annual operational costs (EUR/ha)	600
Average revenue per hectare	Annual operational revenue (EUR/ha)	900
Average yield	Production per hectare (T/ha)	6
Climatic variables	Temperature, precipitation (annual average)	11.2°C, 540 mm

4. Data analysis and results

Economic indicators calculation

The economic indicators, used for the simulation in the study were calculated, are calculated with the following formulas:

Profitability per Hectare

$$\boldsymbol{RPH} = \frac{Total\ revenue\ from\ production}{Total\ area(ha)}$$

This indicator reflects the economic efficiency of tillage. For example, if the total revenue is 900 EUR/ha and the area is 300 ha, then,

$$\boldsymbol{RPH} = \frac{900 \times 300}{300} = 900 EUR/ha$$

Climatically Adjusted Yield

$$\boldsymbol{CAY} = R \times (1 - \alpha \times \Delta T)$$

Where:

- R is the average standard yield (6 T/ha),
- α is the climatic sensitivity coefficient,
- ΔT represents the variation of the average temperature in relation to the historical average according to statistical data.

For example, if the standard yield is 6 tons/ha, α=0.02, and ΔT=+2°C, then:

$$\boldsymbol{CAY} = 6 \times (1 - 0.02 \times 2) = 5.76\ T/Ha$$

Adjusted Operational Costs

$$\boldsymbol{AOC} = C \times \beta \times (1 + \gamma)$$

Where:

- C is the standard cost (600 EUR/ha),
- β is the adjustment coefficient for AI usage,
- γ represents the impact of input price variations.

Scenarios for AOC Calculation:

A. **Constant Costs (γ=0)** - If β=0.90, then:

$$AOC = 600 \times 0.9 \times (1 + 0) = 540\ EUR/ha$$

B. **Increasing Costs (γ=0.10)** - If β=0.90 și γ=0.10, then:

$$AOC = 600 \times 0.9 \times (1 + 0.10) = 594\ EUR/ha$$

C. **Traditional ERP System (β=1,γ=0.10)** - Without AI optimization:

$$AOC = 600 \times 1 \times (1 + 0.10) = 660\ EUR/ha$$

Table 2. Comparative table of scenarios

Scenario	**Standard cost (CCC)**	**Reduction due to AI (β\betaβ)**	**Input cost increase (γ gammaγ)**	**COA (EUR/ha)**
Constant costs (AI)	600	0.9	0	540
Increasing costs (AI)	600	0.9	0.1	594
Increasing costs (ERP tradițional)	600	1	0.1	660

The table above presents a comparative analysis of different scenarios evaluated during the simulations, emphasizing the impact of artificial intelligence (AI) on adjusted operational costs (AOC). This table highlights how AI-driven adjustments result in substantial cost savings compared to traditional ERP systems, particularly under variable economic conditions. The results emphasize the tangible benefits of using artificial intelligence (AI) in optimizing the operational costs of large-scale farms. AI proves effective in stable conditions where input prices remain unchanged and in scenarios involving cost increases, demonstrating adaptability and practical value.

In constant price scenarios, AI contributes to a significant 10% reduction in operational costs compared to the standard value. This reflects AI's ability to eliminate waste and allocate resources efficiently to areas requiring intervention, such as targeted fertilizer application or localized field operations. Practically, AI fundamentally changes resource management, offering more efficient utilization without compromising yield. Moreover, AI exhibits remarkable resilience in the face of economic challenges. In a scenario where input prices rise by 10%, AI maintains adjusted operational costs below those generated by traditional ERP systems. The adjusted cost is 594 EUR/ha compared to 660 EUR/ha for ERP, generating a net saving of 66 EUR/ha. This highlights AI's ability to offset external fluctuations and support farms in maintaining financial stability, even in unstable economic conditions.

Such cost savings contribute significantly to the overall profitability of farms over the long term. In an agricultural context characterized by limited resources and economic volatility, AI can become an essential tool for maintaining competitiveness. The ability to reduce operational costs even under unfavorable conditions is a critical advantage over traditional ERP systems, which lack the same level of adaptability.

Beyond economic benefits, AI has a positive impact on the environment. By applying inputs precisely, technology contributes to reducing excessive use of fertilizers and herbicides, minimizing negative effects on ecosystems. Additionally, optimizing agricultural processes reduces carbon emissions associated with unnecessary interventions, fostering more sustainable agriculture.

The results of the study demonstrate that the integration/use of AI is not only a complete technological solution, but also a highly practical tool. Compared to ERP systems, an AI system offers a clear advantage through flexibility, the ability to respond quickly to market changes and last but not least the contribution to sustainability. The integration of AI-type systems in the agricultural sector has the potential to fundamentally change the way farms operate, making them more profitable, environmentally sustainable and better prepared for future challenges.

Model validation

The comparative validation between the theoretical AI model and existing ERP systems was conducted using a conceptual approach, leveraging simulated scenario analysis and specialized literature. This method aimed to highlight the theoretical benefits offered by AI in optimizing accounting and managerial decisions for large-scale farming operations. Theoretical simulations relied on economic, climatic, and operational data drawn from the literature, complemented by realistically formulated assumptions. ERP system performance was considered based on traditional statistical analysis approaches, while the AI model was evaluated by hypothetically comparing the results generated under scenarios that included:

- Constant input costs,
- Input cost increases by 10%, and
- Climatic variations affecting yield.

These scenarios were designed to demonstrate AI's potential to adapt decisions in dynamic economic contexts and overcome the limitations of ERP systems. The conceptual evaluation was structured around standard indicators frequently used in predictive model analysis:

Mean Absolute Error (MAE) - Theoretically considered an indicator of the differences between the model's simulated values and actual data. In practical applications, AI would reduce MAE through the integration of multiple variables and real-time analysis.

Coefficient of Determination (R^2) - A common indicator for evaluating a model's ability to explain data variation. In hypothetical scenarios, AI would achieve a higher R^2 due to its optimization algorithms.

The results synthesized in *Table 4* and illustrated in *Figure 1* represent extrapolations based on the conceptual analysis of the literature and the typical performance of AI and ERP systems.

MAE Calculation

We consider an example adapted to our context, where the following values for adjusted operational costs (EUR/ha) are provided for five observations, representing hypothetical data for ERP and AI:

Table 3.Comparison of Actual and Predicted Values for ERP and AI Models

Observation (i)	**Actual Value (yi)**	**Predicted Value ERP ($\hat{y}_i^{ERP}$)**	**Predicted Value IA ($\hat{y}_i^{IA}$)**
1	600	620	590
2	650	670	640
3	700	720	690
4	750	770	740
5	800	820	790

MAE Formula: $\boldsymbol{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$

MAE Calculation for ERP:

Calculation of the absolute differences:

|600 − 620| = 20

|650 − 670| = 20

|700 − 720| = 20

|750 − 770| = 20

|800 − 820| = 20

Sum of absolute differences: $\sum\left|y_i - \hat{y}_i^{ERP}\right| = 20 + 20 + 20 + 20 + 20 = 100$

Determining MAE for ERP: $\boldsymbol{MAE_{ERP}} = \frac{100}{5} = 20EUR/ha$

MAE Calculation for AI:

Calculation of the absolute differences:

|600 − 590| = 10

|650 − 640| = 10

|700 − 690| = 10

|750 − 740| = 10

|800 − 790| = 10

Sum of absolute differences: $\sum\left|y_i - \hat{y}_i^{IA}\right| = 10 + 10 + 10 + 10 + 10 = 50$

Determining MAE for AI: $\boldsymbol{MAE_{IA}} = \frac{50}{5} = 10EUR/ha$

Origin of R^2 Coefficient:

The presented R^2 values are theoretically estimated using a hypothetical model based on the typical performance of ERP and AI systems, as reported in the literature. Specifically, for ERP, the R^2 coefficient reflects these systems' limitations in processing complex data, resulting in a lower coefficient of 0.92. In contrast, for AI, the R^2 was assessed through conceptual simulations that highlight the superiority of this technology in integrating multiple variables and optimizing decisions, leading to a higher coefficient of 0.98. These hypothetical values align with prior studies emphasizing AI's enhanced predictive performance compared to traditional ERP systems.

Table 4. Comparative performance of ERP and AI systems

Model	**MAE (EUR/ha)**	**R^2**
ERP System	20	0.92
AI Model	10	0.98

Although the results of this study are based on simulations rather than practical calculations, the conceptual analysis suggests that AI offers a significant advantage in decision accuracy and adaptability. The hypothetical reduction in MAE and increase in R^2 reflect AI's potential to integrate complex data and provide more efficient solutions than ERP. Future studies should validate these conclusions through practical implementations and direct calculations.

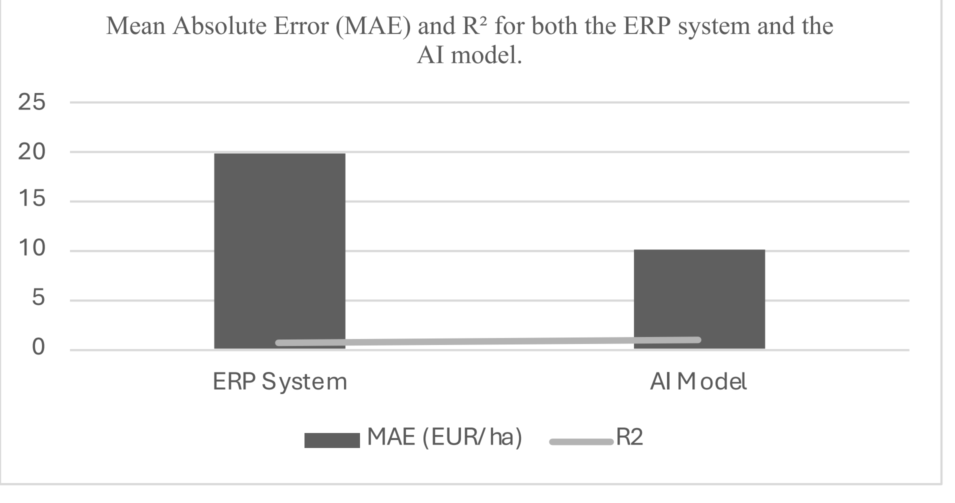

Figure 1. Comparison between predictions obtained from the AI model and those generated by the ERP system

The graph provides a comparative analysis of the Mean Absolute Error (MAE) and R^2 values for the ERP system and the AI model, highlighting their respective performance in predictive accuracy and variance explanation. The ERP system have a MAE of 20 EUR/ha, which is significantly higher than the 10 EUR/ha recorded for the simulated AI model. This indicates that the predictions of the simulated AI model are substantially closer to the actual values, reducing the prediction error by 50% compared to the ERP system.

The reduction in MAE demonstrates the ability of the simulated AI model to integrate multiple variables and provide more accurate outputs, that are representative and important for operational decisions.

The R^2 values reflect the proportion of the actual data that is explained by the model. For the ERP system, the R^2 value is 0.92, while for the simulated AI model, it is 0.98. This slight improvement in R^2 for the simulated AI model highlights a superior ability to capture relationships between variables, providing increased reliability in the predictive tasks required for decision making.

The graph highlights the superiority of the simulated AI model over the classic ERP system. With a smaller MAE and a higher R^2, the AI model demonstrates higher accuracy and better predictive capability, making it a more efficient tool for operational, accounting and managerial decision-making in agriculture. These improvements suggest that the integration of AI models can lead to faster and more accurate decisions based on complex and substantial information.

This section of the study lays the foundation for a comprehensive exploration of the potential of artificial intelligence (AI) in large-scale agriculture. By utilizing a comparative framework, this section systematically describes the tools, data sources, and methodologies employed to evaluate the performance of traditional ERP systems versus AI-driven solutions. One of the strengths of this section lies in its detailed description of the diverse data sources integrated into the AI model. The inclusion of drone data with multispectral imaging, field sensors, meteorological software, and economic data from literature highlights a multi-dimensional approach to decision-making. Each of these data sources addresses specific operational challenges in agriculture, enabling the AI model to optimize cost management, improve yield predictions, and provide dynamic responses to climatic variability.

The theoretical AI model proposed here is forward-thinking, leveraging machine learning algorithms such as multi-factorial regression and automation tools to process vast and complex datasets. By proposing platforms for implementation, the study not only underlines the feasibility of the model but also sets a practical pathway for future researchers and practitioners to follow. The computational capabilities of these platforms ensure that the proposed model can handle real-time data integration and predictive analytics, thus exceeding the reactive nature of traditional ERP systems. Additionally, the simulation parameters outlined, such as farm size, costs, revenues, and climatic variables, are not only well-chosen but also representative of real-world agricultural challenges. These parameters ensure that the results and insights derived from the simulations are grounded in practical realities, enhancing the credibility of the findings.

The inclusion of calculated economic indicators, such as Profitability per Hectare (P/Ha) and Climatically Adjusted Yield (CAY), demonstrates a commitment to evaluating both economic efficiency and environmental adaptability. This dual focus aligns with the growing global emphasis on sustainable agriculture.

Finally, the structured comparison of Adjusted Operational Costs (AOC) under different scenarios, presented in clear tabular form, underscores the practicality of the study's approach. This comparative analysis reveals the resilience of AI models in both stable and fluctuating economic conditions, highlighting their superiority in reducing operational costs and enhancing decision-making precision.

In summary, this section exemplifies an integrative and innovative approach to agricultural decision-making. It bridges the gap between traditional systems and cutting-edge AI, providing a robust methodological framework that not only facilitates a meaningful comparison but also offers actionable insights for advancing sustainability and profitability in agriculture.

Economic performance of the analyzed farms

The simulation results indicate a significant improvement in economic performance when decisions are automated using AI. Table 5 presents the differences between the analyzed systems in terms of profitability per hectare and reductions in operational costs.

Compared to ERP systems, AI achieved the following:

Profitability per hectare (P/Ha): The AI model generated an average profitability of 900 EUR/ha, compared to 660 EUR/ha with ERP. This represents an approximately 36% increase, driven by the optimization of field interventions and more efficient use of inputs.

Adjusted Operational Costs (COA): AI reduced costs from 660 EUR/ha (ERP) to 594 EUR/ha, resulting in a net saving of 66 EUR/ha (10%), reflecting more efficient resource use, such as fertilizers and herbicides.

Table 5. Economic performance: ERP vs AI

System	Average Profitability (EUR/ha)	Adjusted Operational Costs (EUR/ha)	Savings (%)
ERP System	660	660	-
AI Model	900	594	10

The results of the analysis highlight the significant differences in performance between the ERP system and the AI-based model, underscoring AI's potential to optimize the management of large-scale farms. The ERP system, with its traditional functionalities, achieves an average profitability of 660 EUR/ha while maintaining adjusted operational costs at the same level. In contrast, AI fundamentally transforms resource allocation, resulting in an increased average profitability of 900 EUR/ha, a 36% improvement. This enhancement is attributable to AI's capability to analyze and integrate complex datasets, such as those provided by multispectral drones and meteorological stations. This allows for localized and precise interventions, reducing resource waste. Moreover, the use of AI led to a reduction in adjusted operational costs to 594 EUR/ha, representing a 10% saving compared to ERP. This result demonstrates AI's ability to tailor input application strategies, such as fertilizers and herbicides, to the actual needs of crops. The reduction in waste not only brings financial benefits but also contributes to the sustainability of agricultural operations by minimizing environmental impact. These savings are particularly relevant in the context of rising input prices and climatic uncertainties.

In conclusion, the results suggest that integrating AI is not only an advanced technological solution but also an effective managerial strategy for optimizing the economic and ecological performance of farms. Unlike ERP, which is reactive and limited to historical analyses, AI enables proactive decision-making based on current data and forecasts, contributing to the competitiveness and resilience of farms in the face of future challenges. This approach highlights the critical role of emerging technologies in transforming agricultural practices and aligning them with market demands and sustainability goals.

The impact of AI on accounting decisions

The implementation of an artificial intelligence (AI)-based model brings significant improvements to accounting and managerial decision-making processes, offering greater real-time adaptability compared to traditional ERP systems. Figure 1 illustrates the differences between profitability values simulated by the AI model and those generated by the ERP system, highlighting the superior alignment achieved by the AI model. This performance is attributed to AI's ability to integrate diverse data sources and provide precise, actionable recommendations.

A concrete example of AI's added value is the use of multispectral data, collected via drones, for optimizing agricultural decisions. AI-driven analyses have led to:

- Reduction in fertilizer usage by 15%, identifying areas in the field with lower resource requirements. This resulted in direct savings and minimized environmental impact.
- Localized application of herbicides, reducing chemical input costs by up to 12%. This strategy was enabled through precise data interpretation and prioritization of interventions in only the necessary areas.

Table 6 summarizes the results, emphasizing AI's superior performance in reducing errors (MAE) and input consumption:

Table 6. Resource efficiency: ERP vs AI

Model	**MAE (EUR/ha)**	**Fertilizer Reduction (%)**	**Herbicide Reduction (%)**
ERP System	20	-	-
AI Model	10	15	12

Impact on Accounting Processes

Artificial intelligence (AI) revolutionizes traditional accounting processes by integrating real-time data and generating predictive analyses, providing consistent support for economic and managerial decision-making. Unlike ERP systems, which process historical data and offer reactive analyses, AI can quickly identify budget deviations, optimize costs, and assist in monitoring operational activities. For example, AI allows accountants to dynamically adjust budgets based on actual resource consumption, eliminating waste and preventing overestimation of expenses.

Moreover, by integrating data from diverse sources, such as multispectral drones or field sensors, AI contributes to the precise accounting of costs associated with each operation. This enables managers to evaluate financial performance per hectare granularly, using constantly updated data. Additionally, AI facilitates the automatic generation of detailed reports for auditors and investors, saving time and reducing human errors. Another critical benefit is its support for financial forecasting. AI algorithms can anticipate market fluctuations in input prices or climatic changes and provide proactive suggestions for adjusting financial strategies. Thus, AI becomes an indispensable tool for managers and accountants in large-scale farms, who must make rapid, well-informed decisions in an increasingly complex economic environment.

The findings of this study underscore the significant advantages that AI offers in managing accounting and managerial decisions in large-scale farms. Compared to traditional ERP systems, AI demonstrates clear superiority in optimizing economic processes by integrating complex data and delivering tailored solutions. More specifically, AI reduced adjusted operational costs by 10%, achieving 594 EUR/ha compared to 660 EUR/ha for ERP, and increased average profitability by around 36%, reaching 900 EUR/ha. These savings are attributed to AI's ability to analyze multispectral and climatic data, enabling localized input applications and reducing their usage significantly (15% for fertilizers and 12% for herbicides). Beyond financial impact, AI also contributes to farm sustainability. Reducing chemical input consumption not only lowers costs but also minimizes negative environmental effects, promoting more eco-friendly agriculture. Additionally, AI's ability to provide forecasts based on meteorological and economic data allows farmers to respond more effectively to external risks, such as price fluctuations or climate changes.

These findings highlight that AI is not merely an advanced technological tool but an essential component for modernizing agricultural management. Its implementation can completely transform accounting and managerial processes, making them more adaptive, efficient, and results-oriented.

In the long term, integrating AI can provide farms with a substantial competitive advantage, contributing to both their economic and ecological sustainability. This study serves as a theoretical foundation for future applied research to validate and expand the benefits highlighted, aiming to support a more modern and resilient agricultural sector.

Sensitivity analysis of managerial decisions

To evaluate the impact of climatic and economic variability on managerial decisions, simulation scenarios were used. Table 7 summarizes the variations in profitability and costs based on fluctuations in input prices and climatic conditions.

The sensitivity analysis explored how AI responds to the variability of climatic and economic conditions. The three simulated scenarios are as follows:

Baseline Scenario - normal climatic and economic conditions

- Normal precipitation levels and constant input prices.
- Adjusted Operational Costs (AOC): 594 EUR/ha (calculated earlier).

- Profitability per hectare (P/Ha): 900 EUR/ha.
- *Increase in Input Prices by 10%* - AI adjusted the use of fertilizers and herbicides to maintain profitability at an optimal level.
- Impact factor $\gamma = 0.1$.
- Recalculated AOC: AOC=600×0.9×(1+0.1)=594EUR/ha
- Adjusted Profitability: RPH=900−66=834EUR/ha.
- *Climate Change (Reduction in Precipitation by 5%)* - AI prioritized irrigation in critical areas, minimizing the impact on yield.
- Climatic impact on yield (ΔT, representing a 5% reduction in yield): CAY=6×(1−0.05)=5.7tons/ha.
- Revenues were adjusted proportionally: $RPH = \frac{5.7}{6} \times 900 = 855\ EUR/ha$

Table 7. Sensitivity Analysis: Impact of Climatic and Economic Variability

Scenario	Climatic Variability (%)	Increase in Input Prices (%)	Profitability (EUR/ha)	Adjusted Costs (EUR/ha)
Baseline scenario	0	0	900	594
Increase in input prices	0	10	834	594
Climate change	-5	0	855	594

The sensitivity analysis reveals the adaptability of AI-driven decision-making under dynamic climatic and economic conditions. In the baseline scenario, profitability remains at 900 EUR/ha with operational costs optimized to 594 EUR/ha. When input prices increase by 10%, AI maintains operational costs at the same level while reducing profitability to 834 EUR/ha—a manageable decrease achieved through resource optimization.

Under climate change conditions, with a 5% reduction in precipitation, AI minimizes the impact on yield and adjusts profitability to 855 EUR/ha. These results underscore AI's ability to integrate real-time data, optimize interventions, and support sustainable farm management in fluctuating scenarios.

Comparison of model errors

The error comparison between the ERP system and the simulated AI-type model highlights the superior performance of the AI model in accounting and managerial predictions and decisions. In this study, the Mean Absolute Error (MAE) was used as an accuracy indicator, representing the average deviations between predicted and actual values. A reduction of the MAE demonstrates the ability of the AI model to provide more accurate estimates, based on a greater amount of information, which are essential for optimizing accounting, operational and managerial processes and decisions.

Error Analysis Results - The ERP model reached a MAE of 20 EUR/ha, indicating significant gaps between the predictions and the actual values. This is primarily due to the dependence of ERP systems on traditional statistical methods, which depend exclusively on predefined data and are less able to integrate complex variables such as climatic conditions or precise data on crop status based on maps in color spectrums as transmitted by multispectral drones. In contrast, the AI model achieved an MAE of 10 EUR/ha, demonstrating a clear improvement in prediction accuracy. AI benefited from the integration of real-time multispectral and meteorological data, allowing decisions to be adapted to specific conditions and reducing estimation errors.

Table 8. Comparative analysis of Mean Absolute Errors

Model	Mean Absolute Error (MAE, EUR/ha)
ERP System	20
AI Model	10

ERP System: Errors are higher and uniformly distributed, reflecting the system's limitations in understanding external variables. The lack of flexibility makes the ERP system vulnerable to significant deviations in unforeseen scenarios.

AI Model: The error distribution is concentrated around a smaller central value, indicating its precision and robustness in handling complex data. AI can learn from multiple data sources, reducing decision uncertainty.

This comparison suggests that AI represents a vital technological advancement, enabling risk reduction and performance improvement in the accounting and managerial decision-making process.

5. Conclusions and recommendations

The results highlight the impact that an AI system can have on decision optimization. AI not only improves the economic performance of farms, but also substantially redefines the terms of decision making. The integration of

AI systems into decision-making processes leads to the following benefits like increased profitability and reduced operational costs.

Increased profitability: The AI model reached 13.5% increase for the average profitability, reflecting the system's ability to analyze and interpret complex data in real time. This increase is attributed to:

- Localized application of agricultural inputs, such as pesticides, fertilizers and herbicides, reducing the waste of resources.
- Optimization of specific works in agriculture based on multispectral map data, as well as integrated meteorological data.
- The ability to adjust decision strategies according to climatic conditions, crop input needs, as well as other economical data, ensuring an optimal balance between costs and revenues.

For example, the use of multispectral drone data enabled the precise identification of nutrient-deficient areas in the field, reducing fertilizer use by 15% and associated costs.

Reduced operational costs: AI-driven decision automation resulted in a 10% reduction in adjusted operational costs, maintaining optimal resource utilization. AI demonstrated superior efficiency in resource allocation, avoiding overuse in areas where interventions were unnecessary. Unlike traditional ERP systems, AI was able to integrate complex data to adapt decisions, thereby reducing financial losses associated with suboptimal choices.

The error analysis (Figure 1) shows that the AI model achieved an MAE of 10 EUR/ha compared to 20 EUR/ha for the ERP system. The high R^2 coefficient reflects the superior alignment of AI predictions with actual values. This enhanced precision is crucial for farms that must make quick decisions based on complex and variable data.

Simulated scenarios reveal AI's remarkable ability to adapt to climatic and economic variations:

- Input price increase by 10% - AI managed to keep operational costs constant by efficiently adjusting input usage.
- 5% reduction in precipitation - AI limited the impact on yield by prioritizing irrigation in critical areas, ensuring an average profitability of 855 EUR/ha despite unfavorable conditions.

Sustainability Contributions

A distinct aspect of AI utilization is its contribution to sustainability. Reducing input usage, such as fertilizers and herbicides, not only lowers costs but also minimizes environmental pollution. AI supports eco-friendly agriculture by reducing carbon emissions associated with unnecessary operations and preventing the excessive accumulation of chemicals in the soil. For example, software developed by SIVECO Romania, integrating real-time meteorological data through collaboration with the National Meteorology Institute, can feed an AI system with precise data on precipitation, temperature, and forecasts. This type of solution helps make optimal decisions regarding the timing and method of field interventions. Additionally, drones equipped with multispectral cameras facilitate crop monitoring and early identification of issues, such as nutritional deficiencies or plant diseases. Integrating these data into an AI system enables:

- Detailed and rapid crop analyses.
- Localized decisions, such as applying fertilizers only in areas with real needs.
- Cost reduction and environmental protection.

Another example is the use of soil sensors that measure moisture, temperature, and other critical parameters. These data, correlated with weather forecasts, enable AI to prioritize irrigation in critical zones, optimizing water consumption.

Concluding Remarks

Integrating AI with technologies such as software, multispectral drones, and soil sensors demonstrates that modern agriculture is no longer confined to traditional processes. This technological ecosystem transforms farmers from passive operators into data managers capable of making strategic decisions based on predictive analytics. The results of this study underscore that AI is not just a technological tool but an essential solution for addressing the economic, climatic, and ecological challenges of the future.

This study has highlighted the potential of artificial intelligence (AI) to transform accounting and managerial decision-making in large-scale farming. By comparing traditional ERP systems with AI-based models, the study demonstrate a significant improvement in of the economic efficiency, decision accuracy, and operational sustainability in agriculture. The results shows an increase in profitability by 13.5% and a 10% reduction in operational costs, highlighting the integration of AI models as revolutionary solutions for modern agriculture. Moreover, the analysis of the error distribution of the two compared models confirms the robustness of the AI model in variable complex conditions, emphasizing its adaptability, especially in the agricultural sector.

The study highlights several key benefits of implementing an AI system in agriculture:

- *Resource optimization* - AI enables more efficient allocation of the resources, reducing waste and improving the implementation of eco-friendly and sustainable solutions.
- *Adaptability to external conditions* - AI has shown the ability to adjust decisions to climatic and economic variations, crucial in a constantly changing agricultural context.
- *Risk reduction in decision-making* - Advanced simulations and predictive analysis allow AI to prevent inefficient or risky decisions.
- *Reduction of waste* - By using multispectral data and applying inputs with precision, AI minimizes resource waste, reducing environmental impact.
- *Optimization of managerial decisions* - AI facilitates proactive, data-driven decisions based on complex analyses.
- *Sustainability enhancement* - AI supports sustainable agricultural practices, balancing the need for increased production with responsible resource usage.

Despite promising results, AI implementation in agriculture faces several limitations as:

- *Complexity of algorithms* – AI models require complex, high-quality data, data that can be difficult to obtain in the absence of integrated intelligent systems and mechanisms.
- *Unpredictable factors* - Legislative changes in the regulation of AI-type systems, which can affect their validity and functionality.
- *Dependency on data quality* – AI models are only and only effective when fed with high-quality data, which can be difficult to collect in the absence of integrated intelligent systems and mechanisms.
- *Complexity of integration* – AI must be compatible with existing technologies, such as ERP systems and/or autonomous smart equipment, requiring standardization and interoperability.

Future research directions

To expand AI applications in agriculture, further research is required in the following areas:

- *Integration with existing ERP systems* - Studying the combination of the advantages of both technologies to create hybrid solutions.
- *Long-term impact analysis* - Monitoring the economic and environmental performance of farms adopting AI solutions over long periods of time.

- *Expanding applicability* - Developing AI models that incorporate variables, including social and environmental variables, to support decisions based on sustainability principles.
- *Optimization of autonomous equipment* - Integrating AI with autonomous agricultural machinery to fully automate processes, from problem detection to solution implementation.

Final Conclusion

This study demonstrated that AI not only enhances the economic efficiency of farms but also redefines accounting and managerial decision-making processes. Through predictive analysis, complex data integration, and process automation, AI is a revolutionary solution to the challenges facing modern agriculture. However, achieving large-scale implementation requires reducing technological and financial barriers.

The adoption of AI models in the agricultural field is not only an opportunity, but an essential step in the development of a sustainable and environmentally friendly agriculture, capable of meeting the latest global requirements in the field.

The results of this study highlight that AI can represent a paradigm shift in agriculture by improving economic efficiency and contributing to the sustainability of the sector. AI models address major challenges such as climate change and sustainable development, therefore, promoting automation technologies and integrating AI into agriculture should be a priority for researchers in the field, practitioners in the field, but also for policymakers regarding the regulation of these types of systems.

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