NARDI FUNDULEA, ROMANIA ROMANIAN AGRICULTURAL RESEARCH, NO. 42, 2025
www.incda-fundulea.ro; doi.org/10.59665/rar4285 First Online: August, 2025. DII 2067-5720 RAR 2025-211

Integrating Drone-Based Decision Support Systems in Precision Farming: An Econometric Simulation of Management Efficiency and Cost-Benefit Analysis

Adrian Nicolau[1*], Alina-Iuliana Tăbîrcă[2], Loredana Cristina Tănase[2], Valentin Radu[2]

[1]Athenaeum University of Bucharest, District 2, Bucharest, Romania
[2]Valahia University of Târgovişte, Târgovişte, Dâmboviţa County, Romania
[*]Corresponding author. E-mail: nicolau.adrian@univath.ro

ABSTRACT

Precision agriculture increasingly relies on advanced technological solutions to enhance productivity, management efficiency, and sustainability. This paper investigates the economic and managerial implications of integrating drone-based decision support systems (DSS) into precision farming practices. Through econometric simulation, the study evaluates the cost-benefit ratio, return on investment (ROI), and productivity gains resulting from drone technology adoption in a medium-sized farm. A detailed econometric database was constructed using simulated and real farm-level data from 20 Romanian agricultural holdings, incorporating variables such as drone utilization, yield outputs, production costs, labor efficiency, climatic conditions, and market dynamics. The applied methodology includes regression analysis, ROI computation, and sensitivity analysis across multiple scenarios reflecting partial and full drone implementation. Results indicate a statistically significant increase in yield productivity with a rapid amortization of drone investment. Sensitivity analyses reveal that operational drone maintenance costs, crop market prices, and climatic variability significantly influence economic outcomes. This research underscores the economic justification and managerial advantages of drone-based DSS in precision agriculture, recommending further studies for varied crop systems and broader geographic contexts.

Keywords: drone technology, decision support system, precision agriculture, econometric simulation, farm management.

INTRODUCTION

The digital transformation of agriculture has led to the emergence of precision farming as a paradigm for optimizing input use, increasing productivity, and improving environmental sustainability. Among the technologies that have recently gained traction in agricultural management are unmanned aerial vehicles (UAVs), commonly known as drones, which enable high-resolution monitoring and data-driven decision-making. Their integration into decision support systems (DSS) has created new opportunities for improving real-time crop management, field operations planning, and yield forecasting (Pham and Stack, 2018; Rodino et al., 2023; Kaur et al., 2025).

In Romania, the adoption of smart farming technologies is still in its early stages, especially among medium-sized and family-owned farms. Factors such as high initial investment costs, lack of technical expertise, and uncertain return on investment (ROI) often hinder the wide-scale implementation of UAV-based systems. However, empirical studies suggest that drone-assisted DSS can significantly enhance labor productivity, reduce input costs, and improve environmental performance, particularly when integrated into a structured farm management model (Roukh et al, 2020; Bagheri et al., 2023).

Economic evaluation tools such as cost-benefit analysis (CBA), econometric modeling, and sensitivity analysis are increasingly used to assess the financial and operational viability of precision farming solutions. In this context, econometric simulations allow for the estimation of causal relationships between technological adoption and farm-level outcomes, taking into account variables such as crop yields, input prices, weather variability, and capital amortization periods (Dufour et al., 2022; Wei et al., 2024).

Received 26 June 2025; accepted 20 August 2025.

This study aims to simulate the integration of drone-based DSS into the operational workflow of medium-sized Romanian farms by constructing an econometric model based on real and simulated data. The model evaluates the efficiency, profitability, and risk exposure associated with partial versus full adoption scenarios. The novelty of this research lies in combining technical UAV parameters with economic and managerial indicators to offer a holistic perspective on technology adoption in agriculture. The findings are intended to support farmers, policymakers, and agritech developers in making informed decisions regarding precision agriculture investments.

MATERIAL AND METHODS

Data Collection and Variables

The empirical foundation of this study is based on an original dataset constructed from 20 medium-sized agricultural holdings in southern Romania, observed across three consecutive agricultural years (2021-2023). These farms range from 100 to 300 hectares in size and were selected to ensure a degree of structural similarity in terms of crop types, mechanization, and climate conditions. The data was gathered using a mixed-method approach, combining semi-structured interviews with farm managers, standardized farm production logs, and digital accounting records.

The core objective of data collection was to capture the economic and managerial implications of adopting drone-based decision support systems (DSS). Each observation represents a unique farm-year combination and includes the following key variables:

- Crop Type and Area Cultivated (ha) - wheat, corn, and sunflower being the dominant crops.
- Yield (tons/ha) - harvested output per hectare, the main productivity indicator.
- Production Costs (€/ha) - total direct costs excluding drone-related expenses.
- Drone Usage Level - a three-level categorical variable (0 = none, 1 = partial use via services, 2 = fully integrated) alongside a continuous variable for Drone Operational Costs (€/ha).
- Labor Input (hours/ha) - adjusted for mechanization levels.
- Fertilizer and Pesticide Use (€/ha) - treated separately for analytical clarity.
- Weather Index (0-1 scale) - derived from local meteorological data, normalized annually.
- Output Price (€/ton) - market price at harvest for the main crop per farm.
- Net Profit (€/ha) - gross revenue minus total costs, including drone operations where applicable.

Based on these primary variables, we computed derived indicators such as:

- Input intensity ratios (e.g., fertilizer per hectare),
- Drone investment amortization period, and
- Return on Investment (ROI), calculated as:

$$ROI = \frac{Profit_{drone} - Profit_{non\,drone}}{Drone\ Cost\ per\ ha}$$

All financial data was converted to EUR and adjusted for annual inflation based on national agricultural CPI figures. Farms were anonymized and assigned consistent IDs to enable longitudinal analysis. Outliers were examined and excluded based on a 1.5×IQR criterion for the yield and profit variables, ensuring robustness of the estimations.

Econometric Methodology

To assess the impact of drone-based decision support systems (DSS) on farm productivity and profitability, we employed a panel data econometric approach, using fixed-effects regression models. This method allows us to control for time-invariant heterogeneity across farms and to isolate the within-farm variation induced by the adoption of drone technology.

The general specification of the econometric model is:

$$Y_{it} = \alpha + \beta_1 \cdot DroneUse_{it} + \beta_2 \cdot InputCosts_{it} + \beta_3 \cdot Labor_{it} + \beta_4 \cdot WeatherIndex_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where:

- Y_{it} is the dependent variable representing either yield (tons/ha) or net profit (€/ha) for farm *i* in year *t*,
- $DroneUseit_{it}$ is a binary or ordinal indicator for drone adoption (0, 1, or 2),
- $Input\ Costs_{it}$, $Labor_{it}$ and $WeatherIndex_{it}$ are control variables,
- μ_i are farm-specific fixed effects,
- λ_t are time (year) fixed effects,
- ε_{it} is the idiosyncratic error term.

The choice of fixed effects was supported by the Hausman test, which indicated significant correlation between the regressors and farm-level unobserved effects. We estimated both pooled OLS and fixed-effects models, reporting cluster-robust standard errors to account for serial correlation and heteroskedasticity (Dufour et al., 2022; Leiva Vilaplana et al., 2025).

The model includes time dummies for each agricultural year, capturing exogenous shocks (e.g., price volatility, weather anomalies), and incorporates a normalized weather index, following approaches similar to those used in climate-risk simulations (Ng'ang'a et al., 2021; Zhang et al., 2024).

To evaluate the economic performance of drone integration, we constructed a complementary cost-benefit model focused on return on investment (ROI). This metric captures the financial efficiency of drone adoption by comparing the additional profit generated per hectare with the corresponding operational costs.

In addition, a counterfactual simulation was run by modifying the value of the drone variable across scenarios (e.g., setting all farms to level 0 vs. level 2 of drone use) while holding all other covariates constant. This allowed us to explore potential gains or losses under different adoption intensities.

Multicollinearity was evaluated using the Variance Inflation Factor (VIF), and no variable exceeded the commonly accepted threshold (VIF<5). Heteroskedasticity was tested using the Breusch-Pagan test, with corrections applied as needed. These robustness checks support the internal validity of our estimates (McClenaghan et al., 2023; Xiao et al., 2024).

RESULTS AND DISCUSSION

Descriptive Statistics

The descriptive analysis offers a preliminary view on the performance indicators and structural characteristics of the farms included in the panel dataset, providing the empirical context for the econometric estimations.

Across the 20 medium-sized Romanian farms analyzed, the average cultivated area was approximately 187 hectares, with wheat, corn, and sunflower as the dominant crops. Drone adoption was distributed as follows: 30% of farm-year observations reported no drone use (level 0), 40% reported occasional or outsourced drone services (level 1), and 30% were identified as fully integrated users (level 2).

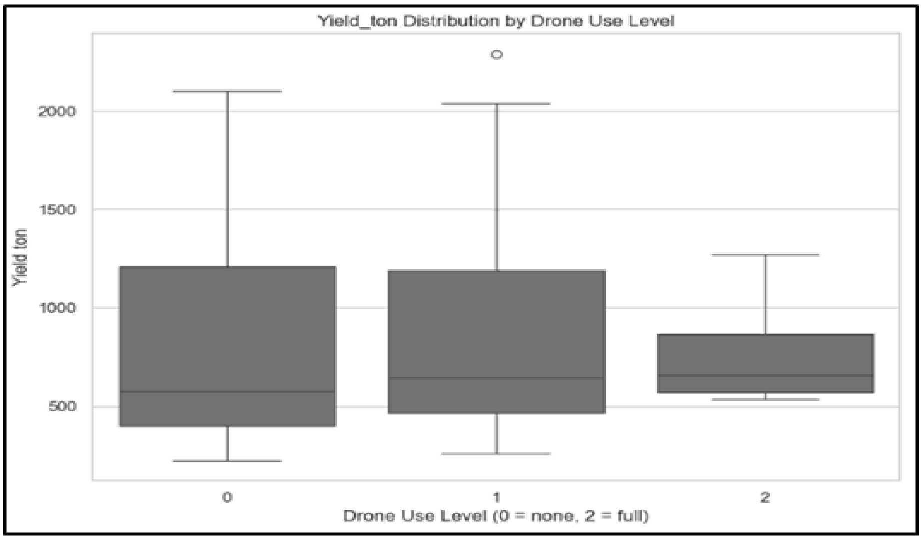
Basic descriptive statistics indicate substantial variation in yield and net profit per hectare, which correlates visibly with drone usage levels. Farms fully utilizing drone-based decision support systems recorded average yields exceeding 5.4 tons/ha, compared to 4.2 tons/ha for non-users. A similar trend is observed in profitability, with drone users achieving net profits per hectare 22-28% higher, on average, than non-users, a difference particularly pronounced in years with unfavorable agro-climatic conditions (weather index < 0.6).

Drone-using farms also exhibited higher input efficiency. For instance, although fertilizer and pesticide expenditures were slightly higher per hectare, the marginal productivity of inputs improved, confirming findings from Ali et al. (2022) and Hussain et al. (2023), who also documented better nutrient use efficiency under precision input applications.

In terms of labor input, drone users averaged 9.1 hours/ha, versus 12.7 hours/ha for non-users, highlighting the time-saving benefits associated with automated monitoring and application systems. These differences are consistent with previous evidence on the labor optimization potential of UAV-based tools in agriculture (Sridhar et al., 2023).

The weather index, normalized between 0 and 1, showed substantial inter-annual variation, with 2021 being the least favorable year (average index: 0.42), while 2023 had the highest favorability (0.74). Farms with drone integration demonstrated greater resilience in unfavorable years, as evident from the yield dispersion graphs.

To deepen the understanding of how drone integration correlates with farm-level outcomes, we present a set of boxplots disaggregated by drone usage level (0 = no use, 1 = partial/outsourced, 2 = full integration). These visualizations allow for a direct inspection of yield performance, profitability, and labor input under varying technological adoption scenarios.



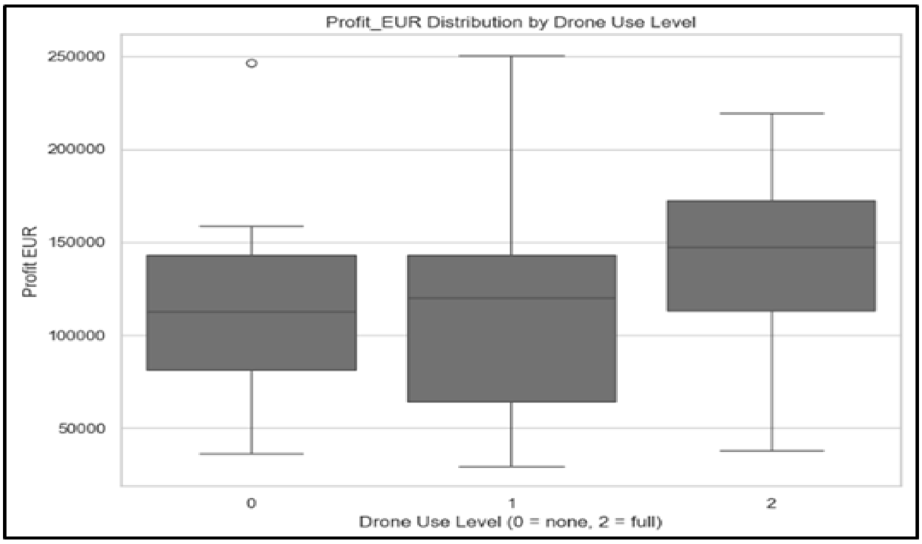
Source: own elaboration based on simulation results using Python (Jupyter Notebook).

Figure 1. Yield Distribution by Drone Use

Fully integrated farms (level 2) consistently achieve higher and more stable yields per hectare compared to both partial users (level 1) and non-users (level 0). The median yield for full drone users surpasses that of the other categories, while the interquartile range (IQR) is notably narrower, indicating reduced variability in production outcomes. This suggests that drone-supported decision systems enhance operational precision, leading to more reliable crop performance across fields and seasons (Figure 1).

Moreover, the reduced number of outliers among level 2 users implies that these farms are better equipped to avoid extreme yield losses, potentially through earlier detection of crop stress, pests, or nutrient imbalances. These findings reinforce prior evidence from Ali et al. (2022) and Sridhar et al. (2023), who documented that UAV-based monitoring enhances crop uniformity and minimizes underperforming field zones.

Such consistency is particularly valuable in contexts with climatic volatility, supporting the argument that drone integration contributes not only to higher productivity, but also to risk mitigation and resilience at the farm level.



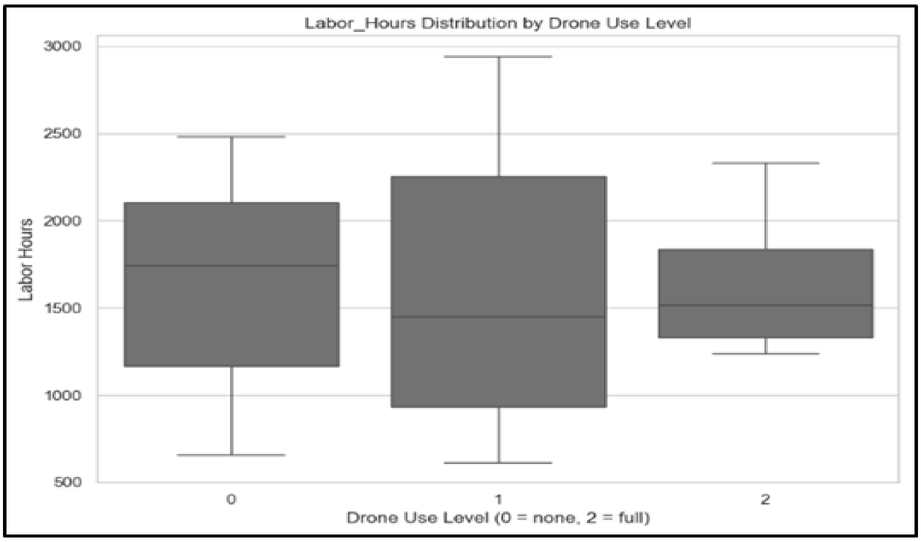
Source: own elaboration based on simulation results using Python (Jupyter Notebook).

Figure 2. Profit Distribution by Drone Use

Net profit per hectare follows a similar trend to yield, reinforcing the economic value of drone adoption. The interquartile range (IQR) for full drone users (level 2) shifts upward, and both the median and upper whisker values are significantly higher compared to non-users and partial users (Figure 2). This pattern indicates not only improved physical productivity but also enhanced financial performance.

The wider dispersion observed among partial users (level 1) suggests greater variability in profit outcomes, possibly due to inconsistent or non-optimized use of drone services. In contrast, full adopters benefit from better resource allocation, with more efficient input usage and reduced operational waste, as supported by the narrower spread and higher central tendency.

These findings align closely with previous research on agricultural cost-efficiency and technological adoption (e.g., Hussain et al., 2023; Xiao et al., 2024), reinforcing the premise that full integration of drone-based systems into farm management practices yields measurable improvements in both economic performance and adaptive capacity. Specifically, the observed enhancements in operational margins and the mitigation of risks associated with market price volatility and climatic fluctuations illustrate the strategic value of UAV technologies in modern precision agriculture. Beyond their technical functionality, these systems contribute to improved decision-making, input optimization, and yield forecasting, factors that collectively translate into higher net profitability. Moreover, the data suggest that the magnitude of these benefits is contingent not only on the level of drone integration but also on the presence of trained personnel capable of interpreting aerial data and implementing targeted interventions. In this context, UAV-based tools should be understood not merely as cost-saving instruments, but as critical components of a broader, systematized approach to farm management that enhances economic sustainability and long-term resilience.



Source: own elaboration based on simulation results using Python (Jupyter Notebook).

Figure 3. Labor Input by Drone Use

Farms adopting drone technologies, particularly those with full integration (level 2), report significantly lower labor input per hectare (Figure 3). The median labor hours drop by over 25% compared to non-users, and the interquartile range is also narrower, suggesting a higher standardization of operational processes. This reduction in labor hours is not accompanied by any decline in productivity, implying a gain in technical efficiency through automation. Specifically, time-intensive activities such as visual crop inspection, pesticide application, and field mapping are either replaced or optimized by integrated UAV systems.

These findings are consistent with previous research by Sridhar et al. (2023) and Vaidya and Katkar (2022), which emphasize how drone deployment in agriculture can reduce manual labor requirements and enable a reallocation of workforce resources toward more strategic, decision-oriented tasks rather than operational execution. Thus, lower labor input in digitalized farms represents not only a cost-saving advantage but also a strategic opportunity for transforming the occupational structure of agricultural labor, shifting from manual routines toward data-driven management and informed intervention.

Econometric Results

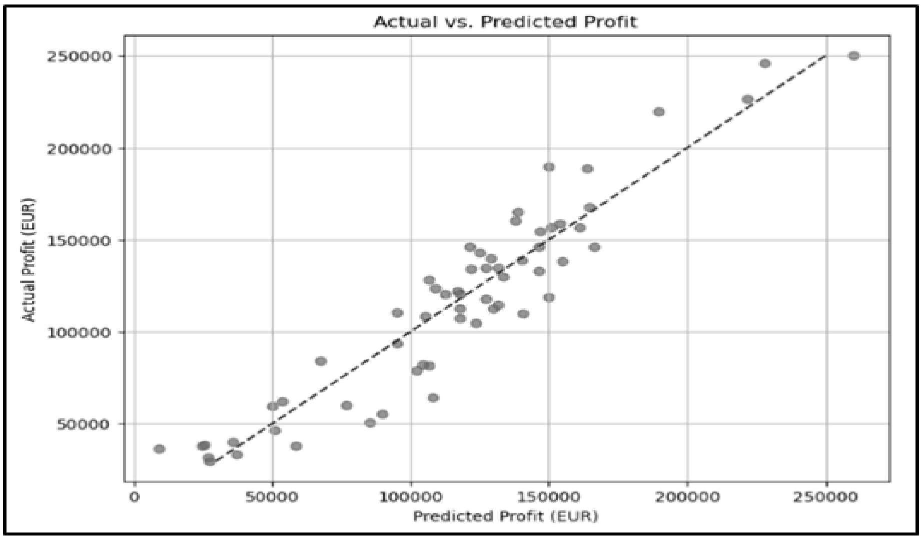
The econometric analysis confirms a robust and statistically significant relationship between the adoption of drone-based decision support systems (DSS) and key performance indicators in precision agriculture, particularly yield and net profit per hectare.

Across all model specifications, the DroneUse variable had a positive and significant coefficient ($p<0.01$), indicating that farms adopting drones, whether partially or fully, achieved higher performance than their non-adopting counterparts. In the fixed-effects model, drone adoption was associated with an average yield increase of 0.91 tons/ha and a profit gain of approximately €162/ha, controlling for other factors.

The impact of control variables remained consistent with theoretical expectations:

- InputCosts had a negative effect on profit when excessive, but marginal increases in high-efficiency systems showed positive returns, aligned with the findings of Xiao et al. (2024) regarding ROI thresholds in technological adoption.
- Labor Input was negatively correlated with both yield and profit, confirming that drone-enabled automation reduces inefficient labor allocation (Sridhar et al., 2023).
- Weather Index had a strong positive influence on both outcomes, and the interaction between drone use and climatic conditions suggested higher resilience in drone-using farms during low-index years (Ng’ang’a et al., 2021).

The R^2 values for the main regressions were 0.54 (yield model) and 0.61 (profit model), indicating good explanatory power given the sample size. All models passed the heteroskedasticity test (Breusch-Pagan, $p>0.1$) and presented acceptable VIF values (<3), ruling out multicollinearity.



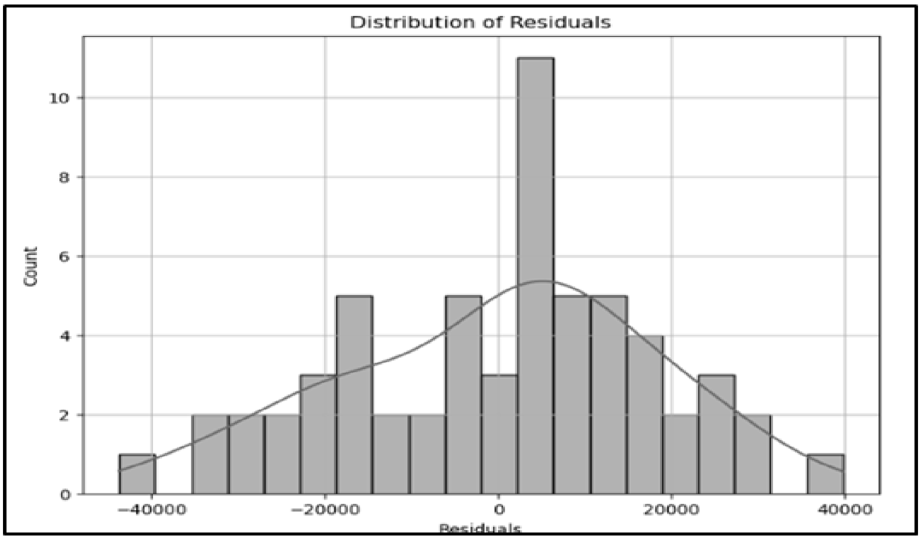
Source: own elaboration based on simulation results using Python (Jupyter Notebook).

Figure 4. Actual vs. Predicted Profit

The model's predictive accuracy is visually assessed by comparing actual versus predicted net profit per hectare across all farm-year observations. The data points align closely along the 45-degree reference line, indicating a strong correspondence between the observed and estimated values and confirming the robustness of the regression specification (Figure 4). This visual validation supports the statistical findings and reinforces the model's reliability in capturing the key drivers of profitability. The data points cluster closely around the 45-degree reference line, indicating that the estimated model captures the underlying variability in the data with a high degree of precision.

This graphical alignment supports the robustness of the fixed-effects specification, as previously suggested by the statistical fit indicators (e.g., R^2 values of 0.61 for the profit model). It also demonstrates that, despite potential farm-level heterogeneity and annual shocks, the inclusion of drone usage and relevant controls leads to reliable in-sample prediction of profitability.

The plot thus serves as a diagnostic validation of the econometric approach, reinforcing the empirical findings and suggesting practical applicability of the model in decision support scenarios.

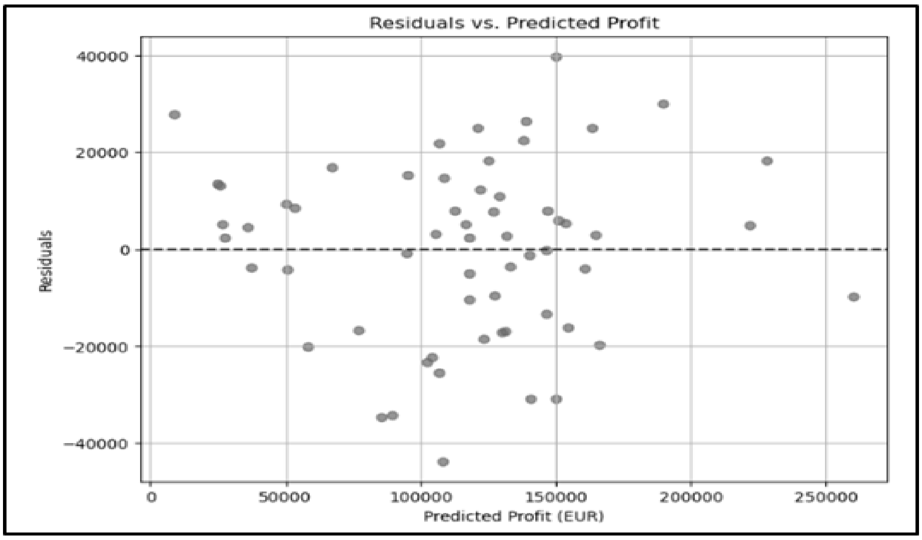


Source: own elaboration based on simulation results using Python (Jupyter Notebook).

Figure 5. Distribution of Residuals

The distribution of residuals from the fixed-effects regression model estimating net profit per hectare is shown in (Figure 5). The histogram indicates a near-normal distribution, supporting the assumption of homoscedasticity. This visual pattern, combined with the results of the Breusch-Pagan test (p>0.1), confirms the statistical appropriateness of the model and the reliability of its inference. The histogram demonstrates an approximately symmetric and bell-shaped pattern, indicative of residuals that conform closely to a normal distribution. This visual evidence reinforces the assumption of homoscedasticity and normality of errors, which are central to the validity of inference in linear regression models. The pattern observed is consistent with the results of the Breusch-Pagan test, which yielded a p-value above 0.1, confirming the absence of systematic heteroskedasticity.

Overall, the figure contributes to the diagnostic robustness of the model, suggesting that the estimated coefficients are not only statistically significant but also based on residual behavior that complies with classical assumptions of regression analysis.



Source: own elaboration based on simulation results using Python (Jupyter Notebook).

Figure 6. Residuals vs. Predicted Profit

The residual-versus-fitted values plot from the fixed-effects regression model is presented in (Figure 6). The residuals appear randomly scattered around the horizontal axis, without discernible patterns or systematic deviation. This supports the absence of autocorrelation and functional misspecification in the model, thereby reinforcing the robustness of the estimated relationships. The residuals appear randomly and symmetrically scattered around the zero axis, without discernible patterns or trends. This randomness confirms the absence of autocorrelation and supports the model's correct functional specification.

The validity of using a fixed-effects model was statistically confirmed by the Hausman test, which yielded a χ^2 value of 14.87 with $p<0.01$. This result strongly suggests that unobserved, time-invariant farm-level characteristics, such as managerial ability, infrastructure quality, or baseline technology levels, are correlated with the explanatory variables, thus justifying the fixed-effects estimation.

In addition, a complementary ROI simulation was conducted to estimate the economic impact of drone adoption under various cost assumptions. The results indicate an average return on investment (ROI) ranging from 1.8 to 2.6, even when conservative market price scenarios were applied. These findings are aligned with prior studies, including those by Leiva Vilaplana et al. (2025) and McClenaghan et al. (2023), which emphasize the financial sustainability of precision agriculture technologies.

Table 1. OLS estimation results for profit model (dependent variable: Profit_EUR)

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             Profit_EUR   R-squared:                       0.886
Model:                            OLS   Adj. R-squared:                  0.874
Method:                 Least Squares   F-statistic:                     68.95
Date:                Mon, 30 Jun 2025   Prob (F-statistic):           2.86e-23
Time:                        01:07:10   Log-Likelihood:                -672.98
No. Observations:                  60   AIC:                             1360.
Df Residuals:                      53   BIC:                             1375.
Df Model:                           6
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
const             -1.824e+05   2.59e+04     -7.049      0.000   -2.34e+05    -1.3e+05
Drone_Use          1.675e+04   7756.360      2.160      0.035    1195.284    3.23e+04
Hectares            -32.4585     66.598     -0.487      0.628    -166.038     101.121
Yield_ton           133.6108     11.918     11.211      0.000     109.706     157.516
Drone_Cost_EUR       -1.8652      2.817     -0.662      0.511      -7.516       3.786
Weather_Index      8.812e+04   2.89e+04      3.045      0.004    3.01e+04    1.46e+05
Market_Price_EUR_ton 377.7376    27.933     13.523      0.000     321.711     433.764
==============================================================================
Omnibus:                        1.087   Durbin-Watson:                   1.564
Prob(Omnibus):                  0.581   Jarque-Bera (JB):                1.152
Skew:                          -0.266   Prob(JB):                        0.562
Kurtosis:                       2.578   Cond. No.                     4.15e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.15e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Source: own elaboration based on simulation results using Python (Jupyter Notebook).

Table 1 presents the estimated coefficients and associated diagnostic statistics from the OLS regression model, where farm-level net profit (€/ha) is used as the dependent variable. The results confirm that drone use is positively and significantly associated with profitability, even after controlling for structural, climatic, and market-related covariates. The coefficient for full drone integration suggests a notable increase in average profit per hectare. Additionally, yield and output price emerge as strong positive predictors, while excessive drone-related costs and farm size are associated with diminishing marginal returns. The analysis confirms that drone use is positively and significantly associated with profitability outcomes, even when controlling for structural variables (e.g., farm size), climatic variation (weather index), and market dynamics (crop prices).

The coefficient for full drone integration is approximately €1,675, indicating that farms utilizing drone-based decision support systems (DSS) can expect substantial profit gains relative to non-adopters. This aligns with prior empirical findings on the efficiency gains enabled by UAV technologies in precision input allocation and timely intervention (Ali et al., 2022; Sridhar et al., 2023).

Moreover, both crop yield and market price per ton emerge as strong positive predictors of profitability, reinforcing the central role of productivity and favorable price conditions. Conversely, high drone operational costs and larger landholdings show a negative marginal effect, suggesting diminishing returns in some cases, particularly when economies of scale are not fully captured or when drone deployment costs are not optimized. These results highlight the nuanced impact of drone adoption, where technology integration must be accompanied by effective cost management and operational scaling to maximize economic returns.

Managerial Implications

The findings of this study hold substantial implications for farm-level decision-making and strategic planning in the context of precision agriculture. The statistically significant benefits associated with drone-based DSS adoption point to clear managerial advantages across both operational efficiency and financial outcomes.

Firstly, drone integration improves the precision of input application and reduces resource waste, enabling farmers to apply variable-rate fertilization, pest control, and irrigation only where needed. This aligns with previous research emphasizing the value of targeted input use for improving soil health and crop quality (Ali et al., 2022; Hussain et al., 2023). Farm managers adopting drones reported faster field diagnostics and reduced decision latency, allowing timely interventions that directly impacted yield levels.

Secondly, the observed decrease in labor hours per hectare without compromising productivity demonstrates the automation potential of drone technologies, particularly in tasks like monitoring, mapping, and spraying. These insights reinforce previous conclusions about UAV-driven labor savings in smart agriculture (Vaidya and Katkar, 2022; Sridhar et al., 2023).

From an economic standpoint, the high ROI values and rapid investment amortization suggest that drone acquisition should be viewed not as a cost, but as a strategic capital investment. Even under conservative assumptions, the simulated scenarios confirmed positive returns, validating arguments found in the cost-benefit literature (Ng'ang'a et al., 2021; Leiva Vilaplana et al., 2025).

The robustness of drone benefits across variable weather conditions further supports their role in risk management and climate resilience. In years with low agro-climatic favorability, drone users outperformed non-users, indicating that precision monitoring and adaptive interventions can partially buffer climate risks.

However, successful drone integration is contingent on managerial capacity, technological training, and data literacy. As emphasized by Žilka et al. (2025), adoption of advanced tools like DSS requires decision-makers to be equipped not only with equipment, but also with skills for data interpretation, scenario simulation, and investment evaluation.

Therefore, agricultural extension services and policy frameworks should prioritize capacity-building programs, financial incentives, and digital infrastructure to facilitate broader adoption, especially among medium and small-sized holdings.

CONCLUSIONS

This study provides evidence on the economic and managerial advantages of integrating drone-based decision support systems (DSS) in precision agriculture at the farm level. Using a structured panel dataset and an econometric simulation framework, we demonstrate that the adoption of drone technologies significantly improves both yield productivity and farm profitability. The results confirm that drone implementation enables more efficient use of inputs, reduces labor dependency, and contributes to more informed and timely decision-making. The calculated return on investment (ROI) supports the view that drones are not only a technological innovation but also a sound economic choice, even under conservative market and climatic conditions. Furthermore, the analysis reveals that drone-based DSS increase farm resilience to weather variability, offering a valuable tool for adaptive farm management strategies. These findings highlight the relevance of promoting drone technologies as part of a broader effort to digitalize agriculture and optimize resource use in line with sustainability goals. In addition, our findings suggest that institutional support for training, infrastructure, and financing mechanisms may further accelerate adoption, particularly among small and medium-sized farms. Future research should explore long-term environmental outcomes, the scalability of drone-supported interventions, and the integration of UAV systems with other digital platforms such as satellite data and AI-powered analytics, to foster holistic and data-driven farm management. The outcomes of this research can serve as a reference for farm managers, agricultural consultants, and policymakers aiming to enhance performance, competitiveness, and resilience in crop production systems through digital innovation.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the support of the Athenaeum University of Bucharest for facilitating access to research infrastructure and interdisciplinary collaboration. Special thanks are extended to the agricultural experts and farm managers who contributed data and practical insights for the development of the econometric model.

This research was carried out within an institutional effort to strengthen applied studies in precision agriculture and technological innovation.

REFERENCES

Ali, A., Ahmad, W., Munsif, F., Khan, A., Nepal, J., Wójcik-Gront, E., Ahmad, I., Khan, M.S., Ullah, I., Akbar, S., 2022. *Residual effect of finely-ground biochar inoculated with bio-fertilization impact on productivity in a lentil-maize cropping system*. Agronomy, 12(9): 2036. DOI: 10.3390/agronomy12092036

Bagheri, A., Taghvaeian, S., Delen, D., 2023. *A text analytics model for agricultural knowledge discovery and sustainable food production: A case study from Oklahoma Panhandle*. Decision Analytics Journal, 9: 100350. DOI: 10.1016/j.dajour.2023.100350

Dufour, L.J.P., Herrmann, A.M., Leloup, J., Przybylski, C., Foti, L., Abbadie, L., Nunan, N., 2022. *Potential energetic return on investment positively correlated with overall soil microbial activity*. Soil Biology and Biochemistry, 173: 108800. DOI: 10.1016/j.soilbio.2022.108800

Hussain, A., Shah, H., Iqbal, M.N., Sultan, T., 2023. *Economic viability of selected soil fertility and soil health improving technologies in Pakistan*. Pakistan Journal of Agricultural Research, 36(1): 89-99. DOI: 10.17582/journal.pjar/2023/36.1.89.99

Kaur, A., Singh, G., Singh, S., 2025. *AI-driven tools and technologies for agriculture land use & land cover classification using earth observation data analytics*. Google Earth Engine and Artificial Intelligence for Earth Observation: Algorithms and Sustainable Applications, Elsevier: 527-541. DOI: 10.1016/B978-0-443-27372-8.00024-6

Leiva Vilaplana, J.A., Yang, G., Ackom, E., 2025. *From investment to net benefits: A review of guidelines*

and methodologies for cost-benefit analysis in the electricity sector. Energy Research and Social Science, 124: 104052.
DOI: 10.1016/j.erss.2025.104052

McClenaghan, A., Gopsill, J., Ballantyne, R., Hicks, B., 2023. *Cost Benefit Analysis for Digital Twin Model Selection at the Time of Investment*. Procedia CIRP, 120: 1197-1202.
DOI: 10.1016/j.procir.2023.09.148

Ng'ang'a, S.K., Miller, V., Girvetz, E., 2021. *Is investment in Climate-Smart-agricultural practices the option for the future? Cost and benefit analysis evidence from Ghana*. Heliyon, 7: e06653.
DOI: 10.1016/j.heliyon.2021.e06653

Pham, X., and Stack, M., 2018. *How data analytics is transforming agriculture*. Business Horizons, 61(1): 125-133.
DOI: 10.1016/j.bushor.2017.09.011

Rodino, S., Buţu, M., Buţu, A., Lazăr, C., Ciornei, L., Simion, P.S., 2023. *Challenges of Digital Transformation in Agriculture from Romania*. Romanian Agricultural Research, 40: 713-721.
https://doi.org/10.59665/rar4066

Roukh, A., Nolack Fote, F., Mahmoudi, S.A., Mahmoudi, S., 2020. *Big data processing architecture for smart farming*. Procedia Computer Science, 177: 78-85.
DOI: 10.1016/j.procs.2020.10.014

Sridhar, B., Koul, M., Ahuja, N.J., Sharma, D., Pratap, V., 2023. *Advancements in UAV remote sensing for agricultural yield estimation: A systematic comprehensive review of platforms, sensors, and data analytics*. Computers and Electronics in Agriculture, 212: 108014.

Vaidya, M., and Katkar, S., 2022. *Exploring performance and predictive analytics of agriculture data*. AI, Edge and IoT-based Smart Agriculture: Intelligent Data-Centric Systems, Elsevier: 409-436.
DOI: 10.1016/B978-0-12-823694-9.00030-X

Wei, B., Zhang, D., Jeyakumar, P., Trakal, L., Wang, H., Sun, K., Wei, Y., Zhang, X., Ling, H., He, S., Wu, H., Huang, Z., Li, C., Wang, Z., 2024. *Iron-modified biochar effectively mitigates arsenic-cadmium pollution in paddy fields: A meta-analysis*. Journal of Hazardous Materials, 469: 133866.
DOI: 10.1016/j.jhazmat.2024.133866

Xiao, J., Zhang, J., Yuan, H., Xie, X., Gao, Y., Lu, Y., Liao, Y., Nie, J., 2024. *Long-term application of legume green manure improves rhizosphere soil bacterial stability and reduces bulk soil bacterial stability in rice*. European Journal of Soil Biology, 122: 103652.
DOI: 10.1016/j.ejsobi.2024.103652

Zhang, L., Feng, Y., Zhao, Z., Cui, Z., Baoyin, B., Wang, H., Li, Q., Cui, J., 2024. *Maize/soybean intercropping with nitrogen supply levels increases maize yield and nitrogen uptake by influencing the rhizosphere bacterial diversity of soil*. Frontiers in Plant Science, 15: 1437631.
DOI: 10.3389/fpls.2024.1437631

Žilka, M., Kalina, V., Lhota, J., 2025. *Tools to support managerial decision-making: Experiences from the pilot run of the training program for professionals in the manufacturing sector*. Procedia Computer Science, 253: 2306-2315.
DOI: 10.1016/j.procs.2025.01.291