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Economic Performance of Precision and Conventional Maize Production: Comparative Analysis Using Hungarian Farm-Level Data

Dávid Horváth [1,*], Levente Szabó [2], László Hadászi [2], Emese Szabó [2], Péter Riczu [2], András Nábrádi [1] and István Szűcs [1]

[1] Faculty of Economics and Business, Institute of Economics, University of Debrecen, 4032 Debrecen, Hungary
[2] KITE Zrt., 4181 Nádudvar, Hungary
* Correspondence: horvath.david@econ.unideb.hu

Abstract

This study evaluates the economic and agronomic performance of precision maize production under drought-stressed conditions using farm-level operational data from Hungary. A 2024 paired-field case study compared a conventionally managed field (46.65 ha) with a precision-managed field (67.61 ha) using variable-rate fertilization and seeding. Data collected via the John Deere Operations Center enabled 10 × 10 m spatial analysis. Results indicate that despite severe moisture limitations, the precision-managed field achieved a 3.85% higher mean yield (6.47 t ha^{-1}) than the conventional system (6.23 t ha^{-1}). The observed economic advantage was associated with a 5.58% reduction in total production costs through site-specific resource allocation. Consequently, net profit increased by 62.98%, rising from 168.95 USD ha^{-1} to 275.36 USD ha^{-1}. Spatial analysis demonstrated that precision management synchronized economic outputs with inherent site potential, with management zones accounting for 70.70% of profit variance, compared to 53.3% in the conventional field. Regression models confirmed a tighter alignment between NDVI (Normalized Difference Vegetation Index) and profitability in the precision system. These findings suggest that under spatial heterogeneity and climatic stress, precision agriculture enhances economic resilience by mitigating inefficient expenditures, providing a strategic buffer against input costs and climate volatility.

Keywords: precision agriculture; maize; variable rate application; economic performance; site-specific input application; drought stress

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1. Introduction

Precision agriculture (PA) is an approach that integrates smart technologies to enable site-specific, data-driven management of agricultural production. PA allows farmers to optimize field management, maximize the cost-benefit ratio and continuously or automatically monitor crop performance, while minimizing environmental impact [1]. In the European Union, this transition is particularly urgent, heavily incentivized by the Green Deal and the Common Agricultural Policy (CAP), which prioritizes reducing agricultural emissions and enhancing resource efficiency without compromising economic competitiveness [2]. Furthermore, systematic reviews confirm that precision technologies globally yield average input savings of 8–20% and yield increases of 2–6%, presenting a reliable pathway for sustainable intensification [3]. Over the past century, agricultural practices

have gradually evolved from manual labor-intensive farming through mechanization and early information-based precision agriculture, ultimately leading to the development of integrated, data-driven farm management systems [4]. PA, now integrated into Agriculture 4.0, leverages digital technologies to improve farm management. Modern tools—such as sensors, automated machinery, data analysis platforms, and artificial intelligence—allow farmers to make more precise decisions, optimize resource use, and monitor crop performance in real time. Although there is room to further develop systems that fully integrate diverse data streams and adapt to changing conditions, existing technologies already offer considerable advantages and practical solutions for sustainable and efficient farming [5]. The transition toward digital agriculture and site-specific crop management is recognized as a fundamental element of the Fourth Industrial Revolution, offering critical pathways to enhance technical efficiency and mitigate environmental impacts under increasingly volatile climatic conditions [6–8].

By collecting and analyzing large amounts of data from sensors, weather stations, and farm management systems, modern precision agriculture supports data-driven decisions instantly, enabling farmers to optimize resource use [9]. These systems—exemplified by platforms like John Deere's Operations Center (MyJohnDeere)—enable real-time data collection from farm machinery, spatial analysis via Geographic Information Systems (GIS) and site-specific application of inputs [10]. The initial step in variable rate application (VRA) is the delineation of management zones, which can be carried out using various approaches. These include leveraging farmer knowledge, analyzing the landscape's geomorphology, conducting traditional soil chemical analyses, classifying soils, examining historical yield maps, assessing crop coverage, or utilizing proximal soil sensors and integrating multiple data sources [11]. Soil mapping provides the essential basis for this variable rate management; however, the methodology has evolved significantly over time. While soil measurements based on grid sampling were initially the primary source of information, modern precision practices typically utilize zone-based management to better address intra-field heterogeneity. By delineating management zones based on soil properties and historical yield potential, these platforms support farmers in optimizing yield, reducing input waste and improving overall farm management efficiency [10]. A key feature of precision agriculture is its ability to apply inputs site-specifically, using variable rate fertilization to match crop and soil needs. This approach allows farmers to reduce the amount of fertilizer applied without compromising yield or quality, thereby enhancing profitability and lowering carbon emissions [12]. Overall, these site-specific management practices contribute to the broader benefits of precision agriculture, including higher crop yields, lower input costs, and reduced environmental impact through more efficient use of resources [13].

Cereal crops dominate arable land use in Hungary, with maize representing one of the most important field crops. In 2025, maize was cultivated on approximately 770,000 hectares, accounting for a substantial share of the country's 2.3 million hectares of sown cereal crops [14]. Given its large production area, maize plays a key role in Hungarian crop production systems and represents a major target crop for the application of advanced farm management technologies [14].

As the demand for higher maize productivity continues to rise alongside the need to limit additional pressure on soil and water resources, PA offers a practical route toward sustainable intensification by supporting more efficient, site-specific input management [15]. Precision agriculture can enhance productivity and input efficiency by applying seeds and fertilizers based on site-specific conditions. For example, a case study in Hungary demonstrated that variable rate fertilization and site-specific crop management improved maize yield while reducing input use in large-scale wheat production [16]. Similarly, a

comparative investigation on multiple crops (including maize) indicated that precision management can lead to higher profit margins than conventional methods, with increased yields, higher production value (gross revenue), and reduced costs [17].

On a broader scale, economic modeling has suggested that widespread adoption of precision farming could lead to significant socioeconomic benefits, including higher yields, increased farm revenue, reduced input costs, and improved resource-use efficiency, while also offering environmental benefits such as reduced fuel and pesticide use and improved soil productivity [18]. Recent research also highlights that the economic benefits of precision input management largely depend on the extent of within-field spatial variability. Fields exhibiting higher heterogeneity generally show a greater potential for profitable variable rate applications, as yield response to differentiated input levels becomes more pronounced. The modified Cambardella Index (CI), which is a normalized indicator used to quantify spatial variability in key soil properties [19], has been shown to correlate positively with profitability outcomes. In a recent analysis, adjusted contribution margins for variable rate application ranged from EUR 847 to EUR 6624 per hectare and these values were positively associated with CI, indicating that VRA is economically most advantageous in highly variable fields [20]. Moreover, recent findings indicate that uncertainties in soil information can substantially influence yield predictions and fertilizer recommendations, thereby affecting the expected economic performance of precision input management [21]. Additionally, sensor-based, field-scale variable rate application of granular nitrogen to maize has been shown to reduce N inputs by up to 34% without yield loss, increase nitrogen use efficiency by 21–30%, and improve returns over N cost, while also decreasing soil nitrate levels [22]. The economic rationale for adopting such site-specific technologies is rooted in the threshold model of adoption [23]. This framework posits that the transition to efficiency-enhancing technologies is driven by the interaction between input costs and spatial heterogeneity. Caswell and Zilberman [23] distinguish between applied and effective inputs, arguing that in fields with marginal land quality or high environmental variability, traditional uniform application leads to substantial inefficiencies. Therefore, the adoption of precision tools becomes economically superior when the marginal gains from improved input-use efficiency (particularly under high input prices or adverse soil conditions) offset the annualized fixed costs of the investment. This theoretical foundation aligns with the observation that the profitability of variable rate applications is fundamentally contingent upon the degree of within-field heterogeneity [20].

While the agronomic and environmental benefits of precision agriculture are widely recognized, the diffusion of technologies such as VRA is often constrained by high initial capital requirements and uncertainties regarding short-term profitability. Consequently, adoption dynamics are heavily influenced by specific farm and operator characteristics. As Canales et al. [24] highlighted, VRA uptake is markedly faster among younger generations of farmers who are more receptive to data-driven practices, as well as in large-scale operations that can leverage economies of scale to minimize per-unit implementation costs. However, technology adoption behavior is a complex decision-making process constrained by technological thresholds, where adequate economic accumulation is essential to mitigate the risk aversion associated with transitioning to intelligent systems [25]. Furthermore, the scalability of these practices is often hindered by technical and operational barriers, including data interoperability, connectivity ranges, and high initial setup costs [26]. These barriers underscore the need to evaluate PA not merely as a technological upgrade, but as an economic investment. For traditional and smaller-scale farms, empirical evidence of clear financial viability is critical to overcoming these investment barriers.

Despite the positive indications, there remains a need for detailed crop-specific analyses of the economic impacts of precision farming under local conditions. Maize production

using advanced precision tools has not been extensively documented in the Hungarian context. To address this gap, this study focuses on maize and utilizes data from the MyJohnDeere system to compare conventional and precision maize production. The primary objective is to evaluate the economic performance (yield, costs, profitability) of precision maize farming relative to traditional practices, using real farm data from 2024. The analysis was conducted on paired fields with similar soil and climate conditions to isolate the effect of the management system.

The primary objective of this study—embedded within the current economic and social environment—is to analytically explore the impact of the differences between conventional and precision-managed maize fields on income-generating capacity, efficiency, profitability, and ultimately on the overall economic result in Hungarian field crop production. To achieve the primary objective, this study addresses the following specific research questions: (1) What are the structural characteristics and compositions of physical inputs and production costs under both management systems? (2) How do output levels and production parameters compare? (3) How do economic outcomes and production efficiencies evolve in the short term within a single growing season? Finally, (4) how is profitability affected by changes in the economic environment, specifically through fluctuations in yields and input/output prices?

Based on the specific study conditions, the 2024 drought-stressed growing season in the region near Perkáta and the high within-field heterogeneity of the site—it is hypothesized that precision management will result in at least comparable yields to traditional practices. Furthermore, it is hypothesized that the site-specific optimization of inputs will lead to lower production costs, thereby increasing overall net profit per hectare even under adverse climatic conditions.

2. Materials and Methods

2.1. Theoretical Framework: The Value of Information

This study evaluates the economic efficiency of precision management through the Value of Information (VoI) framework. In agricultural production systems, VoI quantifies the marginal profit gain achieved when transitioning from uniform input application to decisions based on high-resolution spatial data (management zones). In this analysis, the VoI is empirically determined by calculating the net profit differential between the precision managed field and the conventionally managed field under the 2024 drought year. This approach assesses whether site-specific knowledge provided by the MyJohnDeere-integrated system (John Deere, Moline, IL, USA) effectively mitigates economic risks associated with environmental uncertainty [27].

2.2. Study Design and Site

The study was conducted on a commercial arable farm near Perkáta, in Central Transdanubia, in Hungary, during the 2024 growing season (Figure 1). The total operational size of the farm is 320.28 ha.

Two maize fields located within the same agroecological region were selected for comparison: a conventionally managed field (46.65 ha) and a precision managed field (67.61 ha). The fields share similar topography, soil type, climatic conditions, and both had comparable historical yield levels prior to the study year.

A paired-field case study design was applied, with each field representing a distinct management strategy. The primary difference between the two systems was the input application method: while the conventionally managed field received uniform, fixed rate inputs, the precision managed field utilized VRA for Diammonium phosphate (DAP, KITE Zrt., Nádudvar, Hungary), potash, Urea Ammonium Nitrate (UAN, KITE Zrt., Nádudvar,

Hungary), and sowing seed (KITE Zrt., Nádudvar, Hungary). This approach allows for a direct operational comparison under real farming conditions, while acknowledging the absence of experimental replication.

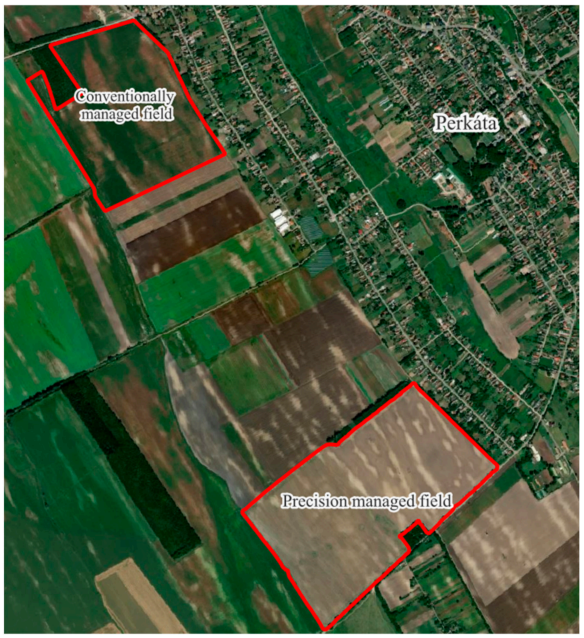


Figure 1. Geographical location of the experimental sites. Source: Own edit.

2.3. Climatic Conditions

Precipitation and temperature data for the 2024 growing season were recorded by our on-site automated meteorological station. In 2024, the total annual precipitation was 682.1 mm, exceeding the long-term average of 657.2 mm. However, the temporal distribution of rainfall was unfavorable for maize development. Despite the positive annual water balance, only 318.7 mm of precipitation was recorded during the growing season (1 March–31 August), representing a 32.9 mm deficit compared to the reference period. The water shortage was most pronounced during the most critical phenological stage, the flowering period in July, when the recorded 10.7 mm of rainfall fell 54.3 mm short of the long-term average. This water deficit was further exacerbated by a significant thermal surplus. The mean annual temperature (16.5 °C) was 5.1 °C higher than average, while the mean temperature in July exceeded the norm by 3.1 °C. The combination of low July precipitation and high temperatures induced atmospheric drought and heat stress, which fundamentally determined the final yields [28].

2.4. Soil Characteristics

Table 1 summarizes the soil analytical results for both experimental sites. Preseason soil sampling was conducted on both fields using standard Hungarian soil analysis methods. The fields were categorized based on the Hungarian Fertilization Guidelines and Farm Calculation Method [29]. The soil of both experimental fields is classified as loamy sand according to the Soil plasticity index (K_A), although the K_A values (30.86 for the precision managed field and 37.24 for the conventionally managed field) represent the opposite ends of the category's range. Both areas exhibit similar chemical properties: they are calcareous, mildly alkaline, and non-saline, which provides a stable baseline for comparing input efficiency. According to the fertilization guidelines, both fields are considered well-supplied with phosphorus (P_2O_5) and potassium (K_2O), and both exhibit a good humus status based on standardized soil analysis interpretation.

Table 1. Soil characteristics of the experimental maize fields under conventional and precision management.

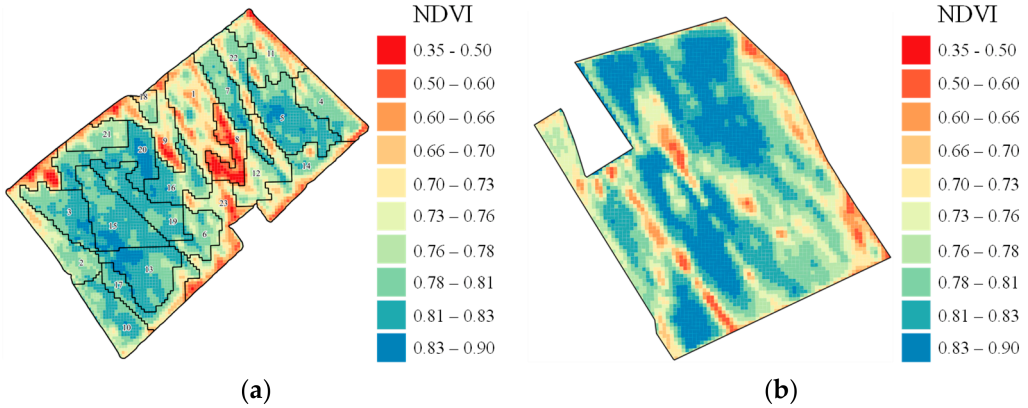
Parameters	Unit	Precision Managed Field	Conventionally Managed Field
Soil plasticity index (K_A)	-	30.86	37.24
Humus content	%	2.02	2.67
P_2O_5 (AL-soluble)	mg kg^{-1}	265.69	186.87
K_2O (AL-soluble)	mg kg^{-1}	175.30	180.18
$CaCO_3$	%	3.46	5.77
pH_{KCL}	-	7.60	7.54
Mg (AL-soluble)	mg kg^{-1}	167.13	61.25
Zn	mg kg^{-1}	1.48	0.94
Cu	mg kg^{-1}	2.88	1.46
Mn	mg kg^{-1}	108.43	61.25
Total soluble salts	%	0.02	0.03
Na (AL-soluble)	mg kg^{-1}	21.56	25.39

Source: Own edit based on soil analysis.

Noticeable differences were observed between the two fields regarding micronutrient status. While the conventionally managed field is only moderately supplied with magnesium and manganese, the precision-managed field is classified as well-supplied. Furthermore, the zinc status in the conventionally managed field is at the threshold between poor and good, whereas the precision-managed field is well-supplied. A similar trend is observed for copper, where the conventionally managed field exhibits a poor status, in contrast to the well-supplied status of the precision-managed area. These micronutrient variations highlight the importance of interpreting soil test results beyond basic fertility, as site-specific management is necessary to address these localized deficiencies.

2.5. Management Zones Delineation and Application Practices

Figure 2a shows the management zones (1–23) established within the precision-managed field, which were delineated using multi-year Normalized Difference Vegetation Index (NDVI) [30] values, together with laboratory soil analysis results. Figure 2b visualizes the multi-year NDVI values of the conventionally managed field.



(**a**) (**b**)

Figure 2. (**a**) Management zones (1–23) delineated by the integration of soil analysis results and multi-year NDVI values of the precision managed field. (**b**) Multi-year NDVI values of the conventionally managed field. Source: Own edit based on historical NDVI records and soil analysis.

The soil properties of these management zones, derived from the laboratory analysis of soil samples, are summarized in Table A1 of Appendix A.

The prescription maps were developed using historical yield data and the yield potential map derived from Sentinel-2 satellite imagery, combined with the agronomic expertise of the local precision agriculture service provider KITE Zrt. Other practices like crop protection were conducted similarly in both fields to maintain crop health, with the precision managed field receiving the same pesticide and herbicide products but applied uniformly (since site-specific pest pressure variation was not targeted in this study). The precision managed field was managed using site-specific variable rate technology enabled by the MyJohnDeere system and associated equipment (Figure 3).

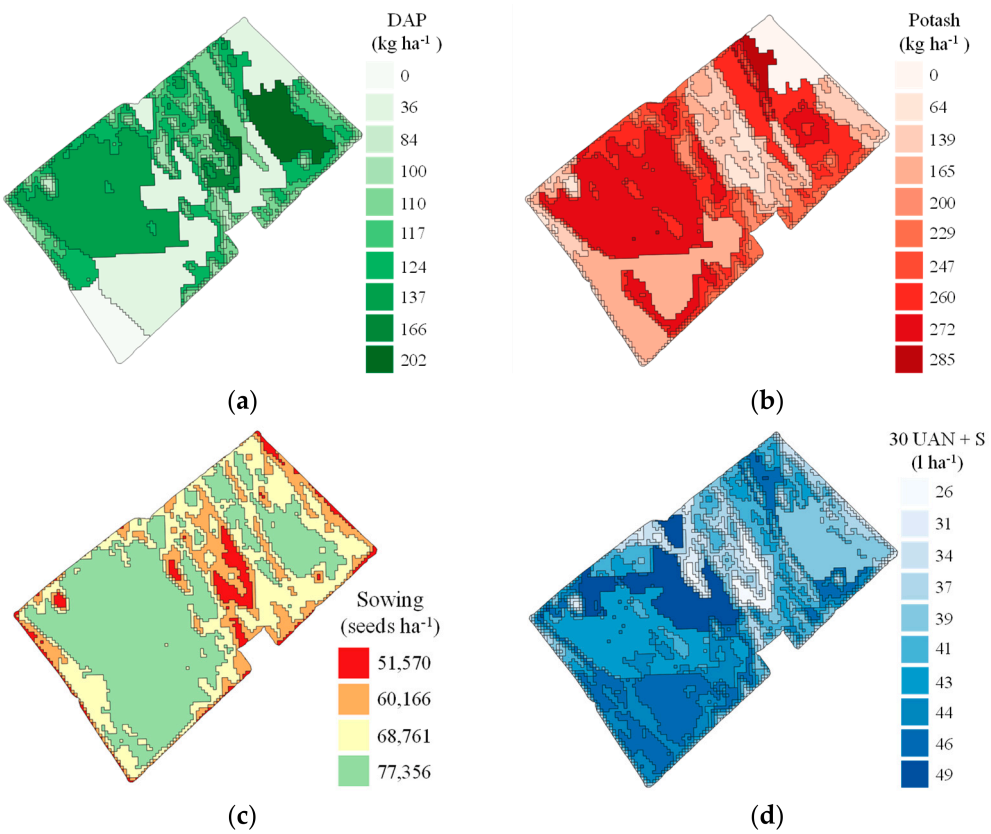


Figure 3. (**a**) VRA of DAP. (**b**) VRA of potash. (**c**) VRA of sowing seeds. (**d**) VRA of 30 UAN + S. Source: Own construction based on MyJohnDeere (2024) database using QGIS software.

At least one major field operation for each input category was implemented in a variable rate manner. Specifically, the nitrogen fertilization regimen included a variable dosed side-dressing: the third N application was differentiated by sub-field zones according to yield potential and soil nutrient supply. Similarly seeding density for maize was adjusted in different parts of the field (higher seeding rates in high-yield potential zones, lower in weaker areas) based on a seeding prescription map.

In contrast, the conventional maize field was managed with uniform prescription-based practices typical of the region. This included a single seeding rate across the entire field (72,000 sown seeds ha^{-1}), uniform basal fertilizer application (Base fertilization DAP: 105 kg ha^{-1} and Potash: 310 kg ha^{-1}; Side dressing: 30 UAN + S: 90 L ha^{-1}) and blanket treatments for crop protection (weed and pest control) as needed. Inputs were applied according to local best practices and the farm's standard agronomic recommendations, without spatial differentiation within the field.

Overall, the precision managed field differed from the conventional field primarily in nutrient management and planting density, which were tailored to intra-field variability, while other operations (tillage, planting timing, harvesting) were comparable (Table A2 of Appendix A). Delineating management zones effectively captures intra-field spatial variability—such as terrain attributes and localized yield potential—which strictly dictates the economic optimum of variable rate inputs compared to uniform applications [31,32].

2.6. Data Collection via MyJohnDeere

A key feature of this study is the utilization of the John Deere Operations Center (branded as MyJohnDeere) for data gathering and farm management. Both fields were equipped with modern John Deere machinery capable of recording detailed operational data. The precision managed field was managed using John Deere precision agriculture setup, including GPS-guided equipment and telematics. During field operations (planting, fertilizing, harvesting, etc.), data such as application rates, machine fuel consumption, and combine yield monitor readings were captured in real time and uploaded to the MyJohnDeere platform. This provided a high-resolution dataset: yields and inputs were documented with spatial coordinates, enabling analysis at a resolution of 10×10 m cells (100 m^2) across each field. Data integrity was ensured by performing cleaning and validation on the raw records—filtering out any erroneous spikes or overlaps in the GPS data that can occur due to signal loss or combine header overlap. The cleaned data layers—like yield—were processed using Quantum GIS (QGIS 3.44 QGIS.org, Grüt, Switzerland) software for spatial analysis. By spatially joining the multiple data layers, a comprehensive per-cell database of yield and input quantities was constructed. Yield, NDVI, and economic maps (gross revenue, net profit) were visualized in QGIS using graduated symbology (10 classes, Natural Breaks) and a Spectral color ramp. In contrast, prescription maps used categorized symbology with operation-specific color scales: 10 classes for fertilization and four classes for seeding rates.

2.7. Analytical Metrics

From the collected data, we derived key metrics for economic comparison at the whole field level. These included: Grain yield in tons per hectare (t ha^{-1}), input usage, and cost, broken down into major categories: seeds (quantity sown per hectare and cost), fertilizers (nutrient amounts per hectare and cost), crop protection chemicals (cost per hectare), and fuel for field operations. Additionally, other variable costs and overhead costs were sourced from the national database of the Research Institute of Agricultural Economics (AKI) [33]. Input costs were calculated using prevailing 2024 input prices and included both material costs and machinery operating costs. The conventional field's management provided baseline input levels, and the precision managed field input differences were quantified. In this study, only the direct fuel costs of field operations are presented. Fixed costs, such as land rental fees, were excluded, as no land rental costs were incurred. Depreciation was calculated based on AKI national benchmarks, adjusted specifically for the precision technology applied. To ensure accuracy, the depreciation values were weighted by the proportion of the precision-capable machinery (variable rate fertilizer spreaders, sowing machines, and cultivators) utilized in each field, thereby reflecting the capital intensity of the precision-specific technological interventions. In addition, we accounted for precision technology costs, which encompass recurring software license fees and specialized services such as grid-based soil sampling, nutrient management planning, planter diagnostics, fertilizer spreader pattern testing, and the generation of VRA application maps. Post-harvest expenses were excluded. Notably, no grain drying costs were incurred, as maize moisture content naturally dropped below 14.50% due to favorable local weather conditions.

Gross revenue per hectare was calculated as yield (t ha^{-1}) multiplied by the farm-gate price for maize grain. A uniform market price was used for both fields, since both produced the same commodity in the same season (any quality differences were negligible). For 2024, the regional average maize price (HUF t^{-1}) was applied based on local market data. Net profit per hectare was calculated as gross revenue minus total production cost per hectare.

All monetary values, including costs and revenues, were originally recorded in Hungarian Forints (HUF). However, to ensure international comparability, all financial data in this study are reported in United States Dollars (USD), converted using the 2024 average mid-market exchange rate of the Central Bank of Hungary (365.24 HUF USD^{-1}) [34]. Consequently, values are presented in USD per hectare (USD ha^{-1}).

To ensure the reliability of the economic analysis, the yield monitor data were cross-referenced and calibrated with certified weighbridge (scale house) records. This adjustment was necessary to compensate for the inherent lack of perfect on-board sensor calibration during field operations. While the spatial data was adjusted to align with the actual harvested quantities, it is important to note that this linear calibration preserves the integrity of the yield maps, as the relative spatial differences and intra-field variability ratios remain accurately documented. This approach ensures that the spatial statistics and the whole-field economic outcomes are consistent and representative of the actual production.

2.8. Spatial Statistical Analysis

For analyzing the data, we used IBM SPSS Statistics (31.0.1.0, IBM, Armonk, NY, USA) software. To characterize intra-field spatial variability and assess production stability, descriptive statistics were calculated for the cleaned yield maps of both fields. These metrics included mean, median, minimum, maximum, standard deviation, coefficient of variation (CV), first quartile (Q1), third quartile (Q3), and the interquartile range (IQR). The CV was specifically used as a normalized indicator of yield heterogeneity.

To delineate homogeneous management units from the high-density combine-mounted yield monitor data, we implemented a spatial clustering approach. We processed the raw sensor data in QGIS to remove noise and align GPS coordinates, then applied a k-means clustering algorithm to group 10 × 10 m cells based on yield potential and soil nutrient supply. We performed spatial smoothing to eliminate outliers caused by sensor signal loss or header overlap.

We compared the management systems using Welch-corrected independent samples *t*-tests to account for unequal variances between the conventional and precision managed fields. We analyzed production parameter differences across management zones using one-way analysis of variance (ANOVA). Relationships between soil nutrients, NDVI, and economic data were quantified using Pearson's correlation (r) and Spearman's rank correlation (ρ). All statistical tests were conducted at a significance level of $p < 0.05$.

2.9. Comparative Analysis

The analysis employs a comparative economic framework based on the Value of Information (VoI) theory to quantify the impact of site-specific management on profitability under environmental stress. This approach follows the premise that precision agriculture information increases in value when data collection, processing, and management actions are integrated [27]. Percent changes from conventional to precision management were calculated for each metric to standardize comparisons. High-resolution data enabled the creation of spatial maps of yield, input distribution, and profit across each field. These maps were analyzed qualitatively to assess how precision management may have influenced spatial variability, for example, whether low-yield zones were mitigated or whether input

reductions corresponded to specific areas. Furthermore, this mapping demonstrates the practical utility of MyJohnDeere data for farm management insights.

In summary, our methodology relies on direct field comparisons using real operational data. By leveraging the MyJohnDeere system, we ensured precise measurement of inputs and outputs, providing a solid foundation for economic analysis. The next section presents the results of this comparison, focusing on maize, with references to similar findings in other crops for context.

2.10. Sensitivity Analysis

Since the empirical analysis was based on a single-year case study, a scenario-based sensitivity analysis was conducted to estimate the variation in economic outcomes under simulated market and climatic conditions. The baseline scenario utilized the actual 2024 production data. To model market price fluctuations, grain prices, and input costs were adjusted by $\pm 10\%$, holding other variables constant [33]. Yields were also adjusted to simulate climate variability. A +35% yield increase was modeled to reflect the regional average (8.60 t ha^{-1}) of the preceding, non-drought year (2023), contrasting with the severe moisture limitations observed in 2024. Conversely, a -15% yield reduction was applied to simulate extreme drought, corresponding to the 2024 regional average (5.58 t ha^{-1}) [35]. A hypothetical "same yield" scenario (6.35 t ha^{-1} for both systems) was also calculated to isolate the economic effect of the input cost differences.

2.11. Investment Evaluation

This study evaluates the incremental investment requirements associated with transitioning to full-scale precision management. The baseline assumption presumes that the tractor fleet is already equipped with basic GPS guidance and auto-steering systems, as these technologies were established as a standard foundation within the observed experimental farm. In the broader national context, these technologies represent the most prevalent precision tools utilized in Hungarian agriculture, where approximately one-third of farmers employ auto-steering systems, and GPS adoption reaches 35% [36]. This rate exhibits a marked increase among younger demographics, with nearly half (48%) of farmers under the age of 40 utilizing GPS technology in their daily operations [37].

The incremental investment cost was quantified by comparing the market prices of conventional machinery with their precision-ready counterparts (specifically fertilizer spreaders, seeders, and cultivators equipped for site-specific liquid application), all equivalent working width. The investment increment was defined as the price differential between the two technological levels. This analysis deliberately excludes the total capital expenditure of the entire machinery fleet, focusing exclusively on the incremental costs necessary to enable precision operations, thereby providing a targeted assessment of economic efficiency. Software-related expenses are classified as annual operating costs rather than capital investments, as these typically involve recurring license or subscription fees that require periodic renewal; consequently, as previously noted, these are accounted for within the operational framework under the precision technology costs.

Given that the payback period for these technologies is highly sensitive to farm size, a scenario analysis was conducted across a range of 20 to 400 hectares—anchored by the empirical farm size of 320 hectares—to demonstrate the impact of economies of scale on the temporal return on investment.

3. Results

3.1. Assessment of Soil Heterogeneity and Management Zone Validity

The spatial variability of the experimental fields was quantified using descriptive statistical indicators to assess the inherent potential for site-specific intervention. In the precision managed field, soil chemical analysis indicated substantial spatial variability across the investigated parameters. Phosphorus (P_2O_5) levels ranged from 146.00 to 700.00 mg kg^{-1} (SD = 122.71 mg kg^{-1}; CV = 45.63%), while potassium (K_2O) concentrations varied between 116.00 and 284.00 mg kg^{-1} (SD = 33.99 mg kg^{-1}; CV = 19.16%). Nitrate (NO_3) concentrations exhibited a range from 12.90 to 47.80 mg kg^{-1} (SD = 6.28 mg kg^{-1}; CV = 28.78%). Furthermore, NDVI demonstrated measurable heterogeneity, with values ranging from 0.393 to 0.850 (SD = 0.068; CV = 8.83%).

The conventionally managed field displayed similarly high levels of inherent variability. Phosphorus (P_2O_5) levels ranged from 78.6 to 445.0 mg kg^{-1} (SD = 82.82 mg kg^{-1}; CV = 43.11%), while potassium (K_2O) concentrations varied between 103.00 and 287.00 mg kg^{-1} (SD = 46.22 mg kg^{-1}; CV = 25.08%). Nitrate (NO_3) concentrations exhibited a range from 2.50 to 11.80 mg kg^{-1} (SD = 2.75 mg kg^{-1}; CV = 43.25%). The NDVI values in this field ranged from 0.359 to 0.901 (SD = 0.062; CV = 7.94%).

The measured coefficients of variation (CV) for soil nutrients and biomass indices indicate spatial heterogeneity within the study area. Statistical analysis (ANOVA) of the inter-zone variance confirmed that the established management zones represent distinct spatial units in terms of their pedological and yield potential characteristics ($p < 0.05$).

3.2. Spatial Yield Distribution Based on Yield Map

The yield data for the maize production were documented at high resolution by the on-board monitoring systems of the harvester. The spatial statistical analysis, derived from validated and calibrated yield maps, provides a comprehensive overview of intra-field variability and the impact of site-specific management (Figure 4a,b).

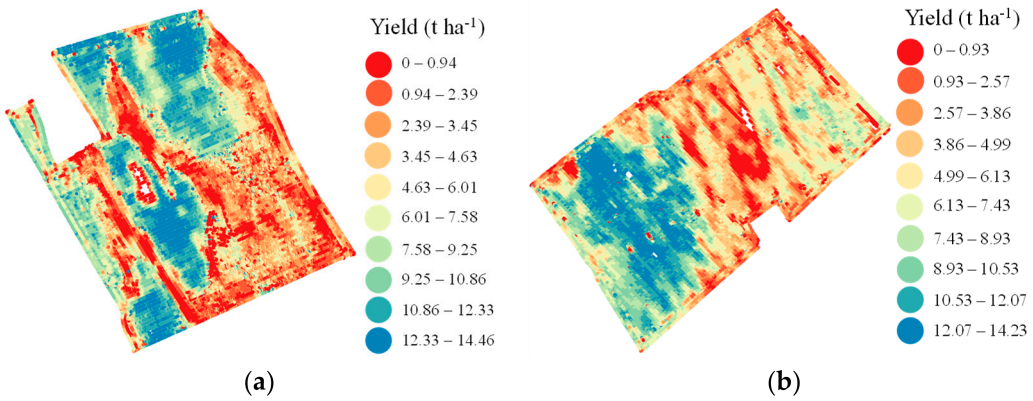


Figure 4. (**a**) Yield map of the conventionally managed field. (**b**) Yield map of the precision managed field. Source: Own construction based on MyJohnDeere (2024) database using QGIS software.

The spatial statistical analysis reveals significant performance differences between the two management systems (Table 2). Based on the statistical inference and econometric evaluation of the high-resolution dataset ($N_{(Precision\ managed\ field)} = 6530$, $N_{(Conventionally\ managed\ field)} = 4695$), the precision-managed field achieved a higher mean yield of 6.47 t ha^{-1} and a median of 5.88 t ha^{-1}, compared to 6.23 t ha^{-1} and 5.49 t ha^{-1} recorded for the conventional field.

Table 2. Descriptive statistical analysis of cleaned yield monitor data for conventional and precision-managed maize fields.

Statistical Metrics	Unit	Conventionally Managed Field	Precision Managed Field
Number of datapoints	points	4695	6530
Minimum	t ha^{-1}	0.00	0.00
Maximum	t ha^{-1}	14.46	14.23
Mean	t ha^{-1}	6.23	6.47
Median	t ha^{-1}	5.49	5.88
Standard deviation	t ha^{-1}	4.03	3.51
Standard error	t ha^{-1}	0.06	0.043
Coefficient of variation	%	64.65	54.24
First quartile	t ha^{-1}	2.76	3.90
Third quartile	t ha^{-1}	10.06	9.39
Interquartile range	t ha^{-1}	7.30	5.49

Source: Own construction based on field-level data using IBM SPSS Statistics software.

The impact of site-specific management is characterized by enhanced production stability and reduced intra-field heterogeneity. The coefficient of variation (CV) decreased significantly from 64.65% in the conventional field to 54.24% in the precision-managed field. This 10.41% reduction in variability observed in the precision managed field indicates a higher degree of crop stand homogeneity, suggesting that VRA mitigated spatial yield gaps. The analysis of quartiles further highlights the technology's impact on risk management.

The implementation of the precision system was associated with an increase in the lower yield threshold, as the first quartile (Q1) yield rose from 2.76 t ha^{-1} to 3.90 t ha^{-1}. This substantial improvement of over 1.14 t ha^{-1} in the lowest-performing areas suggests that site-specific input allocation optimized resources where they were most needed. While the third quartile (Q3) was higher in the conventional field (10.06 t ha^{-1} and 9.39 t ha^{-1}), the narrowing of the interquartile range (IQR) from 7.30 t ha^{-1} to 5.49 t ha^{-1} confirms that precision management prioritized operational resilience and resource-use efficiency over uncontrolled yield maximization in high-potential zones (Table 2).

The distribution of the yield dataset showed skewness values of 0.222 and 0.219, and kurtosis values of −1.290 and −0.900 for the conventionally managed field and precision managed field, respectively. These results indicate a symmetric distribution without extreme outliers, confirming the suitability of the data for parametric statistical testing.

The comparison of field-level mean yields showed that the precision farming system achieved a mean of 6.61 t ha^{-1}, which significantly exceeded the 6.23 t ha^{-1} mean of the conventionally managed field ($p = 4.49 \times 10^{-7}$). To interpret the variability within the high-resolution dataset, yield data were aggregated into NDVI-based productivity groups (clusters).

Clusters were generated for both fields based on mean NDVI values and georeferenced coordinates, resulting in ten relative productivity clusters (K0–K9) per field. Figure 5 illustrates the spatial distribution of these clusters.

The aggregated cluster data were evaluated using independent samples *t*-tests. The results indicate that yield differences between the systems are statistically significant for all clusters ($p < 0.05$). As shown in Figure 6, the precision managed field achieved higher mean yields in clusters K2, K3, K4, K6, K9, and K10, with the K6 cluster exhibiting the most substantial yield advantage of 4.02 t ha^{-1}. Conversely, the conventionally managed field

achieved higher yields in clusters K1, K5, K7, and K8. In the lower productivity clusters (K2–K4), the precision system consistently maintained higher mean yield levels, effectively mitigating the lower yield potential observed in the conventional field.

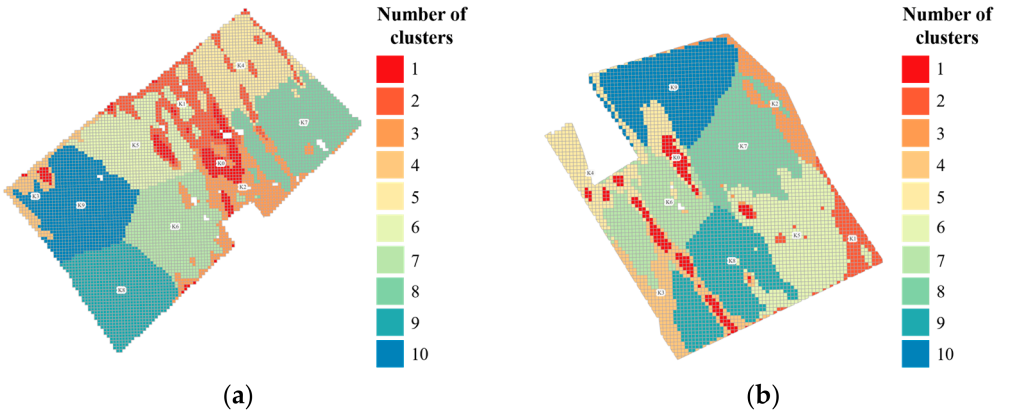


Figure 5. Spatial distribution of the 10 identified clusters across the two management fields. Source: own edit.

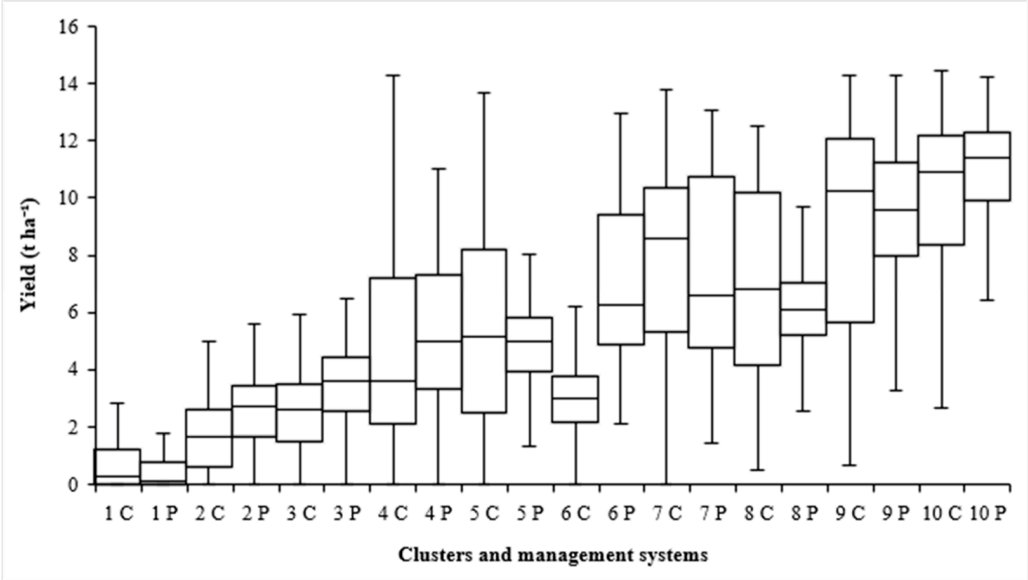
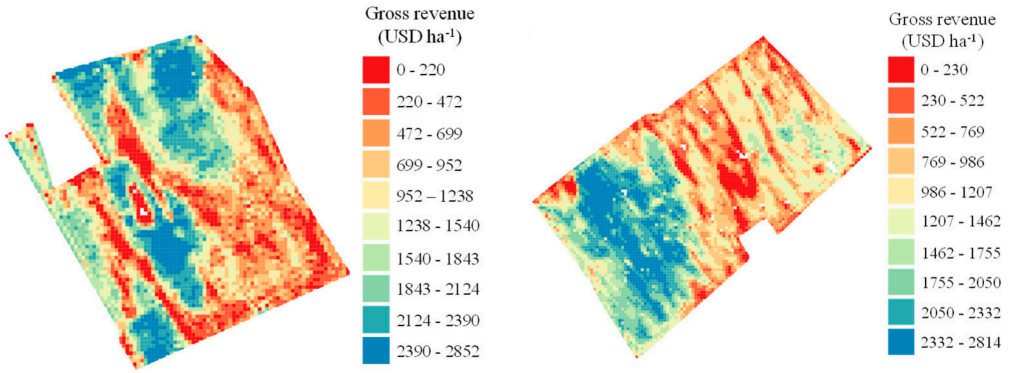


Figure 6. Yield distribution across identified clusters by management system. The X-axis displays the cluster ID (1–10) paired with the management system, where 'C' denotes the conventionally managed field and 'P' denotes the precision managed field. Source: Own edit.

3.3. Gross Revenue

Gross revenue was calculated using a uniform maize grain price of 197.13 USD t^{-1} for both management systems. The precision managed field yielded a gross revenue of 1275.44 USD ha^{-1}, representing a 3.85% increase compared to the 1228.12 USD ha^{-1} recorded for the conventionally managed field (Figure 7a,b).

While the increase in gross revenue contributes to overall performance, the primary economic impact of precision management is derived from the optimization of input allocation. Since conventional management operated with a fixed cost structure, it could not adapt to spatial variability. In contrast, site-specific application allowed for optimized resource allocation. This approach resulted not only in a verified yield surplus but also in a significant reduction in unit production costs, which will be detailed in the following section regarding input savings.



(**a**) (**b**)

Figure 7. (**a**) Gross revenue map of the conventionally managed field. (**b**) Gross revenue map of the precision managed field. Source: Own construction based on MyJohnDeere (2024) database using QGIS software.

3.4. Total Production Cost Structure

The total production cost for the precision-managed field was 1000.08 USD ha^{-1}, while the conventionally managed field incurred a cost of 1059.17 USD ha^{-1}.

The cost breakdown for the two management systems is presented in Table 3. Input costs were 553.01 USD ha^{-1} for the precision-managed field and 663.73 USD ha^{-1} for the conventional field. Machinery operating costs were 94.87 USD ha^{-1} and 114.36 USD ha^{-1}, respectively. Depreciation, calculated based on AKI national benchmarks and adjusted for machine-specific capital intensity, amounted to 131.18 USD ha^{-1} for the precision-managed field and 114.82 USD ha^{-1} for the conventional field. Other variable costs and overhead costs remained constant at 69.99 USD ha^{-1} and 96.27 USD ha^{-1}, respectively, for both systems. The precision-managed field incurred an additional 54.76 USD ha^{-1} in precision technology costs (Table 3).

Table 3. Comparison of production, input cost, and machinery cost between conventionally managed field and precision managed field.

	Conventionally Managed Field (USD ha^{-1})	**Precision Managed Field (USD ha^{-1})**
Total production cost	1059.2	1000.1
Input cost	663.7	553.0
Machinery cost	114.4	94.9
Depreciation	114.8	131.2
Other variable costs	70.0	70.0
Overhead costs	96.3	96.3
Precision technology costs	0	54.8

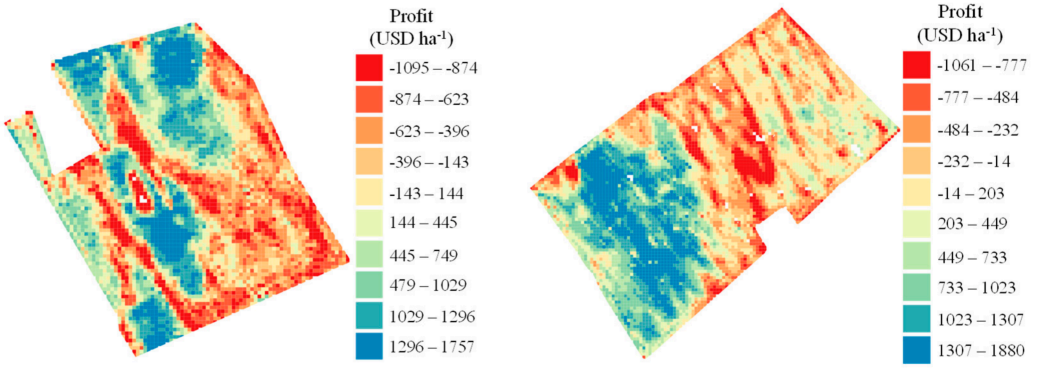
Source: Own calculation based on primary farm-level data and AKI national benchmarks.

3.5. Net Profit per Hectare

The convergence of higher yields and lower production costs resulted in increased profitability for the precision managed field. Net profit reached 275.36 USD ha^{-1} under precision management, which is 62.98% (106.41 USD ha^{-1}) higher compared to the conventionally managed field (168.95 USD ha^{-1}).

In a year characterized by drought-induced yield limitations, this difference is particularly notable. It demonstrates that precision management primarily enhanced profitability

by strategically reducing inefficient expenditures, while simultaneously maintaining—and even slightly increasing—overall yield levels. The spatial distribution of profitability (Figure 8a,b) indicates a reduction in economically unviable zones within the precision managed field. This pattern suggests that precision management mitigates financial risk by aligning input expenditure with site-specific productivity, particularly under drought-stressed conditions.



(**a**) (**b**)

Figure 8. (**a**) Profitability map of the conventionally managed field. (**b**) Profitability map of the precision managed field. Source: Own construction based on MyJohnDeere (2024) database using QGIS software.

While the spatial maps provide a high-resolution visualization of within-field heterogeneity and the resulting site-specific performance, an aggregated field-level synthesis is indispensable for a clear evaluation of the technological impact. Figure 9 provides an integrated synthesis of the economic shifts between the two management systems, quantifying the aggregate impact of VRA on field-level profitability.

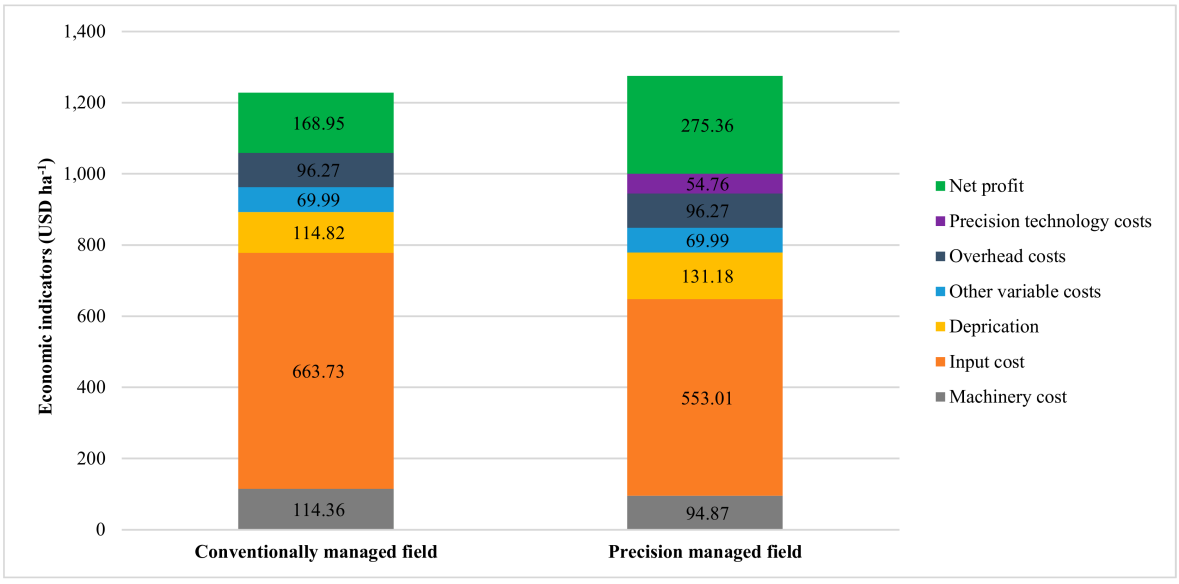


Figure 9. Comparison of key economic performance indicators between conventionally managed field and precision managed field. The chart illustrates the decomposition of gross revenue, highlighting the impact of input costs and machinery expenditures on the net profit. Source: Own edit.

3.6. Investment Payback Analysis

This study evaluates the incremental investment requirements for adopting precision management. The baseline assumption is that the tractor fleet is already equipped with GPS guidance and auto-steering systems.

The incremental investment cost was determined by comparing the market prices of conventional machinery with their precision-capable counterparts of equivalent work capacity. The analysis covers three primary implement categories: fertilizer spreaders, sowing machines, and cultivators equipped for liquid application. The investment increment is defined as the difference between the capital expenditure for the precision-enabled units and the conventional baseline models, as summarized in Table 4.

Table 4. Incremental investment costs for precision technology.

	Conventional Machinery	Precision Machinery	Difference
	(USD)	(USD)	(USD)
Fertilizer spreader	7392.4	21,903.4	14,511.0
Sowing machine	37,509.6	45,997.2	8487.6
Cultivators equipped for liquid application	8213.8	21,903.4	13,689.6
Total investment costs	53,115.8	89,804.0	36,688.2

Source: Own calculation based on 2024 Hungarian market prices converted to USD.

Figure 10 displays the non-linear decrease in the payback period as farm size increases, demonstrating the significant impact of economies of scale. Based on the simulated scenarios, the payback period is over 17 years at the 20-hectare level, decreasing to 6.9 years at 50 hectares, 3.4 years at 100 hectares, 1.7 years at 200 hectares, 1.2 years at 300 hectares, and 0.9 years at 400 hectares.

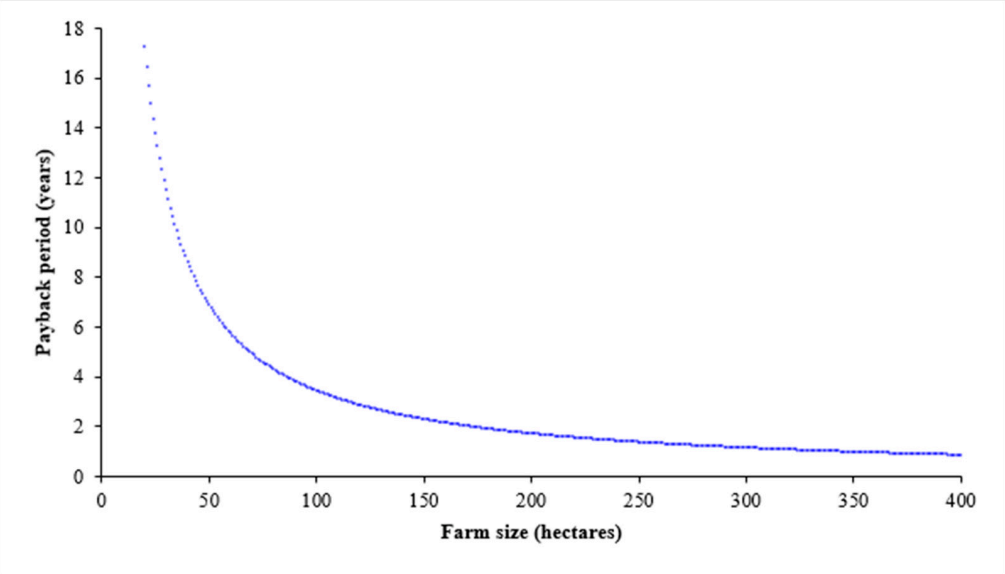


Figure 10. Relationship between farm size and the payback period of precision technology investment. Source: Own edit.

3.7. Quantitative Evaluation of Field Heterogeneity and Vra Statistical Validation

The necessity of the site-specific approach in the precision managed field was evaluated through a one-way analysis of variance (ANOVA) and Welch's robust test of equality of means. Statistical analysis confirmed that the predefined management zones exhibited significant spatial heterogeneity ($p < 0.05$) in terms of NDVI within both the precision managed field and the conventionally managed field.

Analysis of the conventionally managed field indicated that a uniform input structure was maintained despite the statistically significant variance in productivity potential across

zones. For this field, the ANOVA for input cost yielded an F-value of 0.000 ($p = 1.000$) with an effect size (η^2 = eta-squared) of 0.000, confirming that input rates remained homogeneous across all productivity zones. This absence of technological adaptation was associated with significant fluctuations ($p < 0.05$) in net profit, increasing economic risk in low-productivity areas.

Conversely, the precision managed field was characterized by resource allocation tailored to intra-field variability. The Welch test revealed significant variance in input costs across management zones (Welch statistics = 1433.48, $p < 0.05$), supported by a large effect size ($\eta^2 = 0.809$). This statistical output indicates that VRA dynamically reallocated resources based on zone-specific requirements, providing an agronomic and economic rationale for precision intervention.

3.8. Correlation Analysis of Nutrient Supply, NDVI, and Input Allocation

The alignment between environmental heterogeneity and management intervention was evaluated through Pearson correlation analysis. This step validates whether the VRA successfully translated spatial soil and biomass data into site-specific resource allocation.

In the precision managed field, a highly negative correlation was identified between soil P_2O_5 content and the cost of phosphorus fertilizer ($r = -0.643$, $p < 0.05$). This indicates a systematic reduction of inputs in nutrient-rich zones and higher investment in deficient areas. The linear regression analysis (Figure 11) confirmed that soil phosphorus levels accounted for approximately 41.4% of the variance in fertilizer expenditure ($R^2 = 0.414$).

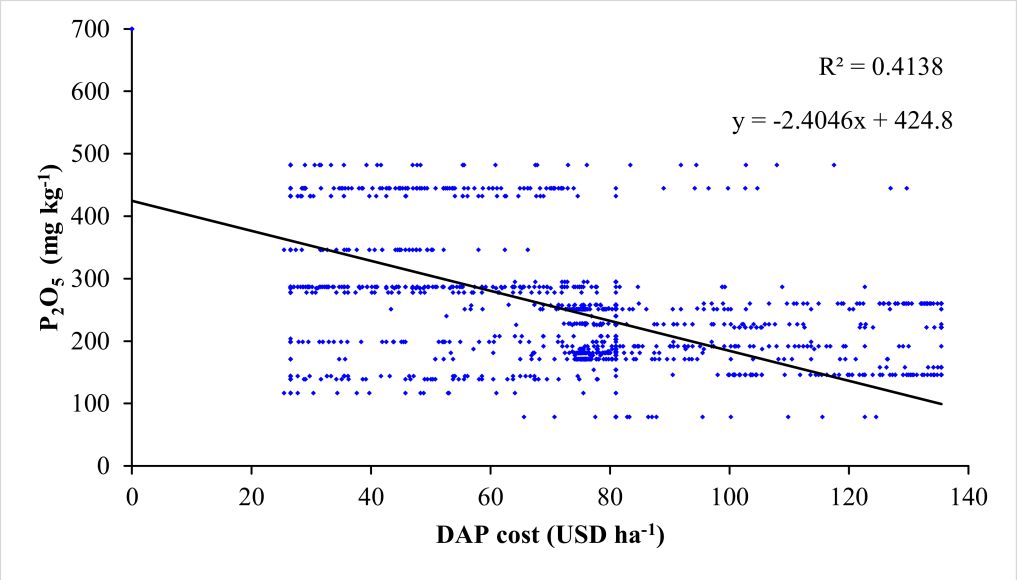


Figure 11. Linear regression analysis between soil P_2O_5 content and the cost of DAP fertilizer in precision managed field. Source: Own construction based on field-level data using IBM SPSS Statistics software.

Conversely, in the conventionally managed field, the correlation was non-computable ($r = 0$) due to the zero variance in application rates, reflecting a lack of adaptation to soil phosphorus variability.

A similar significant negative relationship was confirmed for potassium. In the precision managed field, the correlation between soil K_2O and potash costs reached $r = -0.553$ ($p < 0.05$), with the regression model explaining 30.6% of the cost distribution ($R^2 = 0.306$) (Figure 12). In the conventionally managed field, the application cost remained constant across all zones regardless of soil potassium status, resulting in no statistical relationship between soil supply and input expenditure.

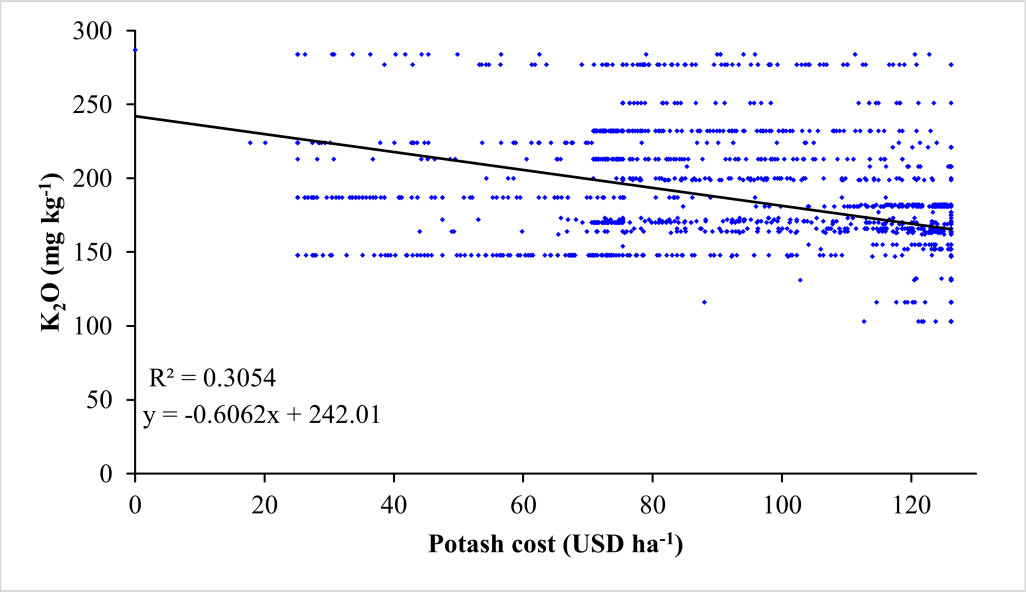


Figure 12. Linear regression analysis between soil K_2O content and the cost of potash fertilizer in precision managed field. Source: Own construction based on field-level data using IBM SPSS Statistics software.

The adjustment of plant density followed a positive logic. In the precision managed field, seeding costs showed a significant positive correlation with NDVI (r = 0.531, $p < 0.05$), with an R^2 value of 0.282 (Figure 13). This confirms that investment in seeds was strategically increased in high-biomass potential zones. In the conventionally managed field, the seeding cost was uniform across the entire area, showing no response to the verified spatial heterogeneity in crop vigor evidenced by the NDVI maps.

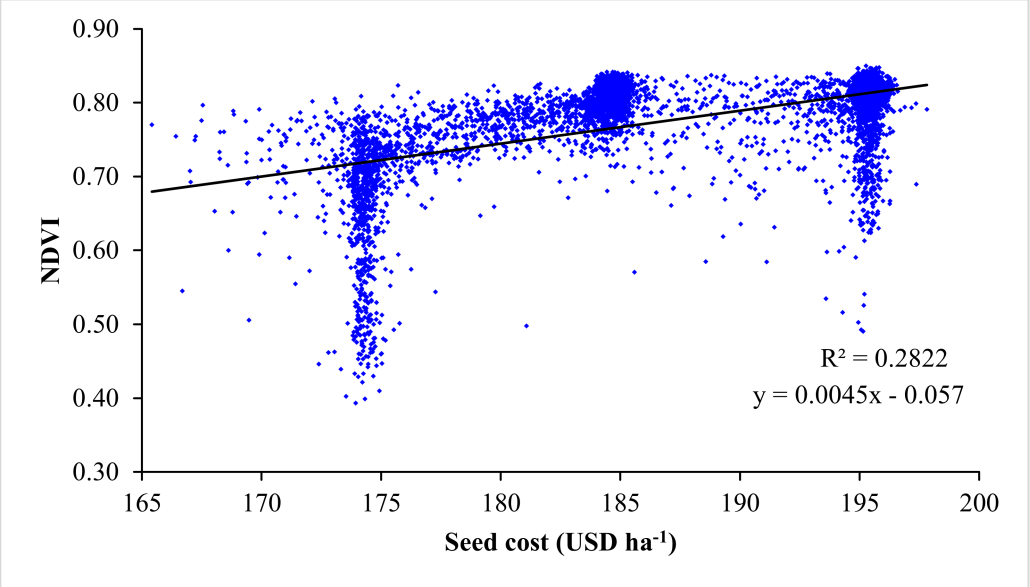


Figure 13. Linear regression analysis between soil NDVI and the cost of sowing seed in precision managed field. Source: Own construction based on field-level data using IBM SPSS Statistics software.

The statistical divergence between the two systems confirms that while the conventionally managed field operated with a fixed cost structure decoupled from field needs, the precision managed field internalized spatial information. The correlation coefficients in the precision system provide empirical evidence that the technological transition from uniform

to site-specific management effectively transformed input allocation into a function of measured environmental variables.

3.9. Spatial Heterogeneity and Its Economic Implications

The relationship between spatial heterogeneity, NDVI, and economic performance was evaluated separately for both management systems to quantify the alignment between biological potential and financial outcomes.

In the conventionally managed field, the management zones accounted for 53.3% of the net profit variance (η^2= 0.533). Correlation analysis indicated a Pearson coefficient of r = 0.686 ($p < 0.05$) between NDVI and net profit, supported by a Spearman's (rho = ρ) rank correlation of ρ = 0.792 ($p < 0.05$). Linear regression analysis confirmed a coefficient of determination of R^2 = 0.471 ($p < 0.05$) (Figure 14a). These results suggest that under uniform management, a significant portion of the economic variance remains independent of the field's measured productivity potential.

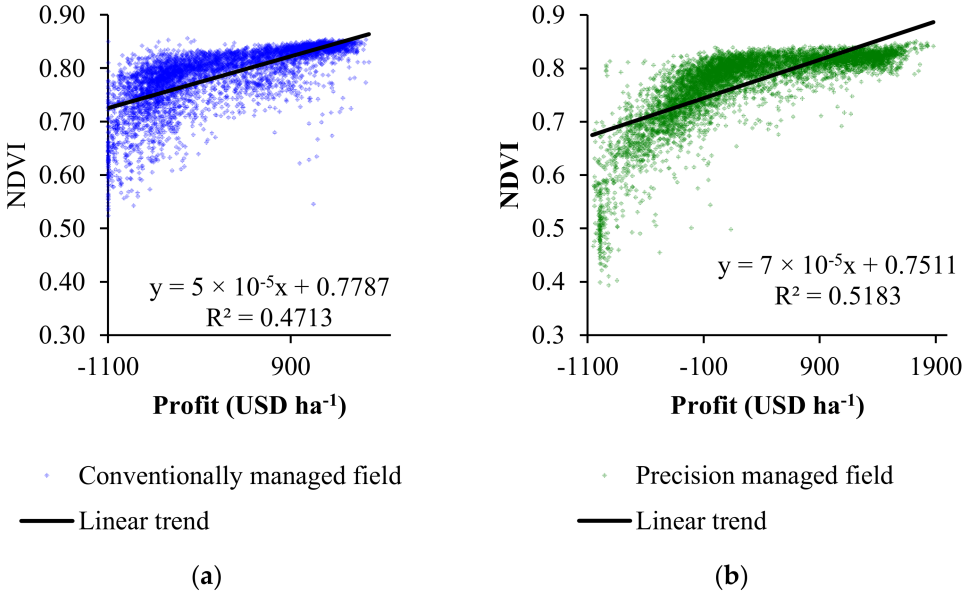


Figure 14. (**a**) Linear regression analysis between NDVI and profit in conventionally managed field. (**b**) Linear regression analysis between NDVI and profit in precision managed field. Source: Own construction based on field-level data using IBM SPSS Statistics software.

In the precision managed field, the proportion of net profit variance accounted for by the management zones was significantly higher, reaching 70.70% (η^2 = 0.707). The synchronization between NDVI and net profit was higher, with a Pearson correlation coefficient of r = 0.719 ($p < 0.05$) and a Spearman's ρ of 0.830 ($p < 0.05$). The linear regression model (Figure 14b) showed a higher coefficient of determination (R^2 = 0.518, $p < 0.05$) compared to the conventional system.

The direct impact of site-specific management on profitability is evidenced by the correlation between management zones and net profit, which was nearly twice as high in the precision managed field (r = 0.189, $p < 0.05$) as in the conventionally managed field (r = 0.096, $p < 0.05$). This disparity indicates that the precision framework successfully transformed intra-field variability into a structured management factor, optimizing the economic response to biomass heterogeneity and reducing the impact of stochastic financial risk.

3.10. Sensitivity of Economic Performance to Climate and Market Volatility

Table 5 presents the calculated net profit outcomes under the simulated market and climatic scenarios. The baseline analysis, using a grain price of 197.13 USD t^{-1} and yields of 6.23 t ha^{-1} and 6.47 t ha^{-1} for the conventionally managed field and the precision managed field, respectively, resulted in a net profit of 168.95 USD ha^{-1} for the conventionally managed field and 275.35 USD ha^{-1} for the precision managed field.

Table 5. Sensitivity of economic performance indicators under simulated market and climatic scenarios.

Simulated Scenario	System	Grain Price	Yield	Gross Revenue	Input Cost	Other Costs	Net Profit	Relative Profit Difference
		USD t^{-1}	t ha^{-1}	USD ha^{-1}	USD ha^{-1}	USD ha^{-1}	USD ha^{-1}	%
Baseline	C	197.13	6.23	1228.12	663.73	395.44	168.95	63%
	P	197.13	6.47	1275.43	553.01	447.07	275.35	
Grain price +10%	C	216.84	6.23	1350.93	663.73	395.44	291.76	38%
	P	216.84	6.47	1402.97	553.01	447.07	402.89	
Grain price −10%	C	177.42	6.23	1105.31	663.73	395.44	46.14	220%
	P	177.42	6.47	1147.89	553.01	447.07	147.81	
Same yield	C	197.13	6.35	1251.78	663.73	395.44	192.60	31%
	P	197.13	6.35	1251.78	553.01	447.07	251.70	
Yield +35%	C	197.13	8.41	1657.96	663.73	395.44	598.79	21%
	P	197.13	8.73	1721.83	553.01	447.07	721.75	
Yield −15%	C	197.13	5.30	1043.90	663.73	395.44	−15.27	-
	P	197.13	5.50	1084.12	553.01	447.07	84.04	
Input cost +10%	C	197.13	6.23	1228.12	730.10	395.44	102.58	115%
	P	197.13	6.47	1275.43	608.31	447.07	220.05	
Input cost −10%	C	197.13	6.23	1228.12	597.36	395.44	235.32	41%
	P	197.13	6.47	1275.43	497.71	447.07	330.65	

Note: In the System column, C denotes the conventionally managed field, and P denotes the precision managed field. Other costs include depreciation, machinery cost, other variable costs, overhead costs, precision technology costs (in the case of precision managed field). Source: Own calculation based on simulated scenarios and primary farm-level data.

In the grain price sensitivity scenarios, a 10% price increase raised the net profit to 291.76 USD ha^{-1} (conventionally managed field) and 402.89 USD ha^{-1} (precision managed field), while a 10% price decrease resulted in profits of 46.14 USD ha^{-1} and 147.81 USD ha^{-1}, respectively.

Under the yield variation scenarios, the comparative performance remained consistent: in the yield +35% scenario (8.41 t ha^{-1} for the conventionally managed field and 8.73 t ha^{-1} for the precision managed field), the precision managed field reached a net profit of 721.75 USD ha^{-1}, whereas the conventionally managed field achieved 598.79 USD ha^{-1}. Conversely, in the severe drought scenario (yield −15%), the conventionally managed field generated a financial loss, dropping to −15.27 USD ha^{-1}, while the precision managed field maintained a positive net profit of 84.04 USD ha^{-1}. Although the relative profit difference is not expressed in percentages for this scenario (as calculating a proportional ratio against a negative base value is mathematically uninterpretable) the absolute economic advantage of site-specific management is highly evident. Under the hypothetical "same yield" scenario (6.35 t ha^{-1} for both fields), the precision managed field achieved a net profit of 251.70 USD ha^{-1}, compared to 192.60 USD ha^{-1} for the conventionally managed field.

In the input cost sensitivity scenarios, a 10% increase reduced the net profit of the conventionally managed field to 102.58 USD ha^{-1} and the precision managed field to 220.05 USD ha^{-1}, while a 10% decrease in input costs improved net profits to 235.32 USD ha^{-1} and 330.65 USD ha^{-1}, respectively.

4. Discussion

The results demonstrate that precision maize production provides substantial economic advantages under Hungarian agroecological conditions, even when yield improvements remain moderate. In this case study, precision management increased grain yield by 3.85% and achieved a 16.68% savings in input materials, while reducing total production costs by 5.58%, resulting in a 62.98% higher net profit per hectare. These empirical outcomes align exceptionally well with recent systematic reviews, which report that precision technologies typically yield average input savings of 8–20% and yield improvements of 2–6% across European crop production [3]. Furthermore, our results strongly parallel the findings of Zhou et al. [38], who documented a 16.4% reduction in nitrogen fertilizer usage and an 8.37% yield increase in summer maize using variable-rate fertilization based on proximal sensing. This confirms that the primary economic driver of precision agriculture in maize is not yield maximization alone, but the multi-objective optimization of resource allocation [39].

The economic sustainability of maize is fundamentally dictated by the dynamic interplay between agroecological conditions, management intensity, and market volatility. Within this theoretical framework, Nagy [40] asserts that the income-generating capacity of maize is not merely a function of absolute yield levels, but rather the result of strategic adaptation to input–output price fluctuations and the mitigation of climate-induced stressors. This dynamic is supported by the bibliometric analysis of Ocwa et al. [41], who concluded that under increasing climatic volatility, relying solely on conventional fertilizer intensification is inadequate; sustainable production requires advanced interventions that improve nutrient use efficiency. Our empirical evidence substantiates these assertions. While precision management achieved only a moderate yield increase, the 62.98% surge in net profit demonstrates that site-specific input allocation optimized the cost-benefit ratio—an outcome that uniform practices failed to deliver. This aligns with DeLay et al. [6], who demonstrated that the primary economic advantage of precision technologies stems from maximizing technical efficiency and reducing input waste rather than shifting the absolute yield frontier. This is further validated by Oppong et al. [42], who demonstrated that variable-rate nitrogen management can sustain yields while substantially improving nitrogen use efficiency and reducing fertilizer costs, reinforcing the value of avoiding excessive, uniform fertilization.

The identified coefficients of variation (CV) for soil nutrients and biomass indices establish the empirical rationale for site-specific management. These spatial differences reflect an inherent heterogeneity that precision agriculture aims to address, as uniform input application fails to align with intra-field productivity patterns. Consequently, the high inter-zone variance confirms that the established management zones represent distinct pedological and yield potential units. These findings are consistent with the spatial variability classification established by Cambardella et al. [19], which categorizes soil parameters with a CV > 35% as highly heterogeneous. In both experimental fields, several parameters (most notably P_2O_5) exceeded this threshold, exhibiting high spatial variability (CV = 45.63% in the precision field and 43.11% in the conventional field). This high degree of heterogeneity provides a strong empirical rationale for abandoning uniform application in favor of site-specific management. Furthermore, our results corroborate the assertions of Zhao et al. [20], who emphasized that the economic potential for variable rate applications

is directly proportional to the coefficient of variation, as increased heterogeneity provides greater opportunities for profitable redistribution input.

In alignment with international research, our results confirm that the primary advantage of VRA lies in resource optimization. Evangelou et al. [22] demonstrated that nitrogen usage could be reduced by 24% without yield losses. Our findings reinforce this: the precision system achieved a 5.58% reduction in total costs and a 16.68% reduction in direct input costs. While Evangelou et al. [22] reported an improvement in Nitrogen Use Efficiency (NUE) of 21–30%, our study observed a 19.77% decrease in input costs per ton of output. This observation aligns with Pedersen and Lind [10], who highlighted that efficient resource utilization is central to maximizing productivity and sustainability in precision farming.

This mechanism supports the theoretical framework of Gebbers and Adamchuk [43], who argue that the most rational economic decision when faced with insurmountable yield-limiting factors—like inadequate water-holding capacity—is to curtail input rates to avoid financial waste. Recent empirical evidence from Arnó et al. [44] strongly supports this approach; their drought-year case study demonstrated that site-specific marginal return analysis justified localized input reductions, or even zero-fertilization, avoiding unproductive financial expenditures in zones where severe water stress constrained crop response. Ultimately, our spatial profitability analysis corroborates DeLay et al. [6], establishing that precision technologies generate value primarily by reducing inefficiency variance. As Pawase and Walunj [45] highlight, constant-rate fertilization frequently results in the over-incorporation of nutrients in zones where environmental variations limit crop response. Our 2024 results confirm this gap; while the conventional approach generated economic losses in moisture-limited areas, VRA allowed for a precise alignment of costs with spatial profitability.

The results of the sensitivity analysis provide empirical extension to these theoretical frameworks. Under the simulated extreme drought scenario (−15% yield), the calculated profit difference expanded to 99.31 USD ha^{-1} in favor of the precision system. This aligns with the observations of Lee et al. [46] and Gebbers and Adamchuk [43], confirming that site-specific input reduction limits financial exposure when environmental constraints restrict crop development. Furthermore, the same yield scenario, which indicated a 13% profit difference without any yield surplus, mathematically isolates the effect of technical efficiency. This supports DeLay et al. [6], demonstrating that precision agriculture affects profitability primarily through input optimization rather than yield maximization alone. Additionally, the simulated 10% increase in input costs widened the relative profit advantage to 23%, indicating that variable rate application functions as a quantifiable economic buffer against market price volatility, corroborating recent findings by Schaub and Benni [47] and Zimmer et al. [48]. Furthermore, while uniform over-application is often a conventional farmer response to weather uncertainty [49], our drought scenario confirms that site-specific input reduction provides critical financial protection where severe environmental constraints limit crop response [50].

When interpreting these results, the costs of adopting precision technologies must be considered. While earlier frameworks [51] cautioned that high financial and labor costs associated with gathering site-specific information could offset agronomic benefits, our findings demonstrate that integrated farm management platforms (e.g., MyJohnDeere) have lowered these barriers. However, as Munz and Schuele [52] point out, economic viability remains strongly dependent on economies of scale. Larger farms possess a higher resilience to external factors and are better positioned to absorb the fixed costs and learning curves associated with yield-enhancing technologies.

As highlighted by Mizik [53], the widespread adoption of precision farming among small-scale farms is fundamentally constrained by five key factors: small land size, high adoption costs, technological complexity, lack of professional support, and insufficient policy backing. Our sensitivity analysis reinforces this scale-dependency: at 21 hectares, which represents the average arable land farm size in Hungary according to the Hungarian Central Statistical Office [54], the payback period exceeds 17 years. As farm size increases, the payback period decreases significantly: at 35 hectares, the investment pays off in 9.8 years—remaining within the typical 10-year useful life of such machinery—while at 100, 200, and 300 hectares, the payback period drops to 3.4, 1.7, and 1.2 years, respectively, illustrating the substantial impact of economies of scale on capital recovery.

In the Hungarian agricultural context, the expansion of precision tools is supported by the 2023–2027 Common Agricultural Policy (CAP) framework and the Digital Agriculture Strategy, which aim to foster widespread adoption and improve workplace comfort through user-friendly features like automated steering [55]. Furthermore, the Ministry of Agriculture's 2021 grant program provided a significant impetus for technology adoption; however, its effectiveness is often tempered by technical obsolescence and the high cost of retrofitting older machinery. Although the budget for these grants was expanded to 400 billion HUF due to overwhelming demand, the requirement for 40–50% co-financing remains a substantial liquidity bottleneck for many farmers. Consequently, while such state and EU-funded subsidies effectively shorten payback periods and improve economic feasibility (particularly for smaller-scale operations), many producers still defer investments, prioritizing immediate profitability over uncertain future gains, especially following weather-challenged years [56].

Nevertheless, even when data acquisition costs decrease, short-term liquidity constraints during the production period remain a critical bottleneck that frequently hinders farmers from financing the necessary variable inputs for site-specific management [57]. This supports Jensen et al. [18], who noted that the economic threshold for adoption is decreasing due to technological development.

Our observations are consistent with Szabó and Nábrádi [58], who found that although precision management on Hungarian farms may involve higher intensity, these expenses are offset by a significant rise in production value. This confirms that the ability to stabilize profitability makes precision management a superior strategy compared to uniform methods. This cycle of measurement, analysis, and adjustment represents a fundamental advantage, as highlighted by Molnár et al. [17], who emphasized that the primary benefit of precision farming in Hungary stems from enhanced input-use efficiency rather than solely yield maximization. These results illustrate how the core principle of precision agriculture—defined by Saini [59] as 'applying the right input at the right place, at the right time'—translates into tangible economic outcomes.

The study has several limitations that should be considered when interpreting the results. This analysis is based on a single-year, paired-field case study, and the findings should be interpreted as indicative. Climatic conditions in 2024 were characterized by drought stress, which may have amplified the advantage of cost-saving strategies. Although the two fields were similar in terms of their soil properties and classification according to the Hungarian soil classification system, some differences in soil characteristics were also observed. These included variations in micronutrient content, particularly Cu, Mn, and Zn, which may have influenced the yield results.

Future research should include multi-year studies and replicated field experiments to further evaluate the robustness of these findings. A crossover design, in which the same fields are managed alternately under conventional and precision farming over multiple years, could help distinguish the effects of management practices from spatial and temporal

variability. Split-field experiments would also provide a valuable framework, as both management systems could be evaluated under the same climatic, agronomic, and soil conditions. Such experimental designs would support a more reliable assessment of long-term effects on soil properties and economic performance and could be complemented by additional sensor-based measurements and environmental indicators, such as nitrogen leaching, under Central European conditions.

5. Conclusions

This study evaluated the economic and agronomic performance of precision versus conventional maize management under drought-stressed conditions in Hungary. The empirical results confirmed the initial hypothesis: despite severe moisture limitations, the precision-managed field achieved a statistically significant yield surplus of 3.85% (6.47 t ha^{-1}) while reducing total production costs by 5.58%. Consequently, site-specific input allocation was associated with an optimized cost-benefit ratio, increasing net profit by 62.98% compared to the conventional uniform application.

The primary economic advantage of precision management in this context was not driven solely by yield maximization, but by the mitigation of intra-field profit variability. Spatial analysis demonstrated that variable-rate application successfully aligned input expenditures with site-specific productivity potential, preventing inefficient resource use in marginal zones. In contrast, the conventional system exhibited larger areas of economic loss where uniformly applied inputs could not be efficiently converted into yield.

These findings demonstrate that precision agriculture functions as a critical risk-mitigation tool under adverse climatic conditions and high input-price volatility. While this single-year case study inherently captures specific interannual conditions, the results strongly suggest that the transition from uniform to site-specific management enhances both economic resilience and environmental sustainability. Future research should prioritize multi-year longitudinal studies to assess the long-term economic and environmental impacts of precision systems across diverse agroecological regions.

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Appendix A

Table A1. Soil characteristics across different management zones in a precision managed field. Soil samples were collected from a depth of 30 cm on 25 May 2022.

Zone	Soil Plasticity Index (K_A)	Humus Content	P_2O_5 (AL-Soluble)	K_2O (AL-Soluble)	$CaCO_3$	pH_{KCL}	NO_3
1	26	1.7	252	171	1.2	7.7	16.2
2	34	1.7	177	213	8.0	7.9	20.4
3	31	2.9	240	166	6.2	7.9	24.6
4	28	1.8	227	164	1.9	7.6	23.2
5	31	2.4	146	155	1.4	7.2	28.0
6	29	1.9	278	199	1.8	7.5	25.7
7	30	2.1	171	164	1.1	7.5	22.8
8	26	1.8	158	173	1.7	7.4	47.8
9	28	2.3	226	132	2.2	7.6	16.5
10	28	1.9	700	170	3.8	7.7	19.6
11	28	1.7	482	284	1.1	7.6	16.5
12	29	1.8	287	200	7.7	7.9	26.0
13	38	2.9	432	232	4.7	7.7	25.5
14	30	1.9	251	163	1.7	7.8	15.2
15	36	2.5	258	182	4.2	7.7	22.1
16	30	1.9	287	177	1.3	7.5	25.0
17	33	2.1	346	181	3.9	7.7	19.7
18	31	1.9	171	175	0.7	6.9	16.4
19	38	2.4	183	170	5.5	7.5	22.5
20	31	2.0	192	152	2.7	7.6	16.9
21	33	2.1	203	131	2.4	7.6	19.1
22	32	1.5	187	116	9.9	7.8	12.9
23	30	1.6	257	162	4.8	7.8	18.2

Source: Own edit based on soil analysis.

Table A2. Agrotechnics and input application rates in maize production.

Operation	Applied Rate	
	Conventionally Managed Field	**Precision Managed Field**
Base fertilization		
Fuel (l ha^{-1})	0.50	0.39
Potash (kg ha^{-1})	303.00	205.72 *
Base fertilization		
Fuel (l ha^{-1})	0.60	0.40
DAP (kg ha^{-1})	102.98	101.88 *

Table A2. *Cont.*

Operation	Applied Rate	
	Conventionally Managed Field	**Precision Managed Field**
Primary tillage		
Fuel (l ha^{-1})	25.22	25.20
Side dressing		
Fuel (l ha^{-1})	9.10	7.49
30 UAN + S (l ha^{-1})	385.00	385.00
Sowing		
Fuel (l ha^{-1})	3.20	3.02
Seed (sown seeds ha^{-1})	72 212.00	70 990.53 *
Weed Control		
Fuel (l ha^{-1})	0.60	0.65
Sulcontrol (l ha^{-1})	2.20	2.20
Side dressing		
Fuel (l ha^{-1})	2.80	2.98
30 UAN + S (l ha^{-1})	80.00	80.00
Side dressing		
Fuel (l ha^{-1})	2.10	1.76
30 UAN + S (l ha^{-1})	90.00	61.28 *
Harvesting		
Fuel (l ha^{-1})	20.40	13.08

Note: * VRA was performed based on site-specific management zones derived from historical yield potential and soil data. The reported values represent the weighted field-level average of the variable amounts applied. Source: Own edit.

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