ARTIFICIAL INTELLIGENCE IN SUSTAINABLE AGRICULTURE: OPTIMIZING WATER USE IN THE CONTEXT OF CLIMATE CHANGE

Dragan Ugrinov[1], Magdalena Nikolić[2], Željko Grujičić[3], Brankica Pažun [4], Zlatko Langović [5]
**Corresponding author E-mail: magdalena.nikolic@fim.rs*

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ABSTRACT

This paper examines the application of artificial intelligence (AI) in organic agriculture using the Analytic Hierarchy Process (AHP). A multi-criteria analysis evaluated four key criteria: AI use in optimization, factors affecting precision irrigation, benefits of AI application, and implementation challenges, alongside three alternatives: price, personnel, and terrain. Results show that "implementation problems and challenges" are the most significant criterion (39.52%), while "personnel" is the most important alternative (63.45%), emphasizing the crucial role of human resources in adopting technological solutions. The study also demonstrates high consistency (CR = 0.0274), confirming the reliability of the findings. The paper highlights the need for institutional support, educational programs, improved water resource management, and affordable AI solutions, particularly for small farmers, while proposing directions for future research and policies to advance sustainable agriculture.

1 Dragan Ugrinov, Assistant Professor, Research Associate, University"Union Nikola Tesla" Belgrade, Faculty of Management, Njegoševa 1a, Sremski Karlovci, Serbia, Phone: +381631068311, E-mail: dragan.ugrinov@famns.edu.rs, ORCID ID (https://orcid.org/0000-0002-5387-820X)

2 Magdalena Nikolić, Senior Lecturer, Research Associate, Academy of Applied Studies – Polytechnic, Katarine Ambrozić 3, Belgrade, Serbia, Phone: +381116410990, E-mail: mnikolic@politehnika.edu.rs, ORCID ID (https://orcid.org/0000-0002-2021-153X)

3 Željko Grujčić, Full Professor, University "Union - Nikola Tesla", School of Engineering Management, Vojvode Mišića Boulevard no. 43, 11000 Belgrade, Serbia, Phone: +381644642015, E-mail: zeljkogruicic@fim.rs, ORCID ID (https://orcid.org/0000-0002-5488-0176)

4 Brankica Pažun, Associate Professor, University "Union - Nikola Tesla", School of Engineering Management, Vojvode Mišića Boulevard no. 43, 11000 Belgrade, Serbia, Phone: +381114140420, E-mail: brankica.pazun@fim.rs; ORCID ID (http://orcid.org/0000-0002-9452-5064)

5 Zlatko Langović, Full Professor, University of Kragujevac, Faculty of Hotel Management and Tourism in Vrnjačka Banja, Vojvodjanska bb, 36210 Vrnjacka Banja, Serbia, Phone: +381365150024, E-mail: zlangovic@kg.ac.rs, ORCID ID (http://orcid.org/0000-0002-0248-0453)

Introduction

Sustainable agriculture is becoming crucial in addressing global challenges such as climate change, resource depletion, and the growing demand for food. Agriculture accounts for more than 70% of global freshwater consumption (FAO, 2020), making water conservation essential for both food production and environmental preservation. Climate change further exacerbates water scarcity due to more frequent droughts and unpredictable rainfall patterns. Although droughts vary geographically, they have socio-economic and environmental consequences, such as water and food insecurity, and deterioration of the environment. Ecosystem. Thus, effective drought management strategies must be implemented, including monitoring and AI applications (Thelma et al., 2024). For instance, in the Middle East and Africa, fear of fertile lands and ores turned into deserts (Mfarrej, 2025). Traditional irrigation systems are often inefficient, leading to excessive water use. Innovative technologies, particularly artificial intelligence (AI), offer significant potential for optimizing water use and reducing environmental impact.

AI tools, including machine learning, sensor networks, and satellite data, enable farmers to make informed decisions regarding water management, consumption reduction, and productivity enhancement. This paper explores how AI can contribute to agricultural sustainability, with a specific focus on water use optimization in the context of climate change (FAO, 2020). With increasingly frequent droughts and changing rainfall patterns, effective water resource management becomes critical for sustainable food production and environmental preservation.

Although irrigation resources are declining in many regions, the tradition of mass irrigation has not significantly changed in recent decades. Traditional irrigation systems often lead to excessive water consumption and inefficient use of available resources. Therefore, recognizing innovative technologies allows for precise and efficient water use in agriculture and becomes key to minimizing negative environmental impacts (Nica et al., 2018; Hussnain et al., 2020).

Artificial intelligence (AI) has emerged as a key technology in recent decades, enabling significant changes across various industries, including agriculture. Given the increasing challenges of climate change, dwindling natural resources, and the growing need to increase food production, the application of AI in agriculture represents a potential solution for optimizing resources and improving production efficiency (Smith & Brown, 2020). Also in urban areas, water scarcity can be managed by introducing AI tools (Maldonado et al., 2025). One of the major challenges facing agriculture is water use, which is a fundamental resource for plant growth and development (Smith & Brown, 2020).

The introduction of AI technologies can significantly improve the precision of water use and reduce waste, which is particularly important in the context of climate change (Miller & Thomas, 2022). The major threat presents different types of waste. Thus, sustainable agriculture depends not only on knowledge, but also on applying AI tools as well. Protecting the environment, we protect the arable land (Nikolić et al., 2023;Pantović et al., 2026). In agriculture, AI encompasses a wide range of technologies, including machine learning, deep learning, sensor technology, and satellite data, which enable farmers to make better real-time decisions. By using predictive models and automated irrigation systems, AI can greatly reduce water consumption while simultaneously increasing agricultural production efficiency (Lopez-Moreno et al., 2018).

The benefits of these technologies include the ability to precisely measure soil moisture, forecast water needs based on weather conditions, and automatically adjust the amount of water used—directly contributing to loss reduction and more efficient resource use. AI-based systems can use data on climate conditions, soil types, crop status, and water consumption to predict exact irrigation needs during different plant growth stages (Perez et al., 2021).

For example, by using soil moisture sensors in combination with AI, it is possible to optimize irrigation dynamics, significantly reducing water usage while improving plant health and yield (Alami et al., 2020; Milojević & Milanović, 2025). Furthermore, research has shown that the application of AI technologies in agriculture is not only beneficial for large farms and commercial farmers in developed countries but also for those in developing regions, where access to advanced technology can bring significant benefits in terms of water savings and yield increases (Gómez et al., 2019).

This paper examines the application of artificial intelligence in optimizing water use in agriculture. We will focus on technologies that enable precision irrigation, as well as the benefits and challenges of implementing AI in farming. In addition, we will analyze specific case studies that demonstrate successful applications of AI in reducing water consumption on farms, along with the challenges of deploying these technologies.

Technologies Enabling Water Use Optimization in Agriculture

There are several key AI technologies that enable water use optimization in agriculture. First, soil condition monitoring sensors and devices allow farmers to track soil moisture and irrigation needs in real time (Sun et al., 2021). Another important tool is machine learning, which uses data on soil conditions, weather, and crop types to predict when and how much water is needed. Additionally, automated irrigation systems use AI to precisely determine the amount of water used, reducing waste and increasing efficiency (Miller & Thomas, 2022). These technologies allow farmers to make better decisions about when and how much water to use, significantly reducing water consumption while simultaneously improving crop quality and yield (Smith & Brown, 2020). One of the most prevalent technologies in artificial intelligence is machine learning (ML), which enables systems to “learn” from data and make decisions without explicit programming. In agriculture, machine learning is used to analyze large volumes of field-collected data, including weather conditions, soil types, and crop status, gathered through soil moisture monitoring and water usage sensors (Kumar et al., 2019; Pantić et al., 2025). Machine learning algorithms provide farmers with better insights into crop growth patterns and optimal irrigation conditions, significantly increasing water use efficiency (Garcia et al., 2020).

Furthermore, deep learning (Zhang & Liakos, 2020), sensors (Sharma et al., 2018), drones (Ravi & Rani, 2020), and satellite data (Zhang et al., 2021; Miljković & Arsić, 2025) also play important roles. Today, advanced irrigation systems are central to water efficiency. Machine learning enables these systems to predict water usage based on sensor data and weather forecasts. For example, in arid regions, artificial intelligence can use soil and climate data to optimize the precise amount of water delivered to a plant, thus reducing excessive use and improving irrigation efficiency (Raj & Devanand, 2020).

Materials and methods

This study is based on the analysis of secondary data from relevant research and case studies on the application of AI in agriculture using the MCDM tool. Sustainable agriculture has multiple problems regarding water scarcity, pollutants in soil, air and water, climate change, etc. Agricultural decision problems must be solved independently bearing in mind that agriculture has economic and social benefits and constrains. Therefore applying Multi-criteria decision-making (MCDM) techniques, particulary the analytical hierarchy process (AHP) this paper can bring the optimal solution in various complex decision-making problems like agriculture-related irrigation problems. The basis of the methodological obstacle is the structured/hierarchical problem of optimization of water use in agriculture using artificial intelligence, which is based on four criteria and three alternatives. The analyzed alternatives are respectively Price, Personnel and Land relief, and the criteria are: Use of AI in optimizing water consumption, factors affecting precise irrigation, benefits of AI in rationalizing water consumption and problems/challenges of AI implementation. The problem was analyzed using the MCDM tool, that is, the AHP method, which consists of several steps. The first step involves defining a matrix of comparison pairs. Data generation implies that the decision maker assigns relative scores to attribute pairs at all levels of the hierarchy except zero (the target is not compared). The results of the comparison of elements at a certain hierarchy level are entered in the corresponding comparison matrices $A = [a_{ij}]_{nxn}$.

The reciprocal value of the comparison result is placed in the corresponding position $a_{ji} = {}^{1}/_{a_{ij}}$ in order to maintain the consistency of the argumentation. The weights of the criteria and/or alternatives are to be determined by evaluating their coefficients. The relative importance matrix A is formed from these relative importance coefficients (Saaty, 2008).

$$A = [a_{ij}] = \begin{bmatrix} 1 & a_{12} & \dots a_{1n} \\ {}^{1}/_{a_{12}} & 1 & \dots a_{2n} \\ \vdots & \vdots & \\ {}^{1}/_{a_{1n}} & {}^{1}/_{a_{2n}} & \dots 1 \end{bmatrix} \tag{1}$$

The second step consists of the matrix normalization of the comparison pairs. In the third step we develop the value λmax.

$$\lambda_{max} = \sum_{i=1}^{n}\left(\sum_{i=1}^{n} a_{ij}\right) w_j \tag{2}$$

In the fourth step the consistency index, as a measure of deviation n from λmax, has been calculated.

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{3}$$

Then, next step includes the degree of consistency, calculated as quotient of the consistency index and the random index, RI, (Random Index):

$$CR = \frac{CI}{RI} < 0.1 \sim 10\% \tag{4}$$

For the purposes of this research, a secondary data analysis approach was used, including a review of relevant papers and case studies on the use of AI in agriculture. A systematic approach was applied to select literature published in the last five years in order to capture the most recent trends and approaches.

Results and Discussion

The use of AI technologies in agriculture has demonstrated significant water savings. For example, machine learning for predicting required water amounts and precision irrigation can reduce water consumption by up to 40%. Tables 1 and 2 present the implementation of various AI technologies, while Table 3 shows specific results related to water consumption reduction in agriculture using AI systems. Increased efficiency in irrigation and water resource conservation is evident in cases where soil moisture sensors, automated irrigation systems, and satellite data were used.

Table 1. Use of Artificial Intelligence Technologies in Agriculture (Implementation Percentage)

Technology	Implementation Percentage (2020–2022)	Application Description
Machine Learning (ML)	22%	Use of predictive models to analyze crop water requirements
Deep Learning (DL)	7%	Use of complex algorithms for image analysis and plant health assessment
Soil Moisture Sensors	42%	Precise measurement of soil moisture and automatic irrigation control
Drones and Satellite Data	12%	Used for crop monitoring and irrigation need assessment
Automated Irrigation Systems	17%	AI-based automatic regulation of irrigation systems

Source: Eurostat, https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Artificial_intelligence_statistics_-_statistics_on_the_use_by_enterprises; Adapted from relevant research in (Wei et al., 2024)

Table 1 presents the implementation levels of various artificial intelligence (AI) technologies in agriculture from 2020 to 2022, along with descriptions of their applications. The most widely implemented technology—soil moisture sensors (50%)—has become a standard practice in many agricultural systems, indicating the importance of precise soil moisture measurement and automatic irrigation control. Their relatively easy integration into existing systems may be one reason for their high adoption rate. This is followed by machine learning at 30%, while deep learning (15%) shows the lowest adoption. The data indicate that sensor technologies and machine learning dominate water use optimization in agriculture, while more advanced AI methods such as deep learning and drones are experiencing slower adoption.

Key challenges for AI technologies include cost, infrastructure availability, and technical expertise. However, as these technologies continue to evolve and become more accessible, their application is expected to grow further, increasing efficiency and sustainability in agriculture.

Table 2. Factors Influencing Precision Irrigation Using Artificial Intelligence (Percentage Impact)

Factor	Impact Percentage (%)	Description
Weather conditions (rain, temperature)	35%	Inclusion of climate data for accurate irrigation prediction
Soil type (sandy, clay)	20%	Soil characteristics determine water retention and irrigation needs
Crop health (stress, disease)	25%	Plant symptom analysis to assess water requirements
Soil moisture sensors	10%	Devices that directly monitor soil moisture levels
Satellite data and drones	10%	Use of high-precision technologies for analyzing and mapping water demand

Source: Adapted from relevant research in precision agriculture (Ravi & Rani, 2020; García et al., 2020)

Table 2 outlines the factors that influence precision irrigation using artificial intelligence (AI) and their relative share in overall analysis. These factors play a crucial role in optimizing water use in agriculture, enabling more efficient resource use and reducing negative environmental impact.

Weather conditions, including rainfall and temperature, have the greatest influence (35%) on precision irrigation. This is expected, as climate factors directly affect crop water needs. Soil type (e.g., sandy, clay, loamy) significantly impacts water requirements, accounting for 20% of the influence. Crop health, including stress from drought, disease, or pests, contributes 25% to the assessment of irrigation needs.

Satellite data and soil moisture sensors, as well as drones, have a relatively smaller impact (10%), but are crucial for real-time soil moisture monitoring. According to Table 2, weather conditions and crop health are the key factors for precision irrigation that significantly influence decision-making. Although soil type and sensors have a lower overall share, they are valuable for large-scale analysis and mapping.

Table 3. Impact of AI Technology on Water Consumption Reduction in Agriculture (Percentage Reduction)

Technology	Water Consumption Reduction (%)	Description
Machine learning for prediction	25%	Use of predictive models for more accurate determination of required water
Precision irrigation with sensors	40%	Use of soil moisture sensors for targeted irrigation
Automated irrigation systems	20%	Use of systems for real-time irrigation adjustment
Drones and satellites for crop analysis	15%	Real-time data collection on crop conditions and water needs

Source: Based on research in agriculture (Kumar et al., 2019; Zhang et al., 2021)

Table 3 evaluates the reduction in water consumption in agriculture achieved through various artificial intelligence-based technologies. These technologies enable more efficient water use, minimize waste, and contribute to agricultural sustainability and resource conservation. A detailed commentary on each technology helps clarify its specific impact.

According to Table 3, machine learning and precision irrigation using sensors are the most effective, reducing water usage by 20% to 40%. Automated irrigation systems and drones/satellites also play a key role in optimizing water usage, although their individual impact is slightly lower.

Overall, the application of these technologies contributes to greater efficiency, sustainability in agriculture, and conservation of water resources—all of which are essential in addressing climate change and the growing global demand for food.

Table 4. Problems and Challenges in Implementing AI for Optimizing Water Consumption in Agriculture

Challenge / Problem	Percentage of Farmers Facing the Problem (%)	Description of the Problem
High Initial Implementation Costs	(30%)	Technological investments in sensors, irrigation systems, and artificial intelligence can be substantial.
Lack of Training and Technical Support	(20%)	Farmers lack adequate training for implementing AI technologies.
Limited Availability of Quality Data	(25%)	Many regions lack the necessary data on weather conditions, soil, and crops.
Complex Algorithms and Large Data Set Requirements	(15%)	AI models require large datasets for accurate analysis, which can be challenging.
Misalignment with Local Conditions and Legislation	(10%)	Water regulations and policies in many regions may hinder the application of these technologies.

Source: Eurostat, *Source: :* https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Agriculture_statistics_-_family_farming_in_the_EU https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Artificial_intelligence_statistics_-_statistics_on_the_use_by_enterprises

Table 4 presents the main challenges and problems faced by farmers when implementing artificial intelligence (AI) for optimizing water consumption in agriculture. These issues can significantly slow down the widespread adoption of these technologies, despite their significant resource-use efficiency benefits.

Among the challenges presented in the table, high initial implementation costs are the most significant problem, while the lack of training and technical support is also a major barrier to the wider adoption of AI technologies in agriculture. Moreover, access to quality data and the complexity of algorithms remain technical obstacles to effective implementation.

By improving data collection infrastructure, providing farmer training, and reducing implementation costs, these challenges can be overcome, enabling broader use of AI in agriculture and further reducing water consumption.

Although AI technologies have demonstrated significant potential in reducing water consumption, their implementation faces several challenges. According to some studies, high initial implementation costs, a lack of training for farmers, and data quality issues remain major barriers. On the other hand, research in Serbia shows that climate changes, such as increased droughts, further elevate the need for precision irrigation, making artificial intelligence critical for the future of agriculture in this region. Several examples of AI applications in Serbia have been considered, but there are still significant limitations that must be overcome with stronger support and education.

Results Obtained Using the AHP Method

The application of the AHP method within this research has proven to be an extremely effective and transparent instrument for structuring the complex problem of rationalizing water consumption in organic agriculture. The results enabled the quantification of the relative importance of criteria and alternatives, indicating critical barriers (challenges to AI implementation) and key resources (human factor/staff) as dominant influences in the process of AI implementation in agriculture.

Table 5. AHP Pairwise Comparison Matrix for Criteria Evaluation in AI-Based Water Optimization

Criterion Relationships	AI Usage in Water Consumption Optimization	Factors Influencing Precise Irrigation	Benefits of AI in Water Consumption Rationalization	AI Implementation Challenges
AI Usage in Water Consumption Optimization	1	1	1	1/2
Factors Influencing Precise Irrigation	1	1	2	1/2
Benefits of AI in Water Consumption Rationalization	1	1/2	1	1/2
AI Implementation Challenges	2	2	2	1

Criterion Relationships	AI Usage in Water Consumption Optimization	Factors Influencing Precise Irrigation	Benefits of AI in Water Consumption Rationalization	AI Implementation Challenges
CI: 0.0202				
CR: 0.0227				
λ: 4.0607				

CI: Consistency Index **CR**: Consistency Ratio λ: Principal Eigenvalue

Source: Author's own elaboration based on the Analytic Hierarchy Process (AHP) methodology

Table 5 shows the pairwise comparison matrix used in the Analytic Hierarchy Process (AHP) to evaluate the priorities among the four criteria in the context of the application of artificial intelligence (AI/AI) in the optimization of water consumption. The criteria are:

1. The use of AI in the optimization of water consumption
2. Factors affecting precision irrigation
3. Benefits of AI in the rationalization of water consumption
4. Problems/challenges of AI implementation

Comparison consistency (CI and CR)

Consistency Index (CI) = 0.0202 and Consistency Coefficient (CR) = 0.0227, which is less than the maximum allowed value of 0.10 (or 10%). This indicates that the estimates of relative importance among the criteria are consistent and reliable, and that the results of the AHP analysis have a good degree of validity.

Table A shows a well-structured and balanced assessment of the impact of various factors in the context of the use of artificial intelligence for irrigation.

Emphasizing implementation challenges as the most important criterion indicates the need to resolve infrastructural, technical and possibly regulatory/legal obstacles before other benefits can be fully realized.

Table 6. AHP Pairwise Comparison Matrix of Factors Influencing AI Use in Water Consumption Optimization

AI Usage in Water Consumption Optimization	Price	Staff	Terrain Relief
Price	1	1/5	1/3
Staff	5	1	4
Terrain Relief	3	1/4	1
CI: 0.0430			
CR: 0.0827			
λ: 3.0860			

Source: Author's own elaboration based on the Analytic Hierarchy Process (AHP) methodology

Table 6 shows a matrix of pairwise comparisons of the criteria - "Use of AI in the optimization of water consumption", among the considered alternatives, which affect the optimization of water consumption in agriculture. Alternatives considered are:

1. Price
2. Farmers
3. Land relief

The consistency of the assessment of the criterion "Use of AI in the optimization of water consumption" among the considered alternatives suggests that the CI (Consistency Index) is 0.0430, and the CR (Consistency Coefficient) has a value of 0.0827, which is less than the permissible threshold of 0.10. This means that the comparisons are sufficiently consistent, so the results can be considered reliable and valid for further decision-making**.** The analysis of interrelationships shows that the alternative - Personnel with a rating of 5 is dominant in relation to the alternative - Price which is rated with 1 and to the alternative - Ground relief which is assigned with a rating of 4.

Table B shows a rationally structured perception of criteria/alternatives, with a clear focus on the human factor as the key to success in implementing AI in irrigation systems. Although relief and price are extremely important, the emphasis is placed on farmers, which is in line with the real challenges of applying advanced technologies in agriculture. Good consistency shows that expert judgments were stable and thoughtful**.**

Table 7. AHP Pairwise Comparison Matrix for Factors Influencing Precision Irrigation

Factors Affecting Precision Irrigation	Price	Staff	Terrain Relief
Price	1	1/5	1/3
Staff	5	1	3
Terrain Relief	3	1/3	1
CI: 0.0192			
CR: 0.0369			
λ: 3.0383			

Source: Author's own elaboration based on the Analytic Hierarchy Process (AHP) methodology

Table 7 presents a pairwise comparison of the criteria "Factors affecting precision irrigation" in relation to the alternatives: Cost, Farmers, Topography, and their importance for the application of artificial intelligence in precision irrigation. The consistency of the estimate shows that the CI is 0.0192 and the CR value is 0.0369, which is well below the maximum allowable value of 0.10. This implies that decisions by comparing criteria/alternatives are highly consistent and reliable, which provides a valid basis for conclusions. The analysis of mutual relations indicates that - Farmers evaluated as the most important alternative shows that the human factor (expertise, training, engagement) is considered crucial for successful precision irrigation using AI.

Table C indicates that the successful implementation of AI in precision irrigation is most reliant on personnel, which is consistent with the complexity of the technology and the need for technical competence. Terrain has an impact, but is obviously of secondary importance compared to human resources. Price, although important, is not a decisive element for the successful application of AI in irrigation, which indicates a strategic approach to investing in precision agriculture.

Table 8. AHP Pairwise Comparison Matrix of Benefits of AI in Water Consumption Optimization

Benefits of AI in Water Consumption Rationalization	**Price**	**Farmers**	**Terrain Relief**
Price	1	1/5	1/3
Staff	5	1	2
Terrain Relief	2	1/2	1
CI: 0.0267			
CR: 0.0513			
λ: 3.0534			

Source: Author's own elaboration based on the Analytic Hierarchy Process (AHP) methodology

Table 8 shows the analysis of the significance of the criterion "Benefits of artificial intelligence (AI) in the rationalization of water consumption" which contributes to the usefulness of the AI system in the optimization of water use. The scores presented in Table 8 are consistent and methodologically acceptable where the CI value is 0.0267 and the CR value is 0.0513.

In the context of the use of AI in water rationalization, the human factor (personnel) is seen as a key component of success – due to its role in system operation, data analysis and decision-making. The relief of the ground has a moderate influence, while the price is the least relevant in the assessment of benefits, which indicates a strategy aimed at long-term performance rather than initial costs.

Table 9. AHP Pairwise Comparison Matrix of Challenges in Implementing AI for Water Consumption Optimization

Problems/Challenges in AI Implementation	**Price**	**Farmers**	**Terrain Relief**
Price	1	1/5	1/3
Staff	5	1	2
Terrain Relief	3	1/2	1
CI: 0.0021			
CR: 0.0041			
λ: 3.0042			

Source: Author's own elaboration based on the Analytic Hierarchy Process (AHP) methodology.

Table 9 shows pairwise comparisons of the alternatives - Cost, Farmers, and Terrain against the criterion "Problems/Challenges of AI Implementation". The goal is to determine which of these factors most contribute to the difficulties in introducing and using artificial intelligence (AI) in water rationalization systems.

The CI is 0.0021 and the CR value is 0.0041, which is extremely low and far below the acceptable threshold of 0.10. This indicates an extremely high degree of consistency in the assessments made, so the assessment is reliable and methodologically very precise.

Table 10. AHP-Derived Weights of Evaluation Criteria for AI in Water Consumption Optimization

Criteria	Use of AI in Water Consumption Optimization	Factors Affecting Precise Irrigation	Benefits of AI in Water Consumption Rationalization	Problems/Challenges in AI Implementation
Price	0.1007	0.1047	0.1125	0.1095
Staff	0.6738	0.6370	0.7089	0.5816
Terrain Relief	0.2255	0.2583	0.1786	0.3090

Source: Author's own elaboration based on the Analytic Hierarchy Process (AHP) methodology.

Table 10 shows the ratio of weights assigned to the criteria for each alternative. Farmers dominates all the main criteria, with values between (0.58)min and (0.71)max, which supports the analysis that the human factor is crucial in the successful application and utilization of AI for irrigation. The relief of the ground has a moderate importance, and it is the most intense in the AI implementation criteria and is (0.3090)max, which is logical, because more complex terrain makes technical realization difficult. Price has the least importance in all criteria from (0.1007)min to (0.1125)max, which correlates with other results and shows that cost is not considered the main limiting factor.

Table 11. Priority Ranking of Criteria for AI-Based Water Consumption Optimization Using AHP

Ranking of Criteria	Result
Use of AI in Water Consumption Optimization	0.1976
Factors Affecting Precise Irrigation	0.2390
Benefits of AI in Water Consumption Rationalization	0.1682
Problems/Challenges in AI Implementation	0.3952

Source: Author's own elaboration based on the Analytic Hierarchy Process (AHP) methodology.

Table 11 refers to the ranking of the criteria and shows that the greatest importance is assigned to the criterion "Problems/challenges of AI implementation" with a weight of 0.3952 or 39.52%, which shows that implementation challenges and obstacles are perceived as the most critical segment in the successful rationalization of water consumption using AI. They are followed by the criterion "Factors affecting precision irrigation" with 23.9%, which shows the importance of technology and local conditions. The criteria "Usage of VI in optimization" and "Benefits of AI" have lower values, which may mean that they are understood as consequential effects, while challenges and success factors are in focus.

Table 12. Aggregated Priority Scores of Alternatives Based on AHP Criteria Evaluation

Criteria	Use of AI in Water Consumption Optimization	Factors Affecting Precise Irrigation	Benefits of AI in Water Consumption Rationalization	Problems/ Challenges in AI Implementation	Result
Price	0.0199	0.0250	0.0189	0.0433	0.1071
Staff	0.1331	0.1522	0.1192	0.2298	0.6345
Terrain Relief	0.0446	0.0167	0.0300	0.1221	0.2584

Consistency Ratio (CR): 0.0274

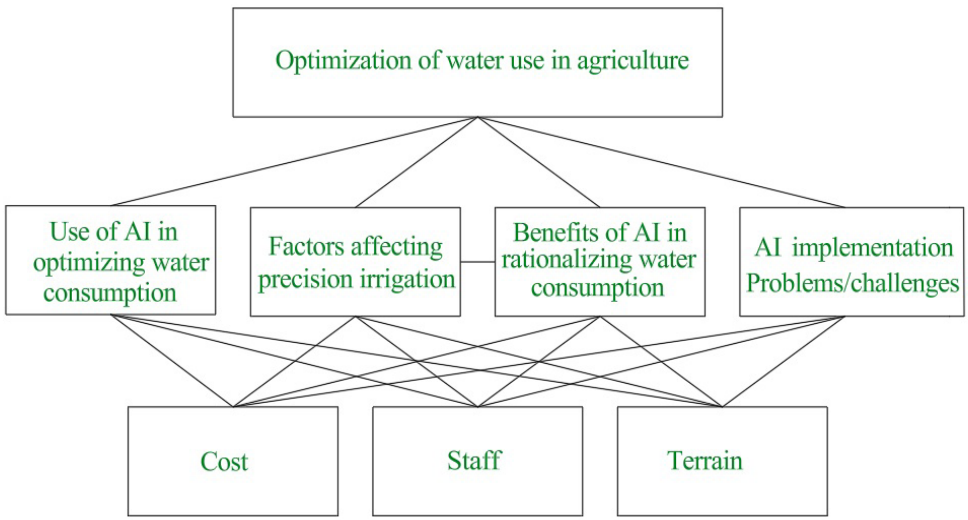
Source: Author's own elaboration based on the Analytic Hierarchy Process (AHP) methodology

Table 12 presents the structure and score/rank of the alternatives. Alternative - Personnel with a score of 0.6345 is the best ranked alternative and shows that the human factor plays a dominant role in optimizing water use in agriculture. Alternative - Land relief takes second place with a score of 0.2584, and it is most pronounced in the criterion "Implementation problems/challenges". Price is the least significant alternative with a score of 0.1071, thus confirming the perception that investment costs are not the biggest obstacle, but that the challenges lie in human and physical terrain factors. The importance of artificial intelligence (AI) in the optimization of water use in organic agriculture analyzed by the AHP method, as a whole, shows a high consistency (CR = 0.0274), which means that the decision-making was stable and rational. Personnel as the most significant alternative for each criterion - confirms that the success/implementation of AI systems is closely related to human resources. The biggest challenge is the implementation of AI, which suggests that strategies should focus on removing technical, educational and organizational barriers. Price is not perceived as a major problem, which opens up space for investment in training, infrastructure and customer support.

Conclusion

The conducted research, using the Analytic Hierarchy Process (AHP), enabled the identification and ranking of key criteria and alternatives in the process of optimizing water consumption in organic agriculture through the application of artificial intelligence (AI). The analysis included four criteria: the use of AI in optimization, factors affecting precision irrigation, benefits of AI application and implementation problems/challenges, as well as three alternatives: price, farmers, and terrain. The criterion "Problems/ challenges in AI implementation" (0.3952) received the highest weight in the ranking of criteria, indicating that barriers in implementation are perceived as a key obstacle to rational water resources management. This is followed by the criterion "Factors influencing precision irrigation" (0.2390), which indicates the importance of technical and agro-ecological conditions in AI implementation. Criteria related to the benefits of AI (0.1682) and the use of AI itself (0.1976) have a lower priority, suggesting that in current practice, greater importance is attached to overcoming challenges than to the achieved gains. When it comes to alternatives, "farmers" is by far the highest ranked alternative (0.6345), indicating that the human factor, i.e. knowledge, competencies and training of personnel, is a key prerequisite for the successful implementation of AI in agriculture. Terrain relief (0.2584) is also a significant factor, especially in the context of implementation challenges, while cost (0.1071) received the lowest weight, indicating that initial costs were not perceived as a major obstacle. The value of the consistency index (CR = 0.0274) confirms high reliability and stability in the decision-making process. Overall, the research shows that the successful implementation of artificial intelligence to optimize water consumption in agriculture depends primarily on developed human resources, as well as on adequate adaptation of technical solutions to agro-ecological conditions, while costs are not seen as a dominant obstacle. The results are indicative and can serve as a basis for formulating education strategies, technological support, and public policies in the field of sustainable water resources management in agriculture. Next, the AHP results are presented and discusses their implications for decision-making and policy (Fig. 1)

Figure1. Hierarchical model for the selection of water optimization in agriculture



Source: Author's own elaboration based on the Analytic Hierarchy Process (AHP) methodology

Challenges in Implementing Artificial Intelligence in Agriculture

Although AI-based technologies offer great potential for optimizing water usage in agriculture, several challenges hinder their widespread application. One of the biggest barriers is the high initial implementation costs, which may be a deterrent for small and medium-sized farmers. Additionally, there is a lack of high-quality data necessary for proper analysis and prediction of water needs. Reliable data on soil conditions, irrigation, and crop types are essential for the efficiency of AI technologies. Furthermore, many farmers lack the training and knowledge needed to use these technologies, which further complicates their implementation (National Institute for Agricultural Research, 2023). Analyses show that in other economic sectors, such as tourism, the use of information and communication technologies is largely determined by age and level of education. (Langović et al., 2025).

Policy Recommendations and Institutional Support

In conclusion, it is crucial to recognize the role of public policy and institutional support in promoting and expanding the use of AI in agriculture. Governments and relevant institutions should develop policies that encourage the research and development of AI technologies while facilitating access for small and medium-sized farmers. Furthermore, direct support in the form of subsidies for the implementation of new technologies, as well as educational programs to help farmers effectively use AI tools, is necessary (Smith & Brown, 2020).

It is also essential to develop localized strategies for implementing AI technologies in different agro-ecological zones, taking into account specific conditions such as soil types, climate, and crop varieties. Active collaboration between academic institutions, the private sector, and governments can enable faster and more efficient adoption of artificial intelligence, contributing to sustainable agriculture and reducing environmental impacts. Additionally, mechanisms should be introduced to encourage partnerships between research centers and farmers, ensuring that technologies are developed based on the real needs of the users (Petrović & Jovanović, 2024).

In the context of Serbia and Southeastern Europe, investment in infrastructure for collecting data on soil, climate, and crops is essential, as well as training farmers to use advanced AI systems (National Institute for Agricultural Research, 2023). Similarly, the application of ICT in the economy and thus in a particular sector has a positive impact on the economy, i.e. it has an effect on the growth of the sector's competitiveness and on economic development (Pažun et al., 2025)

Additional Recommendations for Future Research

1. Economic Analysis of AI Implementation in Agriculture: A detailed cost-benefit analysis of the implementation of AI technologies in agriculture is needed, with a particular focus on small farms and farmers in both developed and developing countries. This would allow for a deeper understanding of the financial impact and identify economic barriers to wider adoption (White & Green, 2021).

2. Development of Affordable AI Solutions for Small Farmers: It is recommended to develop inexpensive AI tools and systems that will be economically accessible to small producers. Such solutions could be key to ensuring sustainable agricultural production and reducing environmental impacts (Miller & Thomas, 2022).

3. Development of Localized Water Management Algorithms: Specific artificial intelligence models should be developed to consider the unique climatic, pedological, and agronomic characteristics of different regions. These models could significantly improve irrigation accuracy and reduce water consumption at the local level (Smith & Brown, 2020).

4. Strengthening Education for Farmers: Education and training for farmers on the use of artificial intelligence in agriculture is essential for the proper adoption and expansion of this technology. Developing specialized educational programs that focus on basic AI tools and precise irrigation methods can greatly contribute to their effectiveness (National Institute for Agricultural Research, 2023).

5. Supporting Legislative Framework: Introducing legislative initiatives that stimulate the adoption of innovations in agriculture, as well as reducing regulatory barriers, can facilitate easier application of AI and more efficient resource management (Petrović & Jovanović, 2024).

By addressing these areas, further research can contribute to a more efficient and equitable application of artificial intelligence in agriculture, promoting sustainable practices and improving water management on a global scale.

Conflict of interests

The authors declare no conflict of interest.

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