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Data-Driven Optimisation of Irrigation Dose Using Machine-Learning Ensembles for Sustainable European Agriculture

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Abstract

This study focuses on predicting irrigation doses using digital technologies and statistical modelling to enhance water resource management in agriculture. Conducted as part of the CODECS project in the semi-arid Nitra region of Slovakia, this study aimed to evaluate the effectiveness of various irrigation systems and to develop predictive models for optimal irrigation doses. The methodology integrates environmental sensor data, agronomic models, and machine learning techniques, utilizing IoT sensors alongside Valley and Irriga control software. A significant challenge was the incompatibility of heterogeneous data from different sources, leading to the creation of a unified method-ology for data collection, validation, and analysis. Analytical tools, such as ex-ploratory data analysis, correlation techniques, and regression models, were employed to identify key factors affecting irrigation efficiency, including precipitation, temperature, soil moisture, and energy consumption. The findings aim to inform sustainable irrigation strategies that reduce water usage, enhance crop productivity, and safeguard soil resources under changing climatic con-ditions.

Keywords

Artificial irrigation, digital agriculture, machine learning, data, statistical modelling, smart farming.

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Introduction

The agricultural sector is the largest consumer of water worldwide (SOLAW, 2021; FAO, 2021). Agricultural productivity, coupled with water scarcity, is becoming an increasing problem, particularly in arid areas, often leading to land degradation. Improved on-farm management practices and proper water and soil management contribute to better crop yields, growth, development, and yield, which depend heavily on a sufficient water supply. AI-powered irrigation systems can reduce water usage by up to 25 %, demonstrating the significant potential of technological interventions in water management (Akkem et al., 2023). Khan et al. (Khan et al., 2006) argued that irrigation is also used to improve the quality and diversity of crops, and not only to increase the quantity of crops produced. However, the benefits of irrigation also bring challenges, such as the proper management of water resources, prevention of soil salinization, and issues regarding sustainability.

Precision irrigation scheduling is directed toward efficient water usage for each plant, where and when it is needed, in the right amounts, to compensate for water loss either through evapotranspiration, erosion or deep percolation, while preventing over- and under-irrigation (Ahmed et al., 2024; García et al., 2020; Vallejo-Gómez et al., 2023). Recent advances in precision agriculture have shown that precision irrigation systems can reduce water usage by up to 50 % compared with traditional methods in agriculture (Hamami and Nassereddine, 2020). Furthermore, agricultural evapotranspiration (ET) represents the amount of water that is "consumed" by agriculture, as this water leaves the watershed entirely through evaporation from soil and transpiration by crops (Sithartan et al., 2023).

There is a growing need for advanced irrigation management solutions to ensure efficient use of available water resources and minimize losses. One of the key strategies in this regard is irrigation modelling, which enables more accurate prediction and optimization of irrigation practices. Jensen et al. (1990) defined irrigation modelling as a tool that uses mathematical equations and computational techniques to create a tool for design, manage, and optimize irrigation strategies. There are different types of irrigation models and each has specific applications, methodologies, and benefits. Different models have been used to predict the water flow and manage irrigation systems under unexpected conditions.

Technical innovations have also brought about advances in irrigation modelling, which have increased their computational power. Allen et al. (Al, 2006) revolutionized irrigation planning and management through the development of spatial systems that use geographic information systems (GIS) and remote sensing. Palková and Rodny (Palková and Rodny, 2018) in their article stated that the basic idea of modelling a real process involving irrigation is possible by simulating real processes through stochastic models that incorporate randomness and uncertainty and are thus essential for managing unpredictability, such as climate change.

Advances in irrigation optimization have also been brought about by artificial intelligence (AI), which is increasingly being integrated into these models and enabled by machine learning, increasing their adaptability and decision-making accuracy. Kersebaum et al. (Kersebaum et al., 2007) pointed to the use of machine-learning algorithms that have improved the efficiency of irrigation models, including more accurate predictions of irrigation needs. AI-guided human–machine collaboration can streamline the integration of user needs, allowing customization towards situational farm management adaptation (Wei et al., 2024).

Recent studies confirmed that artificial intelligence (AI) and machine learning (ML) play key roles in irrigation optimization. Umutoni and Samadi (2024) analyzed 16 studies on ML applied to irrigation demand prediction and highlighted the need to integrate physical models with ML for more accurate and robust decision making. Hossain (Hossain, 2023) presented advanced machine-learning techniques combined with ML to optimize irrigation canal operations, which improved water distribution and increased management efficiency. Bellingham et al. (2023) developed ML regression models to predict soil moisture in drip irrigation systems, and achieved high accuracy in predicting soil moisture in the near future. Precision agriculture, a key application of AI in smart farming, involves the use of sensors, drones, and satellite imagery to monitor crop health, soil conditions, and weather patterns (Sharma et al., 2021).

Recent developments in IoT technology have led to advanced applications in agriculture (Kumar Kasera et al., 2024; Prasath and Akila, 2023). García et al. (2020) provided a comprehensive overview of IoT-based smart irrigation systems, emphasizing recent trends in sensors and IoT systems for precision agriculture. According to research reports, the number of connected agricultural devices is expected to increase from 13 million at the end of 2014 to 225 million by 2024 (García et al., 2020). The integration of real-time data collection through IoT devices enables accurate irrigation management and improves decision-making processes (Bwambale et al., 2022).

Advanced wireless sensor networks have been developed for the comprehensive monitoring of agricultural parametres (Karray et al., 2020). The rebound in 2024 suggests a renewed focus on IoT in irrigation management, possibly reflecting emerging challenges, such as climate change adaptation, water resource optimization, integration with AI-driven decision support systems, and the emergence of low-cost solid-state sensors (Abdelmoneim et al., 2025). These investigations demonstrate that the integration of ML models into drip irrigation systems can yield more accurate predictions and greater water resource efficiency, leading to sustainable and efficient agricultural management.

To use AI and ML models effectively, it is essential to obtain high-quality and relevant data that improve the accuracy of predictions and irrigation optimization. Data on climate, precipitation, temperature, humidity, and wind speed are among the key factors for accurate irrigation management, as reported in a study of evapotranspiration (Allen et al., 2006). Understanding and accurately measuring evapotranspiration can significantly improve water use efficiency in agriculture, ensuring sustainability and crop productivity in both the short and long run (Gao et al., 2024)

The application of AI techniques and robotics in agriculture has continued to evolve (Wakchaure et al., 2023). Big data and the AI revolution in precision agriculture present both opportunities and challenges (Bhat and Huang, 2021). Data on soil texture, structure, and moisture content are essential for accurately determining irrigation requirements (Moriasi et al., 2007). It is also important to provide an overview of water sources, quantity, and quality (Bastola et al., 2011). The integration of field measurements and modelling into irrigation management has been analyzed in a recent study that demonstrated effective irrigation management under different climatic conditions.

Significant advances have been made in the development of technologies for data collection in the field of irrigation management. New methods integrate artificial intelligence and IoT sensors for better monitoring of soil moisture and irrigation requirements. Data accuracy and reliability are key for efficient irrigation management. The need for high-quality input data for accurate modelling and decision-making has been emphasized (Crystal-Ornelas et al., 2022)The impact of data quality on the sustainability and ecological suitability of irrigation systems has been highlighted (Jihani et al., 2024).

Research can be more transparent and collaborative using Findable, Accessible, Interoperable, and Reusable (FAIR) principles to publish Earth and environmental science data (Crystal-Ornelas et al., 2022). The implementation of FAIR data practices in irrigation management can significantly enhance the effectiveness of predictive models by improving data sharing, integrating expertise, and developing standardized data formats (Umutoni and Samadi, 2024). For AI and ML models to work effectively, it is important that these data have a uniform structure and are stored in central databases, from which models can process them efficiently and optimize irrigation practices.

A generic smart irrigation system can be schematically represented as consisting of sensors, Internet of Things (IoT) technologies, and algorithms. Sensors sense the environment and the soil conditions, and adapt and send the sensed values to local or remote processing units in which trained machine learning algorithms can forecast agrotechnical indicators useful to decide if irrigation is needed and eventually the optimal amount of water to be provided to the crops (Kaur et al., 2024). This smart irrigation system allows farmers to control and adjust irrigation practices remotely, with systems achieving up to 60% water savings through automated monitoring of soil moisture and environmental conditions (Dong et al., 2024).

Owing to the impact of climate change on agriculture and the emergence of water security issues, proper irrigation management has become increasingly important to overcome these challenges. Internet of Things (IoT) technology is being utilized in agriculture to collect field information and share it through websites in real time (Abioye et al., 2022).

The prediction of irrigation application rates using digital technologies and statistical modelling has gained significant attention owing to the growing need for efficient water management in agriculture. Various approaches have been developed to improve irrigation scheduling and optimize water consumption, particularly by using artificial intelligence (AI) and machine learning (ML). These methodologies not only improve crop yields but also contribute to sustainable agricultural practices.

Machine learning is a rapidly evolving technology for precision irrigation systems because of its ability to mimic human decision-making, while also addressing the complexities of agricultural environments (Abioye et al., 2020). Agricultural water use accounts for 70% of the total water withdrawal worldwide. The evapotranspiration during crop growth is one of the important hydrological processes in the agricultural water cycle (Boser et al., 2024). AI-based digital systems for intelligent irrigation continue to advance (Raouhi et al., 2023). AI and ML techniques, such as support vector machines and random forests, have been effectively used to predict irrigation needs based on factors, such as soil moisture and temperature (Jones, 2024).

Evapotranspiration (ET) isn't just a scientific term, it's the foundation of efficient irrigation. Understanding and applying ET helps maximize yields while improving water productivity (Wakchaure et al., 2023). The use of evapotranspiration data to fine-tune irrigation scheduling helps to avoid wasteful overwatering and protects precious water supplies. Farmers can reduce their water use and energy bills by using precision irrigation based on ET rates (Raouhi et al., 2023).

Modern technologies, particularly remote sensing and accurate hyperlocal weather data, enable farmers to minimize the time and effort required to calculate and monitor evapotranspiration levels, particularly in large fields (Arulraj and Karthikeyan, 2024).

A significant barrier to the adoption of ML in irrigation is the limited availability of quality data, which hinders its accuracy (Umutoni and Samadi, 2024). The complexity of AI models can lead to challenges in understanding their predictions, which requires the development of more interpretable models (Bhat and Huang, 2021). Combining process models with ML can improve the prediction accuracy and address data limitations (Umutoni and Samadi, 2024).

Various machine learning-based irrigation models have been proposed to minimize water waste. AIDSII, an AI-powered digital application that leverages IoT-based precision agriculture and CNN-LSTM models, offers a comprehensive feedback system through mobile and web technologies, enabling farmers to automate, optimize, and streamline their irrigation processes (Arulraj and Karthikeyan, 2024).

Innovative methods, such as those that predict soil moisture levels, can provide early warnings for irrigation and ensure optimal water use (Jones, 2024). Although digital technologies and statistical modelling offer significant advantages for irrigation management, challenges remain, such as the lack of data, interpretability of models, and the need for physics-informed models. Addressing these issues through improved data sharing, integration of expertise, and the development of FAIR data practices can increase the effectiveness of predictive models (Umutoni and Samadi, 2024).

Traditional irrigation practices face several challenges, ranging from inefficient water usage and overwatering to inadequate distribution systems. This results in water wastage, increased costs, and environmental concerns. Technological innovations address these challenges through precision and micro irrigation systems, soil sensors, etc. (Arulraj and Karthikeyan, 2024). Standardization, power efficiency, security, scalability, cost reduction, and user-centered design are among the critical factors that determine the success of IoT-enabled irrigation solutions (Gao et al., 2024).

The integration of AI, IoT, and precision agriculture technologies represents a paradigm shift toward sustainable water management in agriculture. Future research should focus on developing cost-effective IoT solutions, strengthening security frameworks, and enhancing user-friendly interfaces in order to promote mass adoption. By fostering interdisciplinary research collaborations and leveraging advancements in sensor technology, data analytics, and machine learning, the future of smart irrigation can be both technologically robust and economically viable, ensuring sustainable agricultural water management for years to come.

Materials and methods

The objective of this study was to analyze the efficiency of selected types of irrigation systems under realistic conditions based on sensor data and operational records and to develop prediction models that can reliably predict irrigation efficiency based on the recommended application rate, applied rate, and natural precipitation. As a result, key factors influencing irrigation decision making were identified, and a methodology for their efficient collection and processing was proposed.

The research is carried out within the CODECS (Maximising the CO-benefits of Agricultural Digitalisation Through Conducive Digital Ecosystems) project at the Slovak Living Lab. Within the CODECS project, the Living Lab is a network of farmers, knowledge brokers, stakeholders, and policymakers who come together around an emerging problem in a specific application scenario and are willing to develop solutions through collaboration.

The Slovak Living Lab is a part of the Gamota Group, which operates in agriculture, forestry, fish farming, and foreign trade. The company's main activities include premium production, GMO-free virgin soybean oil (GamoSoy), and high-quality soybean expellers (SoyProFat). The company was founded in 2011 as a small family business that focused on purchasing and exporting agricultural products and integrating smaller businesses providing input products (fertilizers and chemicals) and services such as fertilization, tillage, and harvesting. Owing to its rapid development and strategic investments, the company has become one of the leading players in the Slovak agricultural sector with the aim of developing sustainable solutions for the agrosector's future.

Gamota Group has become a key partner in the Living Lab for Irrigation Management in Slovakia, which focuses on the research and application of sustainable irrigation strategies that simultaneously help minimize water consumption, increase crop production efficiency, and protect soil resources.

The research was conducted in the Nitra region in the town of Hurbanovo, which is characterized by a semi-arid climate and requires supplementary irrigation to ensure optimal crop growth. This location was chosen because of the existing irrigation infrastructure and the interest in introducing innovative solutions for water management. Figure1 shows Living Lab Gamota research farms, where digital technologies, IoT sensors, and machine learning are being tested for precise irrigation management. The goal of this study was to minimize water consumption by predicting irrigation application rates based on current environmental conditions, thereby contributing to greater cropping efficiency and agricultural sustainability in the region. The field study was conducted throughout the 2023 growing season (spring-autumn), allowing seasonal changes in irrigation demand and their impact on soil moisture to be recorded.

The main methodology involved the integration of environmental sensor data, agronomic models, and machine-learning techniques to develop a model capable of predicting optimal irrigation application rates. The experimental design included field trials using IoT sensors and Valley and Irriga control software. Individual sensors provided real-time data on soil moisture levels, which were correlated with meteorological variables such as solar radiation, rainfall, humidity, temperature, and wind speed, obtained from local weather stations.

Pivot irrigation systems have been installed on most plots in Living Lab Gamota and are the dominant technology in precision irrigation. The other fields used pilot systems or were managed without irrigation. The fields were mainly maize (48 %), followed by peas (31 %), and wheat (11 %), with barley, beans, and buckwheat making up the remainder. Digital solutions are implemented on the farm, including automated irrigation systems and Valley and Irriga Global software, which enable optimized irrigation management based on sensory and meteorological data. The analysis confirmed that the Valley and Irriga Global systems provide heterogeneous and hardly compatible data that require complex pre-processing before they can be effectively used in decision-making processes. Therefore, this research focused on designing a unified methodology for data collection, validation, and analysis usable in artificial intelligence (AI) and machine learning (ML) predictive models, specifically for the purpose of determining optimal irrigation application rates. Several analytical tools have been applied to support this objective, including exploratory data analysis (EDA), correlation techniques, and regression models. Statistical analysis allows the identification of key factors influencing irrigation efficiency, such as atmospheric precipitation, temperature, soil moisture, recommended and applied rates, and energy consumption. Correlation analysis helps to reveal the links between variables and supports the selection of the most appropriate predictors. Regression models allow the generation of quantified estimates of irrigation needs based on real conditions.

The methodological framework involves collecting and preprocessing data from different sources, cleaning, normalizing, removing outliers, and integrating them into a common analytical model. Significant attention has been paid to selecting appropriate machine learning models and tuning them for the highest possible prediction accuracy. The main data sources are as follows:

- **Land data:** location, acreage, crops grown, history of interventions.
- **Meteorological data:** microclimatic variables from automatic stations (precipitation, temperature, wind, and humidity).
- **Irrigation systems** (e.g., pivots) include location, system type, frequency, and extent of application.
- **Agrotechnical records:** irrigation rates, measured soil moisture, data from agronomists.
- **Satellite and tabulated values:** NDVI, reference soil moisture, evapotranspiration.

For modelling purposes, daily temporal granularity was chosen, which allowed the synchronization of data from different sources into a single dataset suitable for the statistical analysis and training of machine learning models. Data integration (called data fusion) was designed to respect different measurement frequencies and spatial resolutions, thus ensuring the consistency of the inputs for further calculations.

Within the concept of precision agriculture, in which irrigation benefit modelling is an integral part, the spatial accuracy of the data is extremely important. In practice, this means that the collected data must have a well-defined spatial resolution and must be related to a specific location, typically at the level of a single pivot or field. The extent of the "small neighbourhood, " to which the data are related, depends on the specific application, but in our case, the smallest homogeneous unit is the area farmed by a single irrigation system.

Therefore, when collecting data at the pivot level, it is ideal to collect data for each system separately: crop growth, electricity consumption, irrigation application rate, size and date, microclimatic data, soil moisture values, and other agronomically relevant variables.

In this context, data fusion is the process of combining different types of data (technical, meteorological, agronomic, and satellite) into a single integrated dataset that can then be used for statistical analysis and machine learning. For successful fusion, it is crucial that the data are compatible in terms of both the temporal and spatial resolutions

Results and discussion

Data preprocessing is a key step in ensuring the consistency, quality, and usability of data for statistical modelling. This process involves removing missing values, identifying outliers, transforming the data into an appropriate format, and standardizing the selected variables. The goal was to minimize the noise, reduce the risk of bias, and maximize the reliability of the model outputs.

Because data fusion was implemented in the previous phase, further work was being performed at the individual attribute level. Some variables, such as tabular recommendation values, are left untouched or adjusted in analogy with measured values. The data are primarily used as indicative and do not usually enter directly into the model.

The numerical variables were subjected to a distribution check, search for missing data or outliers, and subsequent consideration for inclusion in the model. The removal or imputation of data depends on the type of attribute, its importance, and frequency of missingness. The decision on model inclusion is based on correlation analysis or by experimentally comparing the performance of models with different combinations of variables.

It is important not only to evaluate the correlation between the target variable (e.g., irrigation rate) and the input variables but also between the inputs themselves because of the risk of multicollinearity. The inclusion of highly correlated variables may negatively affect the accuracy and interpretability of a model.

Numerical variables can be standardized (e.g., change to z-score) or normalized (scaling to the 0–1 interval), particularly when used in scale-sensitive models. This step is particularly important when working with the variables in different units.

Categorical variables are particularly useful for low cardinality (e.g., crop type), where they are clearly interpretable. At higher cardinalities, the information value may be lost, and model complexity may increase. Attributes are encoded using one-hot or label encoding.

Modelling irrigation doses

Modelling represents the final stage of the analytical process, in which statistical and machine learning algorithms are used to create predictive models. The aim was to identify the relationships between the environmental variables and the target value, the optimal irrigation rate, and to use these relationships to make decisions under realistic conditions.

Regression techniques were used to quantify the influence of individual factors while optimizing the input data in terms of predictive accuracy. An important benefit of this phase is the feedback on the data collection process, where the best-performing models indicate which variables have the greatest impact and can be excluded in the future, thus simplifying the entire collection process.

The modelling also allows the simulation of different irrigation scenarios and their impact on efficiency and water consumption, thus supporting decision making in the spirit of sustainability and precision agriculture.

Depending on the problem formulation, two main approaches can be applied in irrigation benefit modelling: regression and classification.

Regression models predict a specific numerical value, such as the required irrigation rate in millimeters (e.g., output = 5 mm).

Classification models decide the category to which a given situation belongs, for example, whether irrigation is required. The classification can be binary (e.g., 0 = do not irrigate, 1 = irrigate) or multiclass (e.g., 0–5 mm = no irrigation, 6–15 mm = moderate irrigation, >15 mm = intensive irrigation).

Transforming the regression problem into a classification problem can simplify decision-making, for example, by setting a threshold of 10 mm below which there is no irrigation and above which there is. The advantages of classification are a wider choice of available algorithms and sometimes better interpretability.

The most commonly used approach is multiple linear regression, if the existence of a linear relationship between the target variable and input attributes is confirmed. The accuracy of the model is most often assessed using the coefficient of determination R^2, which indicates the proportion of variability in the target variable that the model explains (ideally, 1.00).

The model can be optimized using regularization (e.g., Lasso or Ridge), which penalizes less significant variables and reduces the risk of overfitting. The quality of the model can also be visually verified by comparing the predicted and actual values in a dot plot and calculating the average absolute error (e.g., in millimeter irrigation).

A wide range of models is available for classification, from simple (logistic regression, decision trees, and random forests) to complex deep learning architectures. Some models such as support vector machines (SVMs) can be used for both regression and classification.

An important part of classification modelling is hyperparametric tuning, in which different model configurations are tested. Because it is not possible to explore all combinations, a strategy of selecting from a limited set (e.g., grid search or random search) was used.

The models are evaluated using metrics such as:

- accuracy – the proportion of correctly classified cases,
- Precision (precision) and sensitivity (recall) – important in the case of non-uniform classes
- F1-score – harmonic mean of precision and sensitivity.

In the context of irrigation, it is important to minimize false-negative predictions (e.g., the model does not recommend irrigation when needed), which can negatively affect crop yields.

Time-series models can also be used if irrigation is analyzed over time. The best-known are:

- ARIMA – suitable for stationary time series with a relatively stable mean,
- Long Short-Term Memory (LSTM) is a type of recurrent neural network that is suitable for modelling long-term dependencies and nonlinear trends.

These models allow the prediction of future irrigation values based on historical trends and the evolution of environmental factors.

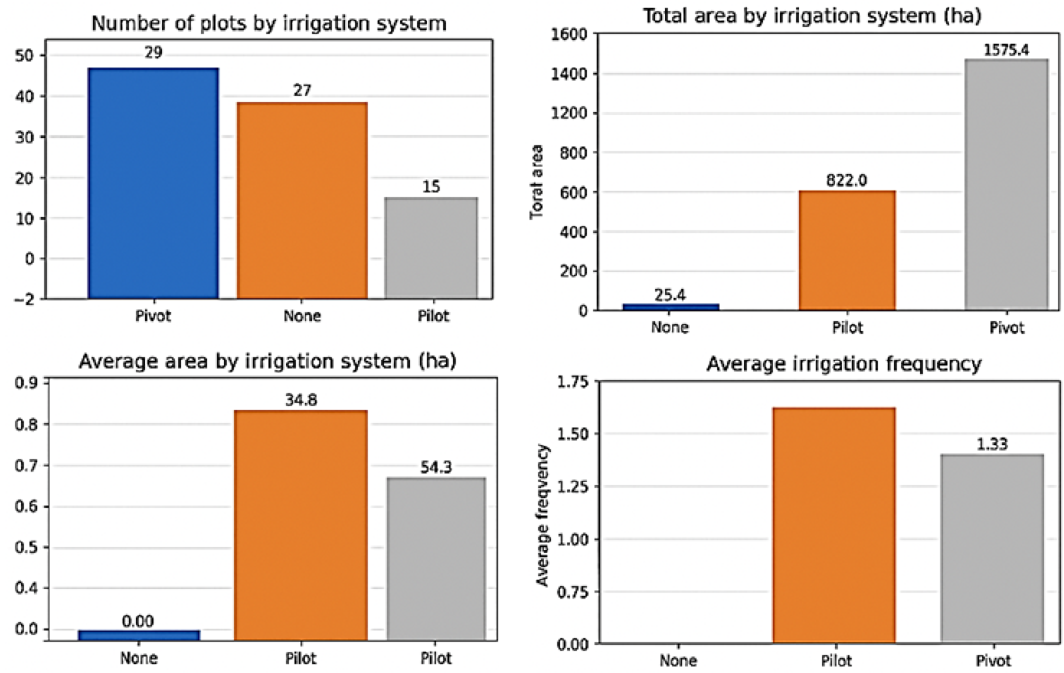
Based on the proposed dataset structure and type of target variable, regression models are more suitable for the accurate prediction of irrigation rates in millimeters. Nevertheless, the problem can be reformulated as a classification problem by categorizing the doses into discrete intervals, according to agronomic recommendations. The choice between regression and classification depends on the model output, data availability, and interpretation requirements.

Efficiency analysis of irrigation systems

Analysis of the spatial distribution and technical parameters of irrigation systems in the study area revealed significant heterogeneity in the implementation of hydromeliorative technologies (Figure 1). Two dominant types of irrigation systems were identified within the set of 71 agricultural plots, pivot and pilot irrigation systems, while 27 plots were managed without the application of artificial irrigation. Pivot systems were installed on 29 plots (40.8 %) with an average irrigated area of 56.17 ha and an average irrigation frequency of 1.38 applications over the study period. Pilot irrigation systems were implemented in 15 plots (21.1 %), with an average irrigated area of 54.16 ha and a higher average irrigation frequency of 2.00 applications per period. Plots without irrigation systems (38.0%) show a significantly lower average area of 0.96 ha, indicating preferential implementation of irrigation technologies on larger agricultural plots.

A comparative analysis of the technical parameters of the identified irrigation systems revealed distinctive characteristics of the individual typological categories. Pivot systems, characterized by the rotational movement of the irrigation boom around a central point, show a lower frequency of irrigation water application but cover a slightly larger average area than pile systems. The total area irrigated by pivot systems was 1,575,40 ha, while pilot systems cover 822,05 ha. A significant difference was identified in the average irrigation efficiency, where pivot systems reached a value of 79.64 %, whereas pilot systems showed an efficiency of 75.10 %. This discrepancy can be attributed to the different technical parameters of irrigation water distribution and the different algorithms used to control the irrigation process.

An important aspect of hydraulic improvement management in the analyzed area was the implementation of the PESSL sensor system for monitoring the soil moisture and meteorological parameters (Figure 2).



Source: Own processing

Figure 1: Distribution of irrigation systems by number of plots, total area, average area and frequency of irrigation.

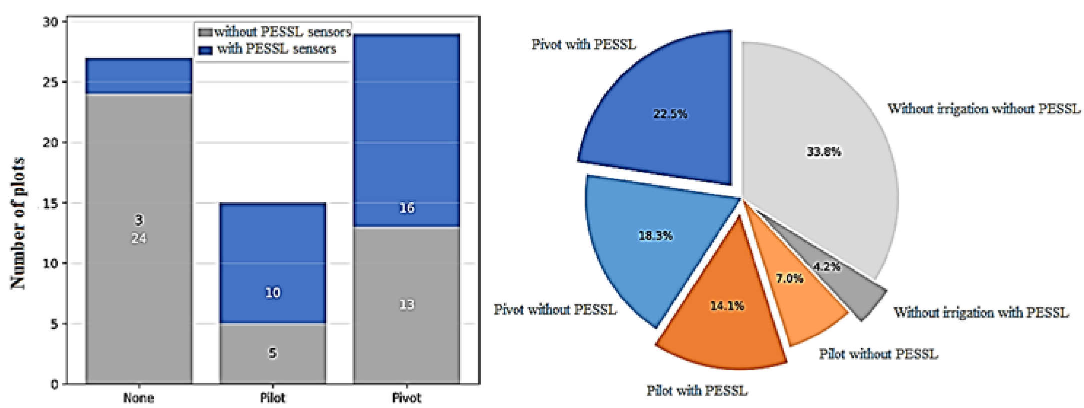


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Figure 2: Distribution of PESSL sensors by the type of the irrigation system.

A total of 29 plots (40.8%) were equipped with these sensors, with an uneven distribution between the different types of irrigation systems. Of the 29 plots with pivot irrigation, 16 (55.2%) were equipped with PESSL sensors, whereas 10 of the 15 plots (66.7%) in the pilot system category were equipped with sensor technology. A surprising finding was the presence of PESSL sensors in three plots without irrigation systems (11.1%), indicating the potential use of sensor data for optimizing further agronomic operations or planning future implementation of irrigation technologies (Table 1).

Analysis of irrigation efficiency, defined as the ratio between the optimum and applied irrigation water quantity, revealed an average value of 75.53%, with significant variability among plots (Table 2).

A comparative analysis of the recommended irrigation (average 129.55 mm) and the actual amount of water applied (average 95.88 mm) indicated a systematic tendency towards under-application of irrigation water, which may be due to economic constraints, technical limitations of irrigation systems, or a conservative approach to water resource management. A significant factor influencing irrigation efficiency was the distribution of natural rainfall, which averaged 186.50 mm over the study period. The correlation analysis between applied irrigation and efficiency showed a moderately strong positive correlation ($r = 0.7256$), indicating that an increase in the amount of irrigation water applied leads to higher water-use efficiency up to a certain saturation point (Figure 3).

Type of system	Number of plots	Average area (ha)	Average frequency	PESSL sensors
Pivot	29	54.32	1.33	16 (55.2 %)
Pilot	15	54.80	1.85	10 (66.7 %)
Without irrigation	27	0.94	0.00	3 (11.1 %)
Total	71	34.12	0.93	29 (40.8 %)

Source: Own processing

Table 1: Key parametres of irrigation systems.

Type of system	Average efficiency (%)	Recommended irrigation (mm)	Applied irrigation (mm)	Precipitation (mm)
Pivot	79.64	126.86	99.53	180.10
Pilot	75.10	131.00	99.38	201.06
Diameter (irrigated)	78.09	128.28	99.48	187.25

Source: Own processing

Table 2: Irrigation efficiency parametres.

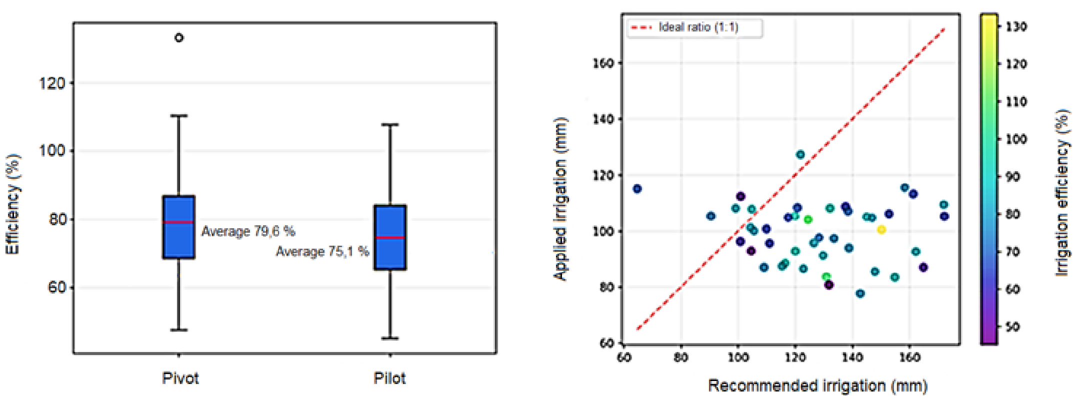

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Figure 3: Irrigation efficiency analysis by the system type and relationship between recommended and applied irrigation.

Irrigation efficiency analysis

Quantitative analysis of the hydroremediation parameters based on data obtained from the PESSL sensor system revealed complex relationships between the different components of the irrigation process. The average recommended irrigation rate was 129.55 mm, while the average applied rate was only 95.88 mm, indicating a systematic tendency to under-application of irrigation water in the range of 25.99%. The average irrigation efficiency, defined as the ratio of the optimum use of applied water to the theoretically required amount, was 75.53%. Atmospheric precipitation was a significant factor influencing the irrigation regime, with an average value of 186.50 mm over the study period, representing the dominant component of the total water input to the soil profile.

Correlation analysis of the hydromeliorative parameters (Figure 4) revealed several statistically significant relationships. The strongest positive correlation ($r = 0.8583$, $p < 0.001$) was detected between the recommended irrigation and rainfall, reflecting the adaptive nature of the irrigation algorithm that integrates the prediction of rainfall into the calculation of the optimal irrigation rate. The moderately strong positive correlation ($r = 0.7256$, $p < 0.001$) between applied irrigation and efficiency indicates that an increase in the amount of irrigation water applied leads to a proportional increase in water use efficiency, probably because of the surpassing of the soil moisture thresholds necessary for optimal water uptake by the plant root system. The weak negative correlation ($r=-0.1027$, $p=0.5964$) between recommended irrigation and efficiency suggests a potential overestimation of optimal irrigation rates by the PESSL algorithm, especially under conditions of higher soil moisture. The medium positive correlation ($r = 0.5149$, $p = 0.0042$) between the recommended and applied irrigations reflects the partial implementation of the sensor system recommendations in practical irrigation management.

Regression analysis of the relationship between applied irrigation and efficiency generated a prediction model (Figure 5) characterized by the equation Efficiency = 0.483 × Applied + 29.27 ($R^2 = 0.527$), which explains more than half of the variability in irrigation efficiency. This model implies that each 10 mm increase in applied irrigation rate leads to an average increase in efficiency of 4.83 percentage points. extrapolation of the model indicated that a theoretical achievement of 100% efficiency would require

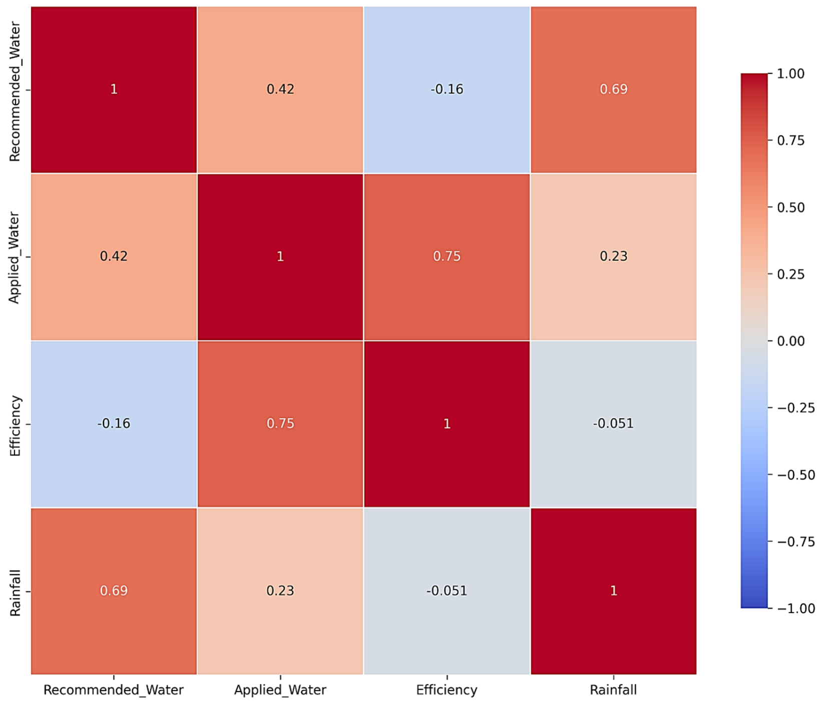

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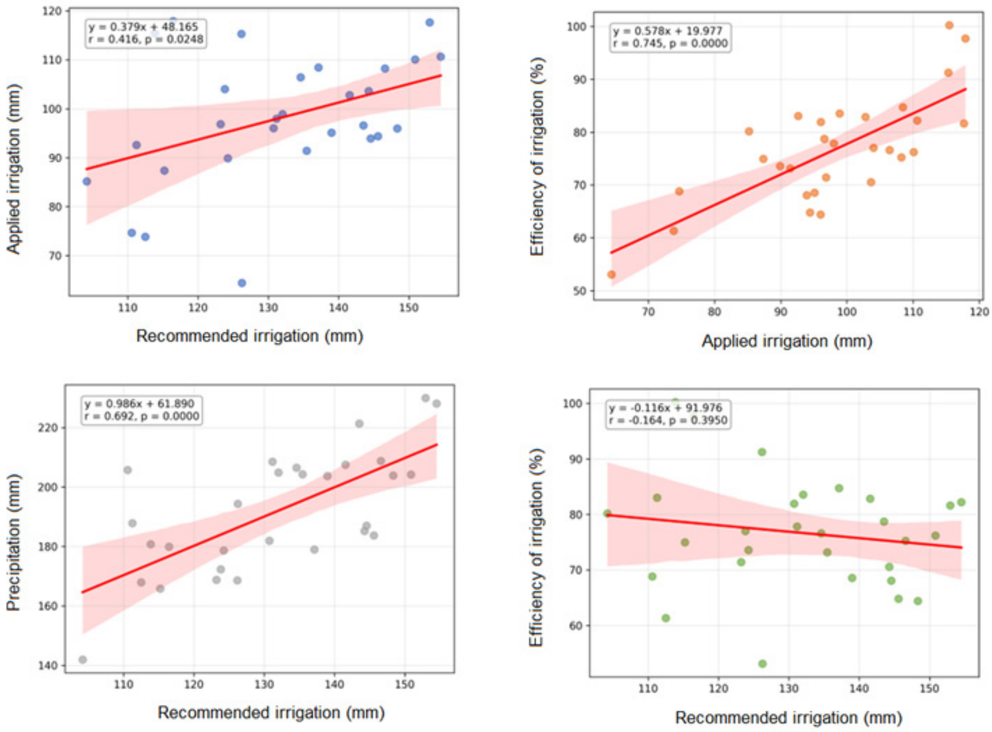
Figure 4: Correlation matrix of irrigation parametres showing the strength and direction of the relationships between the variables.

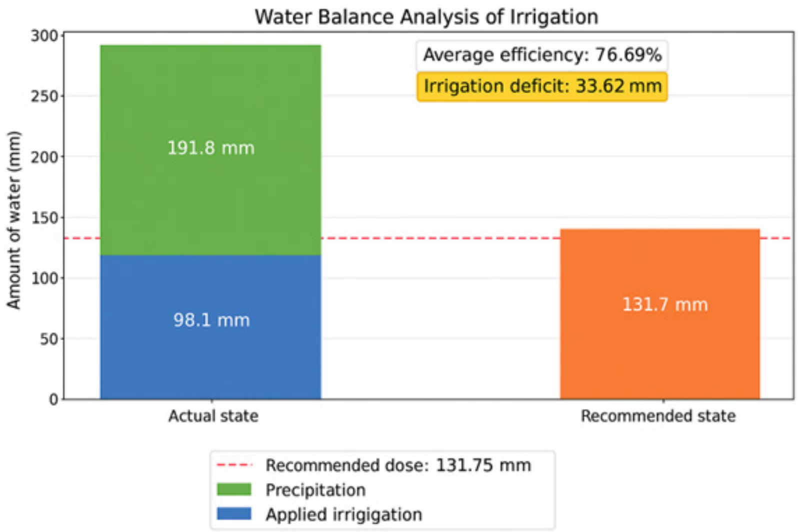


Source: Own processing

Figure 5: Regression analysis of key relationships between irrigation parametres with regression equations and correlation coefficients plotted.

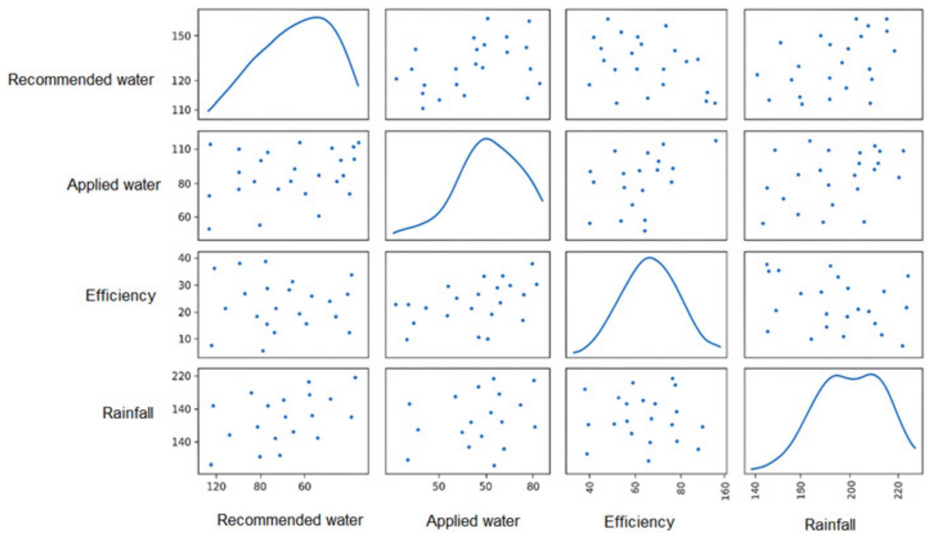
the application of approximately 146.4 mm of irrigation water, which exceeds the average recommended application rate by 13.0%. This discrepancy may be the result of the conservative settings of the PESSL algorithm or specific soil and climate conditions that modify the optimal irrigation parameters. The regression model of the relationship between recommended and applied irrigation (Applied = 0.385 × Recommended + 46.01, R^2 = 0.265) further confirmed a systematic tendency towards underapplication of irrigation water, with the rate of implementation of recommendations decreasing with increasing recommended rate.

The Water balance analysis (Figure 6) revealed that the combination of applied irrigation (95.88 mm) and rainfall (186.50 mm) provided a total water supply of 282.38 mm, which exceeded the average recommended rate (129.55 mm) by 118.0%. However, this apparent surplus must be interpreted in the context of the temporal distribution of rainfall, its infiltration efficiency, and evapotranspiration losses, which significantly reduces the amount of water available to plants. The irrigation deficit, defined as the difference between the recommended rate and the applied rates, was 33,67 mm, which represents 26,0 % of the recommended rate. This deficit is partly compensated by rainfall, but its temporal and spatial variability limits the reliability of this compensation. The implementation of precise irrigation strategies based on continuous monitoring of soil moisture and meteorological parameters has the potential to optimize the efficiency of water use and minimize the irrigation deficit while maintaining the economic efficiency of hydraulic improvement measures. (Tables 3, 4, 5).



Source: Own processing

Figure 6: Regression analysis of key relationships between irrigation parametres with regression equations and correlation coefficients plotted.



Source: Own processing

Figure 7: Dot-plot matrix showing the interrelationships between all the analysed irrigation parametres.

Parameter	Value
Average recommended irrigation rate	131.75 mm
Average applied irrigation rate	98.13 mm
Average irrigation efficiency	76.69%
Average rainfall	191.76 mm
Irrigation deficit	33.62 mm
Total water supply (irrigation + precipitation)	289.89 mm

Source: Own processing

Table 3: Key irrigation parametres and correlations.

Relationship	Correlation coefficient (r)	p-value
Recommended irrigation vs. Precipitation	0.6921	0.0000
Applied irrigation vs. Efficiency	0.7454	0.0000
Recommended irrigation vs. Efficiency	-0.1641	0.3950
Recommended vs. Applied irrigation	0.4159	0.0248
Applied irrigation vs. Precipitation	0.2334	0.2230
Efficiency vs. Collisions	-0.0507	0.7940

Source: Own processing

Table 4: Correlation coefficients between irrigation parametres.

Model	Regression equation	Coefficient of determination (R^2)
Applied irrigation vs. Efficiency	Efficiency = 0.578 × Applied + 19.98	0.556
Recommended vs. Applied irrigation	Applied = 0.379 × Recommended + 48.16	0.173
Recommended irrigation vs. Efficiency	Efficiency = -0.116 × Recommended + 91.98	0.027
Precipitation vs. Recommended irrigation	Recommended = 0.486 × Precipitation + 38.56	0.479

Source: Own processing

Table 5: Regression models for irrigation parametres.

Irrigation efficiency prediction models

For the analysis, four different regression models (Table 6) were developed based on three key variables: the recommended irrigation amount, actual water applied, and natural precipitation. Data were collected using PESSL sensors placed on the selected agricultural plots. The irrigation efficiency was calculated as the ratio between the optimum water use and the actual amount applied and expressed as a percentage.

Analysis of the different prediction models revealed significant differences in their ability to explain variability in irrigation system efficiency. The model based on the recommended irrigation amounts alone (Model 1) showed a low coefficient of determination ($R^2 = 0.0918$), suggesting that the recommended values alone are not sufficient predictors of actual efficiency. The negative coefficient in equation (-0.2606) suggests an inverse relationship, where higher recommended water amounts are paradoxically associated with lower efficiency, which may be due to a tendency to overirrigate at higher recommended values.

The model based on the actual amount of water applied (Model 2) performed significantly better with $R^2 = 0.4121$. A positive coefficient (0.4896) indicates that irrigation efficiency increases as the amount of water applied increases, which may reflect the fact that farmers adapt the amount of water to actual conditions better than the automated recommended values.

Surprisingly, the model based on natural precipitation alone (Model 3) showed the lowest predictive ability ($R^2 = 0.0114$), suggesting that precipitation alone had minimal direct influence on the efficiency of irrigation systems. This result may be due to the fact that farmers already take rainfall into account when making irrigation decisions, thus offsetting its influence.

The multiple regression model (Model 4), which combined all three variables, achieved a significantly higher predictive ability, with $R^2 = 0.8770$. This model explains approximately 87.7% of the variability in irrigation efficiency, a significant improvement over the simple models. The coefficients in Eq. indicate that, while the recommended amount of water has a negative effect on efficiency (-0.8386), the amount actually applied has a positive effect (0.7266). Interestingly, in the context of multiple regression analysis, rainfall had a slightly positive effect (0.1864), suggesting a complex interaction between these variables.

The results of this study have several important implications for optimizing agricultural irrigation practices. First, the significant difference between the predictive abilities of the simple and multiple

Model	Equations	R^2
Model 1: Recommended irrigation	Efficiency = -0.2606 × Recommended + 115.8477	0.0918
Model 2: Applied irrigation	Efficiency = 0.4896 × Applied + 30.7128	0.4121
Model 3: Collisions	Efficiency = -0.0714 × Precipitation + 94.6646	0.0114
Model 4: Multiple regression	Efficiency = 82.6585 - 0.8386 × Recommended + 0.7266 × Applied + 0.1864 × Precipitation	0.8770

Source: Own processing

Table 6: Regression models.

regression models highlights the complex nature of irrigation efficiency, which is simultaneously affected by the interaction of several factors.

Second, the negative relationship between the recommended water quantity and efficiency suggests the potential shortcomings of the current irrigation recommendation algorithms. These algorithms may be too conservative and lead to overirrigation, which reduces the overall efficiency of the water use.

Third, the strong positive relationship between applied water quantity and efficiency highlights the importance of human factors and farmers' experience in irrigation decisions. This result suggests that a combination of automated systems and expert judgment can lead to a more optimal use of water resources.

The multiple regression model is a robust tool for predicting irrigation efficiency and can serve as a basis for the development of advanced decision support systems in precision agriculture. The implementation of this model can lead to significant water savings and improve the sustainability of agricultural practices.

This analysis showed that the efficiency of irrigation systems is a complex phenomenon that cannot be adequately modelled by a single variable. A multiple regression model that takes into account the recommended amount of irrigation, the actual amount of water applied, and natural rainfall provided the best predictive power and explained approximately 87.7% of the variability in irrigation efficiency.

The results highlight the need for a holistic approach to optimizing irrigation practices that considers both technological aspects (sensors, recommendation algorithms) and human factors (farmers' experience and decision-making processes). Future research should focus on integrating other factors such as soil properties, climatic conditions, and crop specificities into prediction models to further increase their accuracy and applicability.

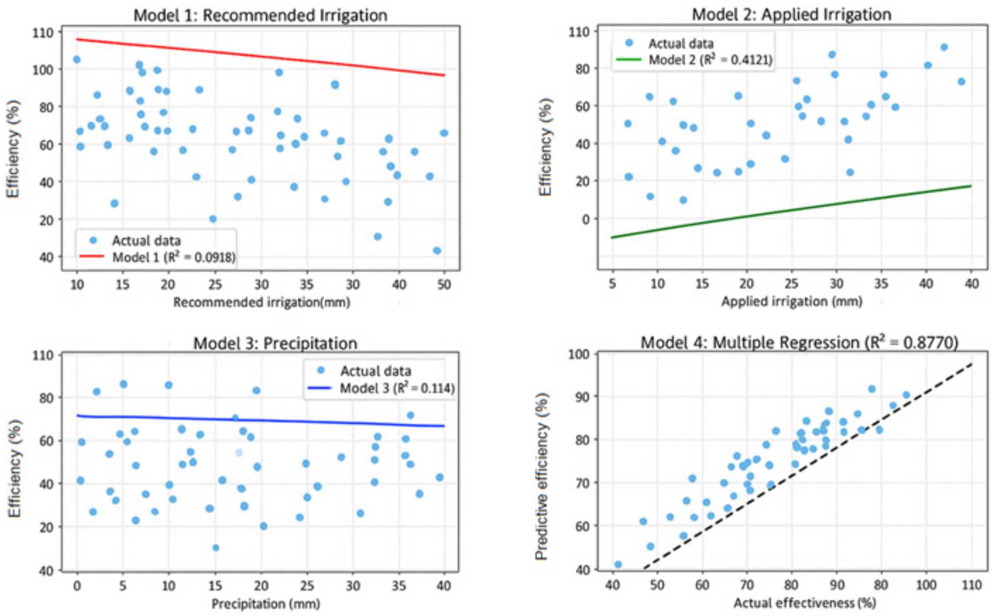
The graphs (Figure 8) show the relationship between each variable and irrigation efficiency for each model. The relationship between the actual and predicted efficiencies in Model 4 (multiple regression) is shown.

The graph (Figure 9) shows the coefficients of determination (R^2) for each model, indicating their ability to explain variability in irrigation efficiency.

A multiple regression model (Model 4) was developed based on three key predictors: recommended irrigation amount, actual water applied, and natural precipitation. This model is defined by the following equation.

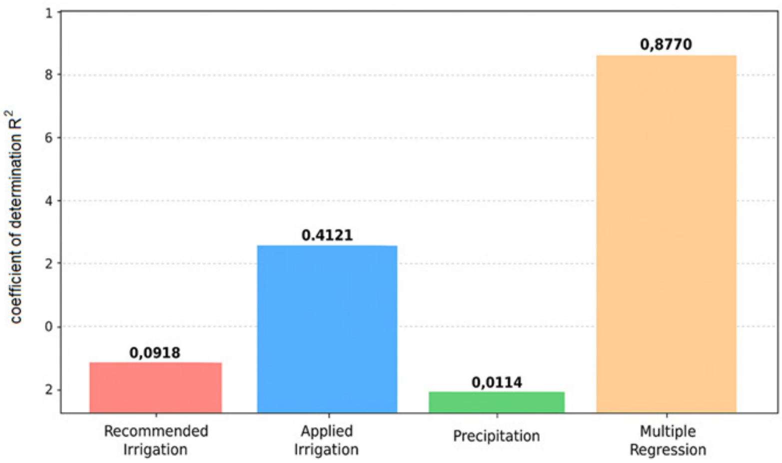
$$Efficiency = 82.6585 - 0.8386 \times Recommended + \\ + 0.7266 \times Applied + 0.1864 \times Precipitation.$$

This model achieves a coefficient of determination $R^2 = 0.8770$, which means that it explains approximately 87.70% of the variability in irrigation efficiency. Compared to simpler models based on single predictors, the multiple regression model represents a significant improvement in predictive ability and provides a more comprehensive view of the factors influencing irrigation system efficiency.



Source: Own processing

Figure 8: Comparison of irrigation efficiency prediction models.



Source: Own processing

Figure 9: Comparison of irrigation efficiency prediction models.

Conclusion

The coefficients of the multiple regression model provided valuable information on the relative influence of individual predictors on irrigation efficiency. Each coefficient represents the change in predicted efficiency when the relevant variable is increased by one unit (1 mm), assuming that the other variables remain constant. This ceteris paribus interpretation allows the effects of each factor to be separately isolated and quantified.

The coefficient for recommended irrigation (-0.8386) shows a negative value, indicating an inverse relationship between the recommended water quantity and irrigation efficiency. Specifically, each 1 mm increase in the recommended amount is associated with a decrease in the predicted efficiency of approximately 0.84 percentage points, holding other variables constant. This negative relationship can be interpreted in several ways. A plausible explanation is that irrigation recommendation algorithms may systematically overestimate the amount of water required, leading to inefficient use of water resources. Alternatively, this relationship may reflect the fact that higher recommended values are generated in more challenging environments, where high irrigation efficiency is more difficult to achieve.

The coefficient for applied irrigation (+0.7266) is positive, indicating that a 1 mm increase in the actual amount of water applied is associated with an increase in the predicted efficiency of approximately 0.73 percentage points, holding other variables constant. This positive relationship may reflect the adaptive behavior of farmers who adjust the amount of water applied to actual conditions based on their experience and observations. The results suggest that farmers' decisions regarding the amount of water applied are often more accurate than automated recommendations, highlighting the importance of human factors in the irrigation process.

The coefficient for precipitation (+0.1864) is slightly positive, indicating that a 1 mm increase in natural precipitation is associated with an increase in the predicted efficiency of approximately 0.19 percentage points, holding other variables constant. This relationship is interesting because in the simple regression model (Model 3), precipitation showed a negative coefficient and very low predictive power ($R^2 = 0.0114$). However, in the context of multiple regression, rainfall positively contributed to efficiency, suggesting a complex interaction between rainfall and other factors. The positive effect of rainfall may be explained by the fact that natural rainfall provides a more optimal distribution of water in the soil than artificial irrigation or by the fact that farmers integrate rainfall information more efficiently into their irrigation decisions.

The model constant (82.6585) represents the predicted irrigation efficiency when all predictors are zero. In a practical context, this value is of limited interpretative value because the null values of the predictors lie outside the range of observed data. However, this constant contributes to the overall accuracy of the model and ensures that predictions are calibrated to the correct level of efficiency.

The multiple regression model provides several important practical implications for optimizing irrigation practices in precision agriculture. First, the negative coefficient for recommended irrigation suggests the need to revise the current algorithms to generate recommendations. These algorithms should be calibrated to better reflect the actual needs of crops and minimize the risk of overirrigation. The implementation of adaptive algorithms that learn from historical data and farmer experience could lead to more accurate recommendations and greater water-use efficiency.

Second, the positive coefficient for applied irrigation highlights the value of farmers' experience and knowledge in making irrigation decisions. Decision support systems should integrate both automated recommendations and manual adjustments based on expert judgement. A hybrid approach that combines technological solutions with human factors can lead to more optimal use of water resources and higher irrigation efficiency.

Third, the positive coefficient for rainfall in the context of multiple regression suggests that effective integration of rainfall data into the decision-making process can improve irrigation efficiency. Advanced rainfall monitoring and weather prediction systems should be part of comprehensive irrigation management solutions. These systems should provide not only historical data, but also short- and medium-term forecasts to enable farmers to plan irrigation activities better.

The multiple regression model can be implemented as part of an advanced decision-support system for precision agriculture. These systems should integrate data from various sources, including soil moisture sensors, weather stations, and satellite imagery, to provide farmers with comprehensive information for optimizing irrigation practices. The implementation of such systems can lead to significant water savings, reduced irrigation costs, and increased sustainability in agricultural practices.

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