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AI-Enhanced Precision Irrigation in Legume Farming: Optimizing Water Use Efficiency

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ABSTRACT

Background: Cultivating legumes, a significant facet of sustainable agriculture, consistently faces challenges in managing water resources. The present study aimed to explore the integration of artificial intelligence (AI) to enhance water use efficiency in legume farming with the potential to reduce the water shortage problem. In this work, Peas as a specific legume is chosen. In Uttar Pradesh, India, precision irrigation was combined with artificial intelligence (AI) to maximize crop productivity, support sustainable farming methods and solve the problem of water constraints. AI-enabled precision irrigation offers significant advantages like precise allocation of water resources, enhanced crop yield, optimal water consumption, cost-effectiveness and a reduction of greenhouse gas emissions.
Methods: By employing a systematic methodology, including data collection, AI modeling and thorough data analysis, this work reveals useful findings. The comparison between traditional and AI-driven precision irrigation shows that artificial intelligence delivers enhanced real-time decision-making capabilities. It optimally tailors' irrigation schedules and water distribution, considering weather, soil conditions and crop requirements. The achieved water savings, combined with improved legume yields, have significant implications for agricultural techniques with limited resources.
Result: Because of a changing climate and decreasing water supplies, farmers, legislators and other stakeholders can greatly benefit from the suggestions that were obtained from the findings, which provide practical direction. This research serves as a milestone in the integration of AI for precision agriculture, creating a way for a more sustainable and productive future in legume farming.

Key words: Artificial intelligence, Conserving water, Legume farming, Water use efficiency.

INTRODUCTION

The integration of artificial intelligence (AI) and agriculture marks the onset of a novel era of innovation, fundamentally altering the approach to sustainable crop production. Applying AI to precision irrigation in this field (Sudha *et al.*, 2018) improves it by using data-driven analysis, optimization and adaptability, while also reflecting nature's remarkable precision (Leh *et al.*, 2019; Blessing *et al.*, 2018). The shortage of water has become more pressing in an era marked by rapidly expanding populations and the forthcoming effects of climate change (R'jeswari *et al.*, 2017). The farming area is a significant consumer of water resources so increasing crop yields with optimal water consumption is an essential requirement for sustainable agriculture (Paul *et al.*, 2020). Securing food production and safeguarding the environment serve as dual priorities. Legume crops, with their essential function in global agriculture, present a unique vision. Because legumes such as peanuts, lentils, soybeans and mungbeans-are essential plant-based protein sources, their production is essential to human nutrition (Kumar *et al.*, 2020; Rawal, 2017). But because of their extremely delicate water needs, conventional farming methods often lead to less-than-ideal water management, risking not just the sustainability of legume cultivation but also food security (Shah *et al.*, 2017; El-Nakhlawy *et al.*, 2017). Artificial Intelligence (AI) offers a novel solution for addressing these issues. Unlike traditional irrigation techniques that operate on pre-established schedules or manual observations (Reddy *et al.*, 2017), AI-driven precision irrigation employs the capabilities of machine learning, data analytics and real-time monitoring to imitate the details of natural ecosystems (Akhter *et al.*, 2022; Yang *et al.*, 2021; Shah, 2009; Upreti, 2022). It adapts to the ever-changing variables in a field, much like how the human body regulates its temperature in response to external conditions. AI is evolving fast as a result of improved computing power and easier access to the cloud, which is allowing more areas of the world economy to make use of its benefits (Bhardwaj *et al.*, 2021; Bhagat *et al.*, 2022). Particularly in the sector of agriculture, artificial intelligence is having a good effect. Applications involve planning yields ahead of time, monitoring crop and soil health, controlling

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weeds and scheduling harvests optimally. While machine learning and artificial intelligence have been investigated as development tools in a range of industries, current advancements highlight their potential to improve agricultural decision-making (Rodzalan *et al*., 2020; Shankar *et al*., 2020; Vyas *et al*., 2022). Legume farming has been transformed by the incorporation of artificial intelligence into precision irrigation systems, especially in the pea crop sector. With human-like accuracy, this state-of-the-art technology optimizes water consumption and ensures that pea crops develop healthily. Farmers may dynamically adjust irrigation schedules by using AI algorithms to analyze real-time environmental data, soil conditions and plant requirements. AI-enhanced precision irrigation promises abundant pea yields with little environmental effect while promoting sustainable agriculture practices and improving water usage efficiency. This creative method is a big step forward for resource-conscious farming in the field of legume growing. Legumes are specifically chosen for analysis in this study due to their outstanding benefits to agriculture. They play an important role in maximizing agricultural techniques owing to their wide range of applications, which include improving soil fertility, offering essential nourishment and acting as important sources of income. When it comes to maximizing water use efficiency with AI-enhanced precision irrigation techniques, legumes are a useful crop for research because of their unique properties, which include high demand, significant production volume, nutritional value and potential economic impact.

High demand

Leguminous crops are in high demand because they are essential for maintaining food security and fulfilling nutritional requirements. The high nutritious value of legumes, especially soybeans, makes them significant parts of diets around the world. For consumption by humans and animals, they are essential because of their high protein level and nutritional value.

Large production volume

Legumes such as Soybeans are produced in large quantities worldwide. Due to their frequency, they have a significant impact on agriculture and highlight the necessity of efficient disease control plans to ensure maximum harvests. Any illnesses that affect these crops have a greater effect because of their huge volume of output.

Wide availability

Legumes are widely available since they are grown in many different parts of the world. The widespread nature of this disease highlights the need for reliable diagnostic instruments that may be used in a range of agroclimatic conditions. Solving the problems that legumes face in various parts of the world can have a significant impact on agriculture worldwide.

Economic significance

As a key component of agriculture, legumes have a substantial economic value. The significance of preserving the health of legume crops is highlighted by their economic impact, which includes their direct involvement in the products trade as well as their support of related businesses like animal feed. Sustainably managed diseases can reduce financial losses and advance agricultural sustainability.

In summary, legume crops particularly soybeans were chosen for this study due to their broad demand, high yields, accessibility throughout the world and noteworthy economic influence.

The present study proposes the integration of AI-enabled precision irrigation in legume farming to optimize efficient water usage, potentially mitigating water scarcity and reducing the cost of irrigation. The objective of this study is to increase the water usage efficiency in legume agriculture, with a focus on peas. In India's Uttar Pradesh, artificial intelligence (AI) and precision irrigation are used to solve water shortages, boost sustainable farming practices and increase crop yield. A systematic approach consisting of data collection, an AI-enabled program and comprehensive data analysis is used to get valuable findings. Precision irrigation powered by AI has the unique ability to increase crop productivity while conserving water resources and imitating the complex water management system observed in nature.

MATERIALS AND METHODS

Data collection

Weather data acquisition

Historical and real-time weather data were collected using meteorological sensors, weather stations, or access to meteorological databases. Parameters including temperature, humidity, wind speed, solar radiation and precipitation were observed.

Soil moisture monitoring

Soil moisture sensors were Installed at various depths within the root zone to measure soil moisture content. Sensors with high accuracy and reliability were used to collect data continuously.

Crop health monitoring

Remote sensing techniques such as satellite imagery or drones equipped with multispectral or hyperspectral cameras were employed to monitor the health and growth of crops. Spectral indices like NDVI (Normalized Difference Vegetation Index) were used for analysis.

Water flow sensors

Flow sensors in the irrigation system were installed to measure the volume of water applied to the fields accurately.

Crop-specific sensors

Sensors specific to legume crops for tracking relevant parameters like leaf temperature, transpiration rate and growth stage were utilized.

AI-system development

Feature engineering

Relevant features such as temperature, precipitation, soil moisture and crop health indices were identified from the collected data. Domain knowledge is utilized to create meaningful features.

Data preprocessing

Clean and preprocess the data, handling missing values, outliers and normalizing data if necessary.

Machine learning algorithms

An appropriate machine learning algorithms is selected for modelling, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), or gradient-boosted trees. Implement the AI model architecture.

Training and validation

Split the dataset into training and validation sets. Train the AI model using historical data and validate its performance using a portion of the data not used in training.

Hyperparameter tuning

Optimize hyperparameters to improve model performance. Explore hyperparameter optimization techniques, such as grid search or Bayesian optimization.

Decision support system integration

Real-time data integration

It involves implementation of a real-time data pipeline that continuously collects and feeds data from weather stations, soil sensors and crop health monitors to the AI model. Fig 1 shows the installation of soil moisture meter in the field. The soil moisture meter can collect data on soil moisture in real-time and send it to the control/monitoring system. A few locations near the plant's stems are selected for the probes' insertion into the soil. The soil moisture sensor meters are solar powered, IP 68 protection class for water and dust proof with a range of 0 to 100% with 0.1% resolution and ±3% accuracy.

To accurately measure the amount of water sprayed into the fields, water flow sensors have been installed in the irrigation system. Real-time flow measurements are sent to the control and monitoring system by the sensor. The sensor is always mounted at the pump's outlet. A minimum of two straight pipe sections, measuring 10 x D (the flowmeter's inner diameter) in front and 5 x D in back, must be placed at the lower end of the horizontal pipeline and in the vertical upward position. Fig 2 presents the appropriate location of water flow sensors. The sensor has a 0.5% accuracy and is powered by 24 or 220 volts.

Model deployment

Deploy the AI model in a cloud or on-premises environment for real-time predictions. Ensure scalability and reliability.

Feedback loop

Establish a feedback loop to continuously update the model based on the most recent data and incorporate machine learning techniques for model adaptation over time.

Experiment design

Peas have been chosen as the legume crop and details about the kind of soil, variety and initial circumstances unique to Uttar Pradesh are provided in the section on experiment design.

Field trials

Conduct controlled field trials with test plots to implement AI-driven precision irrigation. Apply AI-based recommendations to irrigation decisions and compare them with traditional irrigation methods.

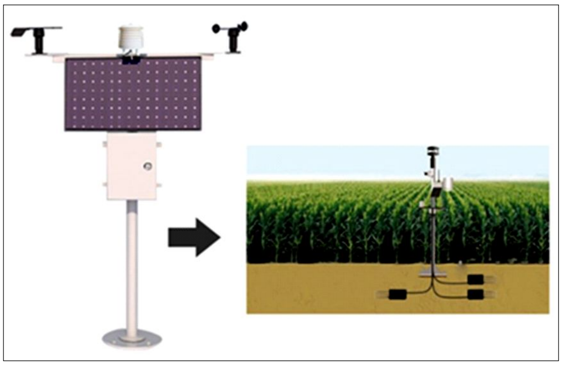

Fig 1: Location and installation of soil moisture meter.

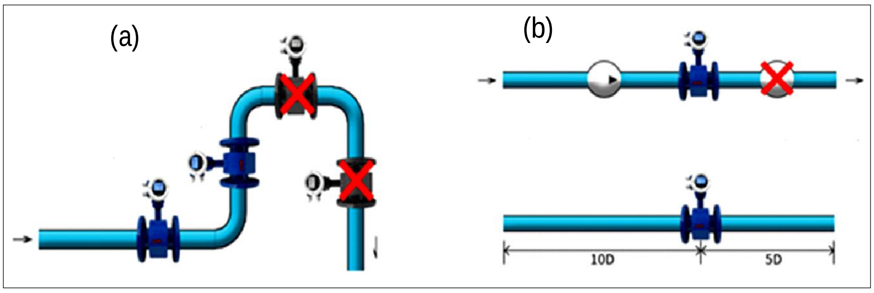

Fig 2: Diagram of water flow sensors showing its location.

Controlled variables

Maintain consistent control of variables in experimental plots, including crop variety, soil type and initial conditions.

Randomization

Randomly assign treatments to experimental plots to minimize bias.

Replication

Replicate experiments across multiple field locations and over multiple growing seasons to ensure statistical robustness.

Data analysis

Statistical tests

Utilize statistical tests such as ANOVA and t-tests to compare the results of AI-driven precision irrigation with traditional methods.

Economic analysis

Calculate the economic benefits of AI-driven precision irrigation by considering water savings, crop yield improvements and operational costs.

Data collection and analysis

Data collection methods

In this study, data collection is carried out through a combination of remote sensing, on-site sensor networks and historical datasets. The following data collection methods were employed:

Remote sensing

Aerial and satellite imagery with high spatial and temporal resolutions were obtained to monitor vegetative indices, soil moisture levels and weather conditions. These remote sensing data sources include.

On-site sensor networks

A network of IoT sensors was strategically deployed within the legume farm to continuously monitor soil moisture, temperature and crop growth parameters. These sensors provide real-time data and are equipped with communication capabilities for data transmission.

Historical datasets

Historical weather data, previous crop yield records and irrigation patterns were collected from the farm's records for comparative analysis and model training.

Data preprocessing

Raw data collected from various sources were pre-processed to ensure consistency and compatibility for analysis. Data preprocessing involved the following steps:

Data cleaning

Removal of outliers, errors and missing values to ensure data integrity and accuracy.

Normalization

Standardization of data to a common scale for proper integration and model compatibility.

Feature engineering

Creation of relevant features such as the calculation of evapotranspiration rates, growth stage indicators and cumulative water usage.

Data analysis

Data analysis was conducted to extract meaningful insights and patterns. The following analytical techniques were employed:

Descriptive statistics

Summary statistics, including mean, median and standard deviation, were calculated to understand the central tendencies and variations in the dataset.

Time series analysis

Time series analysis was used to examine the temporal trends of soil moisture and crop growth parameters. Seasonal and cyclical patterns were identified.

Machine learning models

Various machine learning algorithms, including random forests, support vector machines and deep neural networks, were trained on the data to predict optimal irrigation schedules based on historical data and real-time sensor inputs.

AI-driven insights

The AI models developed in this study provided valuable insights into optimizing water use efficiency in legume farming:

Irrigation scheduling

The AI models determined precise irrigation schedules based on current soil moisture levels, weather forecasts and crop growth stages. This enabled the reduction of water wastage while maintaining crop health (Kumar, 2019).

Early detection of stress

AI models were capable of early stress detection in legume crops by analyzing various vegetative indices. This allowed for prompt corrective actions to be taken (Rahaman *et al*., 2022).

Resource allocation

AI-driven recommendations aided in the allocation of resources, such as water and energy, to maximize crop yield while minimizing resource usage.

Validation and model performance

The AI models were rigorously validated through cross-validation, using historical data and real-world testing (Kim *et al*., 2021). Performance metrics such as mean absolute error (MAE), root mean square error (RMSE) and coefficient of determination (R^2) were employed to assess model accuracy and generalization.

Concerning the pea crop, with a focus on its management and production in the Uttar Pradesh study region. provided details on the launch of AI-powered irrigation testing designed especially for peas. A flowchart of methodology is presented in the Fig 3.

RESULTS AND DISCUSSION

The impact of AI-based precision irrigation is examined in terms of water consumption, enhanced crop yield, cost-effectiveness and reduction of greenhouse gas emissions in legume farming. In this experiment, peas are grown in various field sites, each with unique growing seasons, types of soil, starting circumstances and water consumption needs (Table 1). Location 1 has Alluvial Soil and Sandy Loam throughout the Monsoon and Winter seasons, respectively. Standard and Enriched Soil are the two types of initial conditions. Clayey Soil and Loamy Soil are associated with the Monsoon and Spring seasons, respectively, in Location 2. Starting conditions can vary from Normal to Rich Soil. Summer and winter are encountered at location 3, where clayey loam and sandy soil, respectively, are found. The starting conditions are not always the same as the enriched soil. In addition, a summary of the effects of AI-driven precision irrigation on the effectiveness of water consumption in pea production is included in the table. During the monsoon, 1200 liters are needed at Location 1 and 1100 liters are needed for winter cropping. Location 2 requires 1150 liters in the spring and 1250 liters during the monsoon. At Location 3, summer consumption is 1300 liters and winter usage is 1180 liters. These exact numbers highlight the seasonal and geographic variations in the amount of water needed, offering vital information about effective resource management for productive crop production.

By comparing the water consumption of conventional and AI-driven precision irrigation techniques, one can readily see the advantages of artificial intelligence systems. The water consumed by both irrigation methods in 6 months is presented in Fig 4.

From the data presented in Fig 4, it is evident that AI-driven precision irrigation significantly reduces water consumption compared to traditional methods. The monthly water savings range from 40,000 to 220,000 L. This reduction not only conserves a precious resource but also alleviates the financial burden on farmers. The implementation of AI in irrigation systems optimizes the allocation of water, responding to the specific needs of the crops in real-time, ultimately cultivating more efficient water usage.

Throughout the six months, the AI-driven precision irrigation system continuously shows reduced water use. The water savings that occur each month due to the use of artificial intelligence are enormous, ranging from 40,000 to 220,000 litres. The comparison of yields obtained with and without use of AI is presented in Table 2 which clearly indicated the improved efficiency.

Further, the impact of water consumption on legume crop yield and water use efficiency (WUE) is analyzed. To calculate the WUE parameter, the following equation is used:

$$\text{WUE} = \frac{\text{Total crop yield (kg)}}{\text{Total water consumed (L)}} \qquad ...(1)$$

Table 1: The amount of water used by the pea crop at various field sites in Uttar Pradesh throughout the growing season.

Field location	Growing season	Soil type	Initial conditions	Water consumption (liters)
Location 1	Monsoon	Alluvial soil	Standard	1200
Location 1	Winter	Sandy loam	Enriched soil	1100
Location 2	Monsoon	Clayey soil	Standard	1250
Location 2	Spring	Loamy soil	Fertile soil	1150
Location 3	Summer	Sandy soil	Standard	1300
Location 3	Winter	Clayey loam	Enriched soil	1180

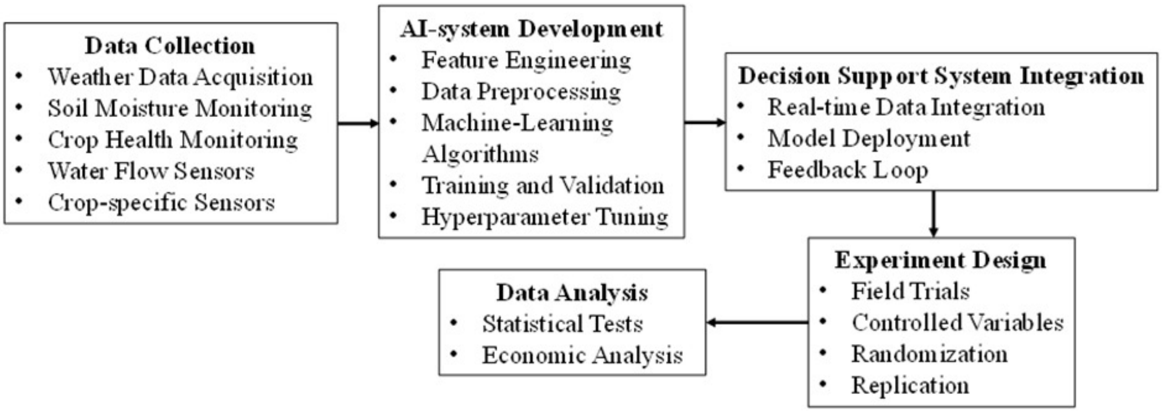

Fig 3: The workflow of model architecture.

The WUE rise from 0.002 to 0.004 kg/L is strong evidence in favor of AI technology use in agriculture. Increased agricultural production, which is essential for ensuring food security in a world where population demands are expanding, is the result of these measurable advancements. A two-sample t-test is conducted to determine the statistical significance of the differences between traditional irrigation and AI-driven precision irrigation in terms of water use efficiency and crop yield. The results, shown in Table 3, indicate that the differences are statistically significant ($p<0.05$).

Table 2: The comparison of crop yield and water use efficiency assessed by traditional and AI-driven precision irrigation.

Method	Total crop yield (kg)	Water use efficiency (kg/L)
Traditional irrigation	900	0.002
AI-driven precision irrigation	1150	0.004

Table 3: Results of two-sample t-test.

Parameter	p-value
Water use efficiency (WUE)	< 0.05
Crop yield	< 0.05

Table 4: Greenhouse gas emissions reduction due to less water consumption.

Month	Emissions reduction (kg CO_2-eq)
Jan	2700
Feb	2900
Mar	3100
Apr	3000
May	2800
Jun	2700

Statistical significance, established by the two-sample t-test underscores the robustness of the findings. The p-values, which are both less than 0.05, show that the variations in crop yield and WUE are caused by the irrigation techniques used rather than being random fluctuations. By highlighting the possible benefits of AI-driven precision irrigation above conventional techniques, this enhances the validity of the research that has been presented.

Moreover, to assess the economic impact of AI-driven precision irrigation, we calculated the cost savings in water usage. The formula used for the calculation is as follows:

$$\text{Cost savings} = \frac{\text{Total water cost - AI-driven water}}{\text{Times water prive (\$/L)}} \quad ...(2)$$

Compared to conventional techniques, crop productivity increases by 27.8% when precision irrigation powered by AI is used. Water usage efficiency (WUE) increases from 0.002 to 0.004 kg/L, a fourfold improvement that highlights the effectiveness of AI technology in agriculture. The monthly cost reductions shown in Fig 5 highlight the financial advantages of precision irrigation powered by AI, showing significant financial gains for farmers.

It is important to recognize the full economic impact of this change. As revealed in Fig 5, the cost savings resulting from reduced water usage are substantial. Over the course of six months, farmers can save thousands of dollars on water costs, directly contributing to their financial stability. This aspect is pivotal, especially for smallholder farmers who often operate on tight budgets. AI-driven precision irrigation simplifies access to sustainable farming methods by reducing the financial restrictions related to water consumption. Moreover, the environmental aspect presents a strong case for the use of AI in agriculture.

The environmental impact, such as the reduction in greenhouse gas emissions, is also evaluated, as shown in Table 4. The calculations are done using the formula given as follows:

$$\text{Emissions reduction (kg } CO_2\text{-eq)} = \text{Water saved (L)} \times \text{Emissions coefficient (kg } CO_2\text{-eq/L)}$$

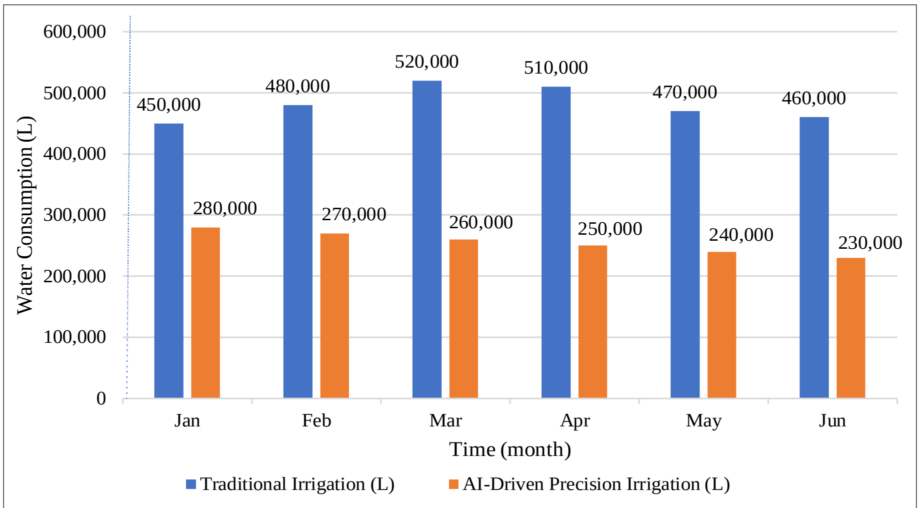

Fig 4: Water consumption in traditional and AI-driven precision irrigation.

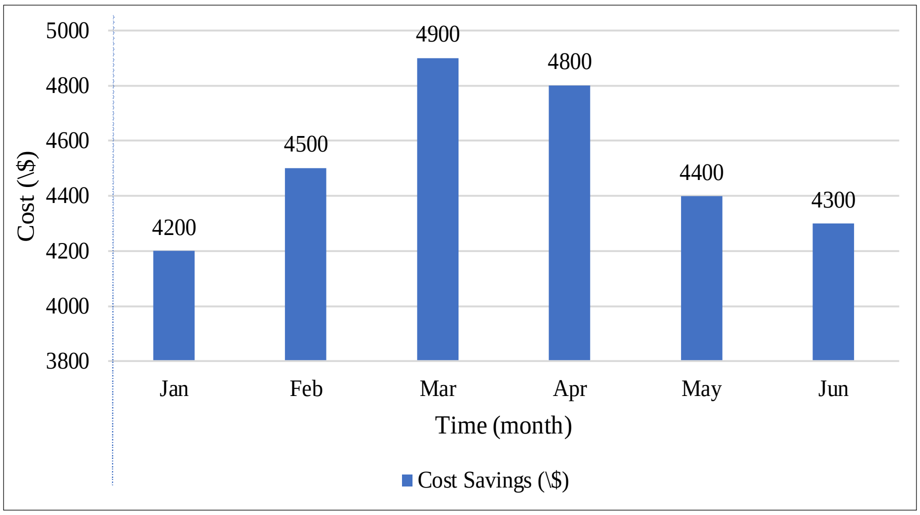

Fig 5: Monthly cost savings resulting from AI-driven precision irrigation.

Precision irrigation powered by AI helps significantly lower greenhouse gas emissions, which is in line with international sustainability objectives. The advantages of using AI technology in agriculture for the environment are emphasized by monthly emissions reduction numbers.

The reduction in water usage not only conserves this finite resource but also shortens greenhouse gas emissions. AI-driven precision irrigation can help mitigate the negative consequences of climate change by lowering the carbon footprint of agriculture and supporting global sustainability goals. The results of the study demonstrate the deep impact of AI-driven precision irrigation on water use efficiency in legume farming. Through comparing AI-powered irrigation solutions with conventional approaches, we have discovered a world of opportunities and advancements that are promising for the environment and the agriculture industry. Finally, the study emphasizes that AI-driven precision irrigation in legume farming can revolutionize the industry. Agriculture and technology working together maximizes crop yields, reduces water usage and has positive effects on the environment and economy. Although implementing AI systems into practice comes with expenses and practical challenges, the benefits are significant. Among the cutting edge technologies now accessible, the use of AI in agriculture stands out as a sign of progress and promise.

CONCLUSION

In summary, incorporating AI-powered precision irrigation into legume farming appears to be an essential step ahead in the search for maximum water efficiency. This research clearly shows that AI-driven irrigation systems perform far better than conventional irrigation techniques in terms of cost savings, increased crop output and water conservation. Through an in-depth investigation of the data, the research has demonstrated the remarkable savings in water consumption that are possible with AI precision irrigation. The reductions have an impact, especially in areas where there is a shortage of water. The computed water use efficiency (WUE) values provide a concrete measure of this accomplishment, highlighting the role AI plays in improving agricultural sustainability. Notably, the statistical significance of the observed differences underscores the reliability and reproducibility of these findings. Furthermore, the cost-benefit analysis reveals a compelling economic argument for adopting AI-driven precision irrigation, illustrating the potential for substantial financial gains for farmers. AI-driven precision irrigation is friendly to the environment, as seen by the significant decrease in greenhouse gas emissions that result from reduced water usage. These reductions in emissions are not only important numbers in a world that is dealing with climate change and its broad implications; they are a real step toward sustainability. The innovative abilities of AI-driven precision irrigation go well beyond the boundaries of agricultural land. It represents a technological solution that takes into account agronomic, economic and ecological factors. As a result, it presents a multidimensional change in the field of sustainable agriculture.

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Author contributions

The authors contributed toward data analysis, drafting and revising the paper and agreed to be responsible for all aspects of this work.

Consent for publication

The authors has provided their consent for publication in the journal 'Legume Research'.

Availability of data and materials

Not applicable.

Declaration of conflicts of interests

Authors report no conflict of interest.

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