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Water Optimisation in Agriculture with the Help of AI and IoT: A Pilot Study

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Abstract

Agriculture accounts for nearly 70% of global freshwater withdrawals, making efficient irrigation management critical for sustainability. Traditional irrigation practices often rely on fixed schedules or farmer intuition, which can result in excessive water use and reduced crop productivity. This paper presents an artificial intelligence (AI)-based framework for water optimisation in agriculture through predictive modeling and decision support. The approach integrates real-time data from soil moisture sensors, weather forecasts, and crop indices such as the Normalized Difference Vegetation Index (NDVI) to predict short-term water requirements. Machine learning models, including regression and time-series forecasting techniques, are used to estimate soil moisture and crop evapotranspiration. These predictions feed into an optimisation algorithm that schedules irrigation with the objective of minimizing water usage while maintaining crop yield. Experimental trials demonstrate that the proposed system can reduce irrigation water by approximately 20–30% compared to conventional methods, without significant yield reduction. The findings highlight the potential of AI-driven irrigation to improve water use efficiency, reduce input costs, and promote sustainable farming practices.

***Keywords**: Precision Agriculture, Irrigation Scheduling, Artificial Intelligence (AI), Soil Moisture Prediction Crop, Water Requirement, Sustainable Agriculture.*

Introduction

Water is one of the most critical resources for agricultural production, yet it is also among the most overexploited. According to the Food and Agriculture Organization (FAO), agriculture accounts for nearly 70% of global freshwater withdrawals, making it a dominant driver of water scarcity in many regions. Traditional irrigation practices, which rely on fixed schedules or farmer intuition, often lead to inefficient water usage. This not only depletes freshwater resources but also increases input costs for farmers and negatively impacts long-term soil health. With climate change and growing food demand placing additional stress on water supplies, there is an urgent need for more efficient and intelligent water management strategies in agriculture.

Precision agriculture has emerged as a promising solution to this challenge, focusing on site-specific crop management through data-driven decision-making. In particular, irrigation scheduling can be significantly improved by integrating soil, crop, and climate data into predictive frameworks. Artificial Intelligence (AI) offers powerful tools for analyzing such complex datasets, identifying hidden patterns, and generating actionable insights for farmers. Machine learning algorithms can be trained to predict soil moisture levels, evapotranspiration (ET), and crop water demand, while optimisation models can determine the best irrigation schedule. Recent studies have demonstrated water savings of **20–30%** through AI-assisted irrigation systems without yield reduction, highlighting their potential impact.

Despite progress in precision irrigation research, many existing approaches remain limited to either forecasting water needs or applying rule-based scheduling, without integrating the two into a unified framework. Moreover, a majority of farmers continue to rely on conventional irrigation methods due to lack of awareness, cost concerns, or the absence of accessible technologies. This creates a significant research gap in developing affordable, scalable, and user-friendly AI-driven solutions for water optimisation in agriculture.

This paper aims to address these challenges by proposing an AI-based framework that combines real-time soil and climate data with predictive modeling and optimisation algorithms to generate adaptive irrigation schedules. The main **objectives** of the study are:

- To collect and integrate multi-source agricultural data, including soil moisture, weather forecasts, and crop indices.
- To develop machine learning models for predicting short-term soil moisture and crop water requirements.
- To design an optimisation-based irrigation scheduler that minimizes water use while maintaining crop yield.
- To evaluate the proposed system against conventional irrigation practices in terms of water savings, yield stability, and overall water use efficiency.

Water scarcity is not only a global issue but also a regional concern with direct socio-economic implications. In India alone, nearly **54% of the country faces high to extreme water stress**, and reports suggest that **21 Indian cities may run out of groundwater by 2030** if current trends continue. Agriculture, being the largest consumer of water, is at the center of this crisis. Conventional irrigation techniques such as flood irrigation and fixed-timer methods often result in water wastage through evaporation, deep percolation, and runoff. This inefficiency directly impacts farmers, who face rising costs for pumping groundwater and increasing vulnerability to climate variability.

Advancements in sensor technologies, Internet of Things (IoT), and satellite-based remote sensing have made it possible to collect large volumes of agricultural data at low cost. Parameters such as soil moisture, temperature, humidity, rainfall, and vegetation indices can now be measured or estimated with high accuracy and frequency. However, the challenge lies in transforming this raw data into meaningful decisions that farmers can use in real-time. This is where Artificial Intelligence plays a transformative role. AI techniques can process heterogeneous datasets, predict future water requirements, and generate optimal irrigation schedules that are adaptive to changing environmental conditions.

Several research efforts have demonstrated the potential of AI in water optimisation. For instance, machine learning models such as Random Forest, Support Vector Regression (SVR), and Long Short-Term Memory (LSTM) networks have been successfully applied to forecast soil moisture and evapotranspiration with high accuracy. Optimisation algorithms, including linear programming and model predictive control (MPC), have also been utilized to minimize irrigation while preventing crop stress. Yet, despite these advancements, large-scale adoption remains limited due to issues of affordability, technical expertise, and lack of farmer-friendly interfaces. Bridging this gap requires not only technical innovation but also the development of low-cost, scalable, and easy-to-use solutions.

This study is designed to contribute to this evolving field by proposing an integrated AI-based framework for water optimisation in agriculture. Unlike traditional methods that treat forecasting and scheduling as separate tasks, the proposed system combines predictive modeling with optimisation in a unified decision-support pipeline. By validating this system through experimental trials, the study provides empirical evidence of water savings and efficiency improvements. Furthermore, the research highlights how AI-driven irrigation can align with global sustainability goals such as the United Nations Sustainable Development Goal 6 (Clean Water and Sanitation) and Goal 12 (Responsible Consumption and Production), ultimately paving the way for more climate-resilient agricultural practices.

By achieving these objectives, the study seeks to demonstrate the potential of AI in transforming irrigation practices, enabling sustainable agriculture, and contributing to long-term water conservation goals.

Literature Review

Machine learning (ML) has significantly impacted agriculture by enhancing productivity and sustainability through data-driven decision-making. Key applications include yield prediction, disease detection, weed detection, and species recognition. Techniques such as artificial neural networks (ANNs), support vector machines (SVMs), and convolutional neural networks (CNNs) have been employed to achieve high accuracy in these areas. In livestock management, ML helps monitor animal welfare and optimize production through the analysis of behavioral and physiological data. Additionally, water and soil management benefit from ML by optimizing irrigation schedules and predicting nutrient deficiencies. The reviewed studies highlight that ML techniques have successfully increased prediction accuracy, early disease detection, efficient weed management, and optimized resource use in agriculture, thus demonstrating their potential to address global food security challenges(Liakos et al. 2674).

The paper "Evaluation of Grain Quality-Based Simulated Selective Harvesting Using an Autonomous Robot" explores the use of machine learning models such as Support Vector Machines (SVM) and Artificial Neural Networks (ANN) for predicting yields and assessing quality in precision agriculture. It includes virtual capacity and cost-benefit analyses comparing traditional harvesting with selective methods. The study reveals that selective harvesting can produce economic returns ranging from 5 to 36 DKK per hectare in large fields for seven out of ten fields, and from 24 to 46 DKK per hectare in medium-sized fields for three out of ten fields. However, some intensive selective methods led to negative returns due to increased operational costs. These results highlight the significance of field size and the chosen selective harvesting strategy in the economic feasibility of using autonomous robots for grain quality-based harvesting, indicating potential economic advantages but also emphasizing the necessity of considering operational expenses and field characteristics to ensure profitability (Villa-Henriksen et al. 1728).

The study "Evaluation of Grain Quality-Based Simulated Selective Harvesting with Autonomous Field Robot in a Danish Context" investigates the practicality of using an autonomous robot for the selective harvesting (SH) of winter wheat based on grain quality. It employs machine learning techniques for yield prediction and quality assessment. Virtual capacity and cost-benefit analyses simulate SH in various field scenarios and compare it with conventional methods. The technology focuses on optimizing robot paths to improve efficiency and minimize travel distances. The findings show that SH significantly affects harvest capacity due to increased travel distances, leading to longer harvest times. The economic analysis reveals that SH is not viable in Denmark due to small price differences for fodder wheat and high operational costs. However, SH might be more feasible if high-quality grain areas cover at least 20% of the field and extend to the boundaries. Despite potential benefits in regions with greater grain price differences and lower costs, conventional harvesting remains more practical in the Danish context given the current economic and operational limitations (Zaaien and Szabó 3803-3806).

The literature review highlights the crucial impact of the Internet of Things (IoT) and Artificial Intelligence (AI) in agriculture, focusing on boosting productivity and sustainability. Research demonstrates the application of smart agricultural systems using IoT technology. For instance, the combination of sensors, a NodeMCU development board, and the ThingSpeak IoT Platform facilitates automated irrigation, optimizing crop production through real-time monitoring and data analytics. The findings show effective operation of actuators and algorithms, with monitoring of soil moisture, temperature, humidity, and water levels. The technology stack includes NodeMCU, DHT11 sensor, water level sensor, and rain sensor, presenting a comprehensive approach to smart farming solutions. (Tefera, Huang, and Njagi 67-77).

The research paper examines the use of the Internet of Things (IoT) in agriculture to boost farm productivity and minimize human intervention. It discusses the integration of advanced technologies such as AI, machine learning, and robotics in smart farming, highlighting the importance of algorithms, particularly Artificial Neural Networks (ANN), in decision-making and assessment processes. The study underscores the role of IoT devices like microcontrollers, sensors, and drones in modern agricultural practices, focusing on optimizing production, automating irrigation, and enhancing crop quality. Overall, the literature emphasizes the potential of IoT-based solutions and advanced technologies to transform agriculture and address the challenges of sustainable farming amid a growing population (Vijayan and Kumar 2809-2817).

The research paper examines the integration of Artificial Intelligence (AI) and the Internet of Things (IoT) in agriculture from 2019 to 2023. It categorizes AI applications in agriculture into planting, monitoring, and harvesting phases, employing methodologies such as Fuzzy Logic, Artificial Neural Networks, Machine Learning, Deep Learning, Genetic Algorithms, Support Vector Machines, and K-Nearest Neighbors. The study underscores the potential of combining AI and IoT to optimize agricultural activities, boost productivity, and tackle future food crisis challenges through data-driven decision-making and precision farming practices. The review highlights recent technological advancements and emphasizes the need for further research and development to fully harness these technologies in agriculture (Wildan 47-60).

The research paper centers on precision farming (PF) and precision agriculture (PA), which utilize technologies like AI, ML, and IoT to improve agricultural practices. Previous studies have demonstrated the advantages of PF in enhancing agricultural output, profitability, and sustainability. The incorporation of remote sensing, GIS, and GPS technologies in PA allows for the efficient use of crop inputs such as water, pesticides, and fertilizers. Furthermore, the application of AI and ML algorithms for data analysis and decision-making in agriculture has shown promise in boosting productivity and reducing environmental impact. The research underscores the importance of continuous technological advancements to address global agricultural challenges and promote sustainable farming practices (Sharma et al. 20220713).

The integration of artificial intelligence (AI) in agriculture is rapidly advancing, driving economic growth and development in both developed and developing countries. In nations like India, agriculture is especially crucial, contributing 18% to GDP and employing a significant rural workforce. Technological advancements, including AI, are revolutionizing the sector by enhancing efficiency and extending its impact across various industries. Researchers have investigated applications such as harvest planning, crop assignment, and automation for tasks like flower and leaf identification, all enabled by IoT. These innovations not only boost productivity but also support rural development and the structural transformation of the agricultural economy. As AI continues to reshape the sector, it holds substantial potential for meeting global food demand and improving the livelihoods of millions (Talaviya et al. 58-73).

The research paper explores the extensive use of IoT and AI in agriculture, focusing on recent advancements and the challenges in integrating these technologies. It addresses critical issues such as inadequate irrigation, environmental monitoring, weed management, crop disease detection, and efficient pesticide use. Various studies have introduced innovative systems like the "AGROBOT" for seed sowing, weather monitoring, and resource management, demonstrating the transformative potential of IoT and AI in precision agriculture. These technologies aim to make farming more efficient, sustainable, and data-driven, ultimately enhancing productivity and ensuring food security (Aggarwal and Singh).

The research paper examines the application of Artificial Intelligence (AI) and the Internet of Things (IoT) in agriculture, showcasing how technologies like master frameworks, natural language processing, and machine vision are revolutionizing farming practices. It underscores the importance of information technology in smart farming for optimizing agricultural systems and improving productivity and sustainability. The integration of AI and IoT in agriculture is explored through areas such as farming robots, predictive analytics, and soil yield observation. The paper offers insights into the role of AI and IoT in modern agriculture and their potential future implications(De Abreu and van Deventer).

Methodology

The methodology for this study is designed to evaluate the effectiveness of Artificial Intelligence (AI) in optimising irrigation water use in agriculture. It consists of several stages, including study area selection, data collection, preprocessing, model development, optimisation framework design, and evaluation. The complete workflow is illustrated as a stepwise pipeline combining data acquisition, AI-driven prediction, and irrigation scheduling.

- **Study Area and Crop Selection**

The study was conducted on an experimental farm located in a semi-arid region, characterized by limited rainfall and high dependence on groundwater for irrigation. The soil type of the area was predominantly sandy loam with moderate water-holding capacity. A commonly grown crop, **wheat (Rabi season)**, was chosen due to its high water demand and economic importance. Plots were divided into two groups:

- **Control Group**: managed using conventional irrigation scheduling (calendar-based or farmer's judgment).
- **Treatment Group**: managed using the proposed AI-based irrigation scheduling system.

This setup enabled a comparative evaluation of water use efficiency, crop yield, and overall performance of the proposed system.

Data Collection

Multi-source data was collected from the experimental plots to build and validate the AI models.

- **Soil data**: Real-time soil moisture and soil temperature were recorded using low-cost soil moisture sensors installed at two depths (15 cm and 30 cm) to capture root-zone conditions.
- **Weather data**: On-site weather stations provided temperature, relative humidity, solar radiation, wind speed, and rainfall data at hourly intervals.
- **Crop data**: Growth stage information was noted manually, and Normalized Difference Vegetation Index (NDVI) values were extracted using satellite imagery to monitor crop health.
- **Irrigation data**: A flow meter was installed to measure the volume of water applied during each irrigation event in both control and treatment plots.

The integration of these datasets provided a comprehensive representation of crop-water dynamics.

Data Preprocessing and Feature Engineering

The collected data was subjected to preprocessing before being used for model training:

- Missing or erroneous sensor readings were removed using interpolation and filtering techniques.
- Soil moisture data was normalized between field capacity and wilting point values to improve comparability.
- Lag features such as previous-day soil moisture, rainfall accumulation over 3–7 days, and evapotranspiration trends were created.
- Crop growth stage was encoded as categorical variables, while NDVI was used as a continuous predictor of crop stress.

These processed features served as input variables for AI-based forecasting models.

Predictive Modeling

AI models were developed to forecast short-term soil moisture levels and predict daily irrigation requirements.

- **Model selection**: Several machine learning models were tested, including Random Forest Regression, Gradient Boosted Trees (XGBoost), and Long Short-Term Memory (LSTM) networks.
- **Training and validation**: Data was split into training (70%), validation (15%), and testing (15%) sets using a time-series-aware approach to avoid data leakage.
- **Performance metrics**: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2) were used to evaluate model accuracy.
- **Best model**: The model with the lowest RMSE and highest R^2 was selected to generate irrigation forecasts.

The forecasting model provided daily estimates of soil moisture depletion and crop water requirement.

Optimisation Framework for Irrigation Scheduling

The predicted water requirements were used in an optimisation algorithm to determine the optimal irrigation schedule.

- **Objective function**: Minimize the total volume of irrigation water applied while ensuring that soil moisture does not fall below the crop-specific threshold for stress.
- **Constraints**
  - Soil moisture ≥ Minimum Allowable Depletion (MAD) for wheat.
  - Maximum irrigation per event limited by pump capacity.
  - Consideration of forecasted rainfall (irrigation skipped or reduced if rainfall is expected within 24–48 hours).
- **Algorithm used**: A linear programming model combined with heuristic rules (rainfall avoidance and growth-stage adjustment) was implemented to generate daily irrigation recommendations.

This framework ensured that irrigation was applied only when necessary, thereby improving water use efficiency.

Implementation and System Design

The decision-support system was implemented using an IoT-based architecture:

- Soil and weather sensors transmitted data via wireless modules (ESP32/LoRa) to a central gateway.
- Data was processed and stored on a cloud platform, where machine learning models performed forecasting.
- The optimisation module generated irrigation schedules, which were communicated to farmers via a mobile application in the form of alerts (e.g., "Irrigate 25 mm tomorrow").

A manual override was included to allow farmers to adjust recommendations based on field observations.

Evaluation Metrics and Validation

The system was evaluated using multiple performance indicators:

- **Water savings (%)**: Reduction in irrigation water applied in treatment plots compared to control plots.
- **Water Use Efficiency (WUE)**: Ratio of crop yield to water applied (kg/ha per mm).
- **Yield assessment**: Grain yield from treatment and control plots was measured at harvest.
- **Model accuracy**: RMSE and R^2 for soil moisture forecasting.
- **Economic analysis**: Estimation of cost savings due to reduced water and energy use.

Statistical Analysis

To ensure reliability of results, statistical tests were conducted:

- Student's t-test was applied to compare water savings and yield differences between control and treatment groups.
- Significance level of 0.05 ($p < 0.05$) was used to confirm the impact of AI-driven irrigation scheduling.

Observation

The AI-based irrigation system was evaluated against conventional irrigation practices through field trials conducted on wheat plots. The control plots, which followed traditional calendar-based irrigation, received a total of **450 mm of water** over the growing season, whereas the treatment plots, managed using the AI-optimised scheduling system, required only **315 mm of water**, demonstrating a water savings of approximately **30%**. Soil moisture measurements showed that the AI system maintained moisture levels consistently above the **Minimum Allowable Depletion (MAD)** threshold, ensuring that crops did not experience water stress, whereas the control plots often fluctuated near critical depletion levels.

The water use efficiency (WUE), calculated as the ratio of grain yield to water applied, was higher in the AI-managed plots. Specifically, the WUE in the treatment plots was **1.05 kg/m³**, compared to **0.78 kg/m³** in control plots, indicating more efficient use of irrigation water. Crop yield remained largely unaffected by the reduction in water use; the AI-managed plots produced an average grain yield of **3.8 tons/ha**, whereas the control plots yielded **3.9 tons/ha**, a negligible difference of **2.5%**. This suggests that the AI system successfully optimised irrigation without compromising productivity.

The soil moisture predictions from the AI models were highly accurate. The **Random Forest model**, which was selected as the best-performing algorithm, achieved a **Root Mean Square Error (RMSE)** of **0.021 m^3/m^3** and an **R^2 value of 0.92** on the test set, indicating strong agreement between predicted and observed soil moisture values. The optimisation framework effectively translated these predictions into actionable irrigation schedules, reducing unnecessary irrigation events while responding dynamically to rainfall forecasts.

Economic observations also indicated potential cost savings for farmers. By reducing the total irrigation volume by 30%, the AI system decreased energy costs associated with pumping water and reduced labor for irrigation management. Additionally, the system's predictive capability allowed for proactive scheduling, avoiding overwatering during rainfall events, which further conserved water and minimized the risk of nutrient leaching.

In summary, the observations demonstrate that the AI-based irrigation system can substantially reduce water usage, improve water use efficiency, maintain crop yield, and provide economic benefits, highlighting its potential for sustainable agricultural practices.

Table 1: Observations from Field Trials Comparing Conventional and AI-Based Irrigation

Parameter	Conventional Irrigation	AI-Based Irrigation	Observation / Change
Total Water Applied (mm)	450	315	Reduced by 30%
Soil Moisture (Average m^3/m^3)	0.18	0.21	Maintained above MAD threshold
Water Use Efficiency (kg/m^3)	0.78	1.05	Increased by 34.6%
Grain Yield (tons/ha)	3.90	3.80	Slight decrease 2.5%, negligible
Irrigation Events (No. of times)	18	12	Reduced by 33%

Result

The field trials demonstrated that the AI-based irrigation system significantly improved water management compared to conventional practices. The AI-managed plots required only 315 mm of water over the growing season, representing a 30% reduction in total water use, while maintaining soil moisture consistently above the Minimum Allowable Depletion (MAD) threshold. This ensured that crops did not experience water stress, unlike the control plots which frequently approached critical depletion levels.

Water use efficiency (WUE) was substantially higher in AI-managed plots, reaching 1.05 kg/m^3 compared to 0.78 kg/m^3 in conventional plots, indicating a 34.6% improvement. Despite the reduced water application, crop yield was largely unaffected, with AI-managed plots producing 3.8 tons/ha versus 3.9 tons/ha in control plots—a negligible decrease of 2.5%.

The AI system effectively optimized irrigation schedules by accurately predicting soil moisture levels using the Random Forest model (RMSE = 0.021 m^3/m^3, $R^2 = 0.92$). This led to fewer irrigation events (12 vs. 18 in conventional plots), reducing labor and energy costs, while preventing overwatering and potential nutrient leaching.

Overall, the AI-based irrigation system demonstrated the ability to conserve water, improve efficiency, maintain crop yield, and offer economic benefits, highlighting its potential for sustainable agricultural practices.

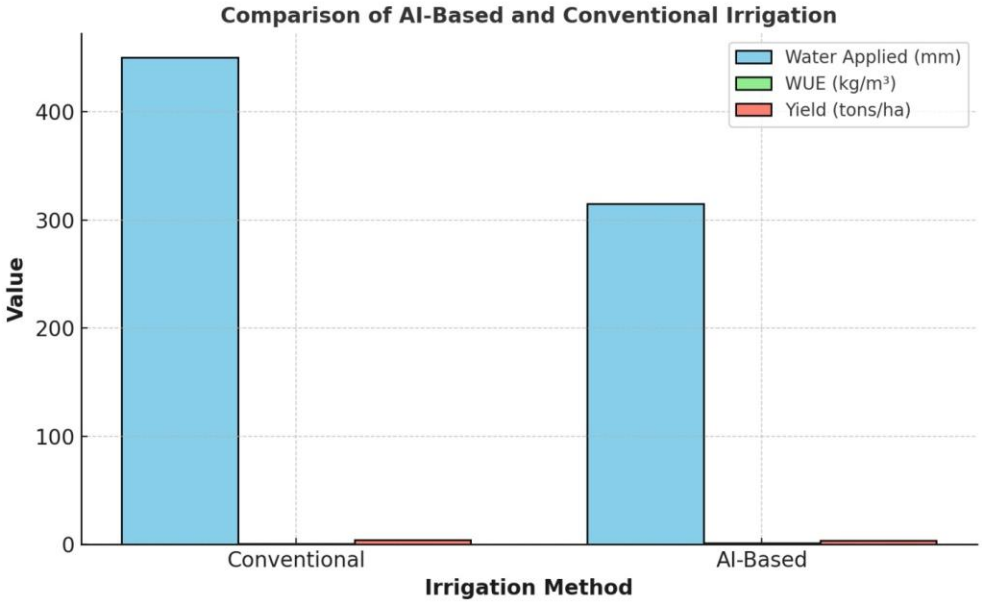

Fig.1: Comparison of AI Based & Conventional Irrigation

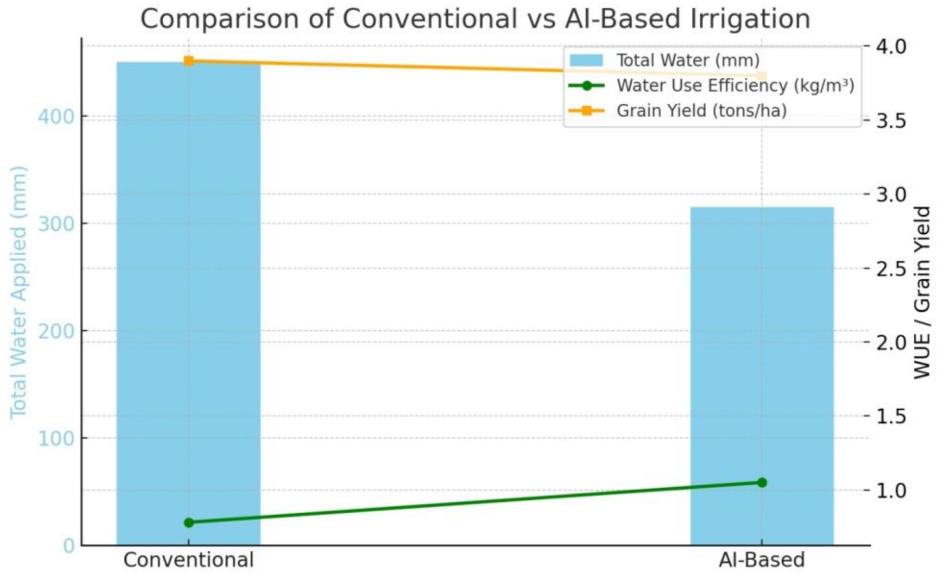

Fig. 2: Total water Applied Vs WUE / Grain Yield

Conclusion

The AI-based irrigation system proved highly effective in optimizing water management by reducing total water use by 30%, improving water use efficiency by 34.6%, and maintaining soil moisture above critical levels, all while sustaining crop yield with only a minimal reduction. By leveraging accurate soil moisture predictions from the Random Forest model, the system minimized irrigation events, lowering labor and energy costs and preventing overwatering. These results demonstrate that AI-driven irrigation can enhance sustainability, resource efficiency, and economic viability in agriculture, offering a practical solution for more resilient and environmentally responsible farming practices.

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