Precision Irrigation Scheduling using Real-Time Environmental Data

Mujahid Tabassum *

Lecturer, Department of Mathematics and Computing, South East Technological University, Cork Rd, Kilbarry, Waterford, Ireland.
Email –Id : mujahid.tabassum@setu.ie

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Abstract

Water use is a sensitive factor in crop production, especially in areas where water is scarce; thus, good water management is very encouraging in the farming sector. The other important factor in efficient water use is the time and quantity of water to use, also known as irrigation scheduling. Nonetheless, conventional approaches to watering frequently result in wastage of water or, conversely, an insufficient supply of water because the data accrued is not in real-time. To this end, this study aims to develop a precision irrigation scheduling framework that integrates IoT sensors and M-L models. Constant online control is implemented on irrigation scheduling by developing two models namely linear regression and decision tree models using environmental parameters such as moisture, temperature, and humidity. The data inputs are improved through sensor fusion techniques making further refinements to the decisions about irrigation. Simulation results show that these real-time, data-driven approaches outperform traditional methods, improving water usage efficiency by 15% and crop yield by 11%. Of these, the decision-tree model appears to be more versatile about changes in its environment. These findings support the premise that incorporating monitoring of the environment in real-time coupled with AI, can enhance water management practices in smart agriculture. More research could be done to investigate the other variables such as nutrient distribution, thus coming up with a package solution to manage crops.

Keywords

Precision irrigation, real-time environmental data, IoT sensors, machine learning, predictive models, sensor fusion, water conservation, crop yield.

1. Introduction

Water is one of the most critical factors in supporting agriculture, and with the current climate change challenges, climate variability, water scarcity, and increase in the size of the global population, efficient management of this irreplaceable resource is quickly gaining importance. In areas where water scarcity is an acute issue, the appropriate application for water in the production of food crops has gradually become one of the most pressing questions to guarantee food security and sustainable usage of water resources. According to the Food and Agriculture Organization (FAO), food production must rise by 70 percent by 2050 to feed the growing population of the world and this is set to exert even more pressure on water supply which is already scarce in many regions of the globe [1]. More conventional means of approaching its management such as an inflexible watering regime or imagined water requirements fail here because, while too much water hurts the plant through leaching the nutrients, too little hurts it through stressing it [2].

This problem pioneered how enhanced data-based kinetic calculations in rendering irrigation techniques most especially the precision irrigation systems, which use information on the environmental conditions to water plants at such points in time and space in which such will prove most useful. Precision irrigation is derived from the larger concept of precision agriculture and is generally understood as a system that provides for water delivery with the most precision and efficiency. By implementing indicators accompanied by the newest technologies like IoT, AI, and data analytics, precision irrigation enables farmers to adjust irrigation depending on accurate data obtained from the sensors installed in the environment [3]. It has subsequently stimulated efficiency in water and enhanced crop outcomes, which are crucial issues on issues of water usage and climate variability astringent in agriculture [4].

Since most of the above techniques apply traditional farming practices, irrigation in the crops is most often based on seasons or previous experiences. Such methods, though seemingly applied, cannot be used to suit the changing circumstances that may be present within two months of the planting season or even within two different regions of the same field. Consequently, traditional irrigation typically results in waste. A special case of excess in irrigation is presented in over-irrigation, in which the soil is saturated with water and most of it will run out without being used by the plants, leaching important nutrients, while the under-irrigation situation would cause water stress in plants, which greatly affects crops productivity and quality. In areas that are already strained for water resources, these inefficiencies impinge on local water scarcity making it a threat to food production as well as the sustainability of the regions [5].

In addition, the continuing effects of climate change including increased incidence and duration of droughts together with unpredictable rainfall; and high temperatures also complicate traditional irrigation systems. These factors have led to requirements for more adaptive and dynamic irrigation systems capable of adapting themselves dynamically to the changes at run time. It has therefore become apparent that the inconsistencies of the conventional methods are what has necessitated the development of precision irrigation technologies [6].

Precision irrigation thus stands out from such practices by leveraging IoT devices, environment sensors, virtual intelligence, and cloud computing. These technologies make it possible to provide the right quantities of water at the right time and place, making a big difference to the efficiency with which water can be used by crops [7]. IoT sensors, for instance, can be placed in fields to collect important environmental parameters like moisture content of the soil, air temperatures, and humidity among others. The real-time data is then sent to infrastructure in the cloud where AI algorithms estimate fitted irrigation time and amount with threshold conditions of the past as well as current climatic conditions.

These systems are currently providing farmers best possible information about irrigation decisions including when and how much to irrigate Water is therefore used in the most efficient ways possible. Unlike some rigid timetables or estimates, farmers can apply actual time principles and vary the irrigation depending on the existing conditions such as occasional courage or scorching heat [8]. These two attributes not only save water but also ensure that the crop does not receive water at the wrong time therefore reducing stress on the crop to improve both yield and crop quality.

The basis of precision irrigation is the IoT sensors that in this case gather information about different environmental factors. These are planted in different parts of the field to monitor the soil moisture status, air temperature, and humidity, which are important for the estimation of crop water requirements [9]. For instance, soil moisture sensors are tactfully installed at various levels to give a continuous water status in the root zone where it is required for crops. If the moisture level is below its capacity, the system can be set to water the plants immediately and avoid water stresses in them. In addition, temperature and humidity sensors enable the system to factor in aspects such as the rates of evaporation in determining the amount of water required in coming up with suitable environmental conditions for growth.

It has been found that the constant receipt of real-time data produces a far superior picture of the field’s environment to that acquired using standard methods. Further, since IoT sensors can collect data autonomously, farmers do not have to spend much time monitoring the output of the sensors. Continuous monitoring of field conditions also results in timely identification of problems that may be developing, for example, drought stress or nutrient imbalance and farmers can then take corrective action before these factors begin to affect yield adversely [10].

Although the collection of real-time data concerning the environment is useful for precision irrigation most of the value of this data is actually in the analysis of this data. IoT sensors gather a vast amount of data, and artificial intelligence and machine learning help to process this data. These models can indeed discover correlations within the data that may not be clear to a human analyst and utilize these correlations to forecast future irrigation requirements [11]. For instance, by training a machine learning model using historical data of crop water application together with the information on the state of the soil and the prevailing weather conditions, accurate predictions may be made of when a particular crop will require irrigation, or when it is likely to require the next application and how much water is likely to be effective for effective absorption or uptake by the plants.

Such models also make it possible for the system to predict changes in environmental factors and alter the irrigation schedules as well. For instance, if a heat wave is expected the system can enhance irrigation early enough to counter water scarcity. On the other hand, if the climate outlook points to a rainy period, the system will be able to postpone irrigation so as to avoid water logging and nutrient runoff. Such control is inconceivable with conventional irrigation techniques, which rely on static schedules regardless of on–ground prevailing conditions.

Cloud computing is also very useful in enabling precision irrigation since it offers a service for the storage of data and computation. It can be provided for farmers as an application to the smartphone or computer, so the farmer doesn't have to be in the field physically to know the conditions of the fields and to be able to decide on when the irrigation should be done. Real-time knowledge can be obtained from various sources including; soil sensors, weather stations, and remote sensing technologies, and by processing the acquired information a platform can obtain useful insights. Such understandings can then be utilized to control irrigation systems from a distance so that water can be applied just where it is required and when [12].

This improves on remote management thereby minimising the need for farmers to manually intervene and make irrigation decisions through and through especially on large or multiple fields. It also allows for more flexible irrigation regimes as the level of control can be fine-tuned in real-time mode. For instance, in case there is unexpected rainfall, the system can automatically reduce or cancel irrigation to prevent waterlogging, while during droughts, they can increase the irrigation rate to maintain moisture levels in the soil.

Another important advantage is the saving in water used when practicing precision irrigation. world's freshwater consumption, and in many regions, inefficient water use is a major contributor to water shortages [13]. While conventional drip irrigation only aims to deliver water directly to the plant roots, precision irrigation provides only the right volume of water to the plant's root zone with greater accuracy and efficiency of water usage.

Precision irrigation systems also improve water efficiency in specific areas by managing water requirements. The conditions are likely to vary with areas to be covered in each field, the type of soil, water availability, and the temperature that the plant has to endure, hence, a generalized approach makes the irrigation system to be somehow ineffective. However, precision irrigation systems can deliver the water according to the requirements needed by the areas to be irrigated, thus, eventually preventing wastage and boosting the growth and yields of the crops [14]. A digital solution that claims to use nothing but IoT sensors, AI, and cloud computing, precision irrigation empowers farmers with water efficiencies and the potential for crop enhancement. This paper presents an analysis of the ability of precision irrigation agriculture to meet food needs while sustaining the world's water problems such as climate change and water scarcity. Promising that the application of the principles of precision irrigation is in the present, future development of new knowledge and perspectives advancements in this field will contribute to improving the systems so that they can remain a staple component of modern agricultural practices [15].

This study is organized as follows. The subsequent section discussed the existing literature review on precision irrigation and real-time environmental monitoring research. This is succeeded by the problem formulation and research objectives part with elaborated clarification of the problem. Under the method section, there is a description of the technical implementation of the proposed models in the form of equations for simulation. In the results section, the author provides the simulation results of the two models under consideration and concludes with a discussion of the contributions of this study toward advancements in precision agriculture.

2. Related Research

Several researchers have proposed methods to apply real-time data for precision irrigation to overcome the difficulties of the method, with a focus on creating a synergistic cooperative between sensor networks, data analysis, and artificial intelligence models for water control. One of the earliest works in this domain is [16], which proposed a real-time irrigation system using soil moisture sensors. The study proposed that by continuously monitoring soil moisture levels and automating irrigation based on predefined thresholds, water consumption could be significantly reduced without affecting crop yield. However, the disadvantage of this approach is that it depends on fixed values of thresholds, which do not account for dynamic environmental conditions such as temperature or humidity.

A more dynamic approach was suggested in [17], where the authors developed a model that incorporates soil moisture data with weather conditions to adjust irrigation schedules. This method performed very well as far as water conservation was concerned but was restrained by the quality of the weather forecast. To solve this problem, [18] proposed a sensor fusion method that aggregates data from more than one source such as soil moisture, temperature, and humidity sensors to enhance the efficiency of the irrigation control. This investigation stressed the fact that to control irrigation to higher levels of accuracy, multiple environmental parameters must be used.

More recently, real-time analyzed environmental data has been used for machine-learning models in precision irrigation. In [19], the authors applied a linear regression model to predict soil moisture values based on historical data and environmental conditions. The model was able to predict irrigation needs with reasonable accuracy, but its performance deteriorated in highly dynamic environments where sudden changes in weather conditions occurred. To counteract this downside, [20] recommends making use of decision-tree models of the presentation of the environmental variable since these are acknowledged to determine non-linear associations. This work concluded that decision trees were more accurate and more resistant to changes, as compared to linear models in conditions of uncertainty.

Besides these models, [21] examine the application of neural networks for irrigation scheduling. It showed that an artificial neural network is capable of identifying the dynamics of the environmental data and further making a proper prediction of the irrigation requirements. However, the use of neural networks entails high computational costs, and therefore, the algorithms are not very appropriate for real-time decisions. However, since decision-tree models are comparatively less computationally intensive they can be used for real-time irrigation suggestions with the same level of precision.

3. Problem Statement & Research Objectives

Water management is an important task in agriculture and is more complicated in areas where water amounts are limited. Old methods of irrigation tend to produce either surplus or insufficient water; therefore, they are disadvantageous in crop production. It is worth the need for sophisticated sprinkler systems capable of adapting to environmental changes and changing the program of irrigation to maximize water usage while also maximizing yields. The specific goal of this research is to create, implement, and compare two models that could be used for real-time, precision irrigation scheduling: a linear regression model and a decision tree-based model. These two models will be run on real-time environmental data from IoT sensors with an emphasis on water consumption for the provision of optimum water supply for irrigation as well as cultivating the yield of crop production. The specific research objectives are:

1. To collect real-time environmental data such as soil moisture, temperature, and humidity using IoT sensors.
2. To establish a linear regression model for predicting irrigation needs based on this data.
3. To develop a decision-tree model for real-time irrigation control.
4. To evaluate the performance of both models in terms of water usage efficiency and crop yield improvement.
5. To compare and evaluate the robustness of both models under varying environmental conditions.

4. Methodology

This section describes the methodology used to design and deploy a precision irrigation scheduling system based on real-time environmental data collected from IoT sensors. The system is built on two predictive models: a linear regression model and a decision tree model. Both models seek to achieve a real-time approximation of the amount of water needed for irrigation under environmental conditions, including moisture content of the soil, temperature, and humidity. It also aims to optimize the efficiency at which water is used in irrigation to promote crop yields while using the right data. To achieve this, data from IoT sensors are collected to capture near real-time environmental data and these are then input into the models. The performance of both models is tested on a simulation basis using water usage, the accuracy of an estimate of irrigation requirements, and the influence of the developed systems on yield as the main factors.

4.1 Data Collection

This study incorporates extensive data collection, which is by the use of IoT sensors spreading across an agricultural field. These sensors regularly measure several environmental inputs affecting the water requirements of crops. The key parameters measured are:

- **Soil moisture (θ)**: Measured as the percentage of volumetric water content of the soil. Soil moisture values directly indicate the amount of water present in the root zone of plants, which is important for irrigation purposes.
- **Temperature (T)**: The air temperature of the environment and it requires the air temperature to be measured in degrees Celsius. This causes variation in the rates of evapotranspiration, which determines the amounts of water needed for crops.
- **Humidity (H)**: Specifically, the amount of shared way of water in the air in form relative humidity in terms of percentage. Higher humidity levels result in less amount of water loss through evaporation, which affects the irrigation regimen.

The use of the sensor network allows for deploying the sensors in different parts of the field so the obtained data encompasses all the variabilities in the field related to the soil and environment heterogeneity. Every single sensor is integrated with a wireless communication module that allows it to use standard communication protocols like LoRa or Zigbee to upload the data to a server. Information is obtained on a fixed schedule (every 10 minutes), which allows for tracking short-term fluctuations in the environment, used as the basis for modeling.

The mathematical relation given in Eq. (1) is used to represent the relationship between the environmental parameters and the amount of water required for irrigation:

$$I(t) = \alpha . \theta(t) + \beta . T(t) + \gamma . H(t) + \epsilon \quad (1)$$

Where $I(t)$ is the predicted irrigation amount at time t, θ(t) represents the soil moisture at time t, T(t) is the temperature at time t, H(t) represents the humidity at time t, α, β, and γ are coefficients that indicate the influence of each environmental variable on irrigation needs, ϵ is the error term, accounting for variations not captured by the model.

4.2 Data Storage and Pre-processing

The data collected from the IoT sensors is transmitted to a central server where it is stored in a cloud-based platform for further analysis. Before being used in model development, the data undergoes several pre-processing steps to ensure its quality and relevance. The pre-processed dataset is divided into training (70%) and testing (30%) sets to develop and evaluate the models.

4.3 Model Development

4.3.1 Linear Regression Model

The first model is the linear regression model [22] which employed the previous water usage data and current environmental data. Soil moisture, Temperature, and Humidity affecting the water requirement for irrigation are considered in a linear form and are described by Eq. (1). Using the linear regression model the constants, α, β, and γ should be adjusted to minimize the mean squared error (MSE) between the predicted and actual irrigation requirements.

4.3.2 Decision Tree Model

The second model is decision-tree-based [23], thought to be more suitable for accommodating non-linear dependencies between environmental factors and irrigation requirements. In a decision tree, the data is divided into subsets, and each node of the tree is a test based on any of the environmental variables.

The decision tree model applies a recursive algorithm to split the data based on the environmental variables that provide the highest information gain. The decision rules are represented by Eq. (2), (3) and (4) as:

- Soil Moisture Rule: If soil moisture $\theta(t)$ at time t is below a certain threshold θ_{th}, increase irrigation.

$$I(t) = \begin{cases} \text{Increase irrigation} & \text{If } \theta(t) < \theta_{th} \\ \text{Maintain irrigation level} & \text{If } \theta(t) \geq \theta_{th} \end{cases} \quad (2)$$

- Temperature Rule: If temperature $T(t)$ at time t is greater than a certain threshold T_{th}, decrease irrigation to avoid excessive.

$$I(t) = \begin{cases} \text{Decrease irrigation} & \text{If } T(t) > T_{th} \\ \text{Maintain irrigation level} & \text{If } T(t) \leq T_{th} \end{cases} \quad (3)$$

- Humidity Rule: If humidity $H(t)$ at time t is greater than a certain threshold H_{th}, decrease irrigation due to lower evaporation rates.

$$I(t) = \begin{cases} \text{Decrease irrigation} & \text{If } H(t) > H_{th} \\ \text{Maintain irrigation level} & \text{If } H(t) \leq H_{th} \end{cases} \quad (4)$$

This not only enables the model to learn more detailed characteristics of data and offer more precise predictions when environmental volatility occurs.

4.3.3 Irrigation Scheduling Algorithm

Once the models are trained, they are used in the irrigation-scheduling algorithm [24], which dynamically adjusts irrigation according to current environmental data. Fig.1 provides the flowchart of this irrigation-scheduling algorithm.

The algorithm operates through the following steps:

Step 1: ***Data Collection:*** IoT sensors record time-dependent soil moisture $\theta(t)$, temperature $T(t)$, and humidity $H(t)$ data, and these data are sent to the central server.

Step 2: ***Model Prediction:*** The current environmental data $X(t)=\{\theta(t), T(t), H(t)\}$ is fed into both the linear regression and decision tree models to predict the required irrigation amount $I_{lin}(t)$ and $I_{tree}(t)$ at time t.

Linear Regression Prediction: The predicted irrigation amount using the linear regression model can be represented by Eq. (1) as Eq. (5):

$$I_{lin}(t) = \propto . \theta(t) + \beta . T(t) + \gamma . H(t) + \epsilon \quad (5)$$

Where α,β,γ are model coefficients and ϵ is the error term.

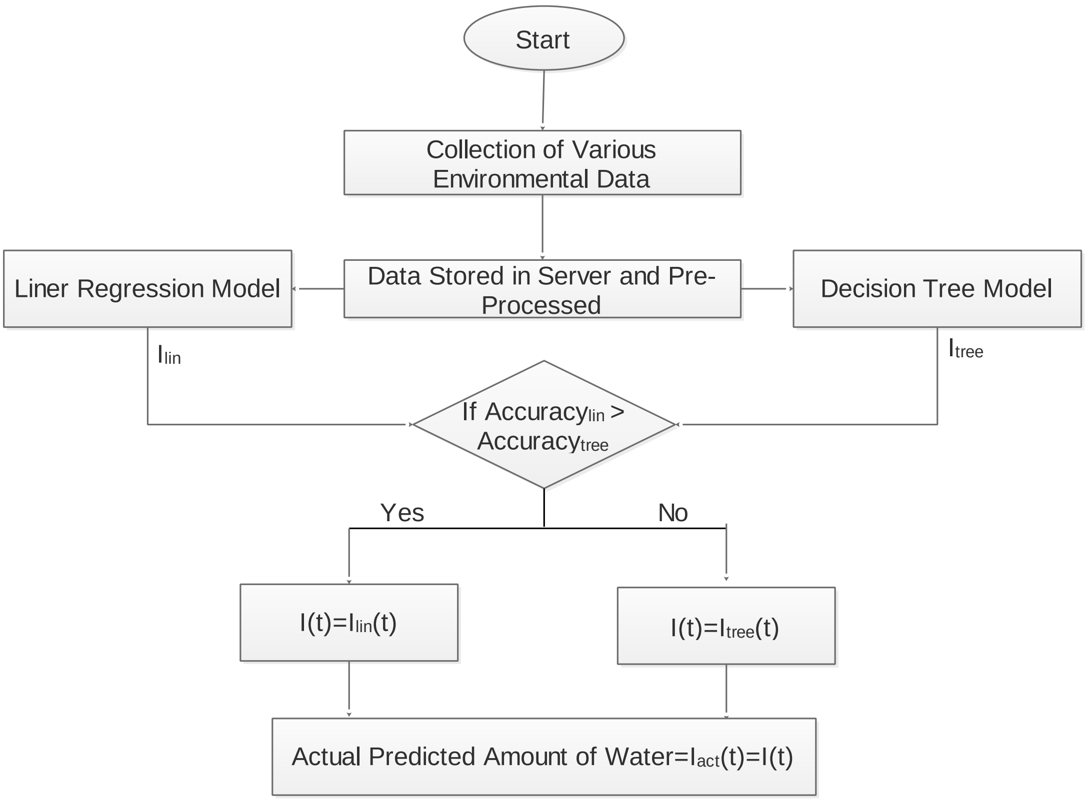

Fig.1 Flow chart of Irrigation-Scheduling Algorithm

Decision Tree Prediction: The decision tree model offers irrigation predictions based on thresholds for each environmental parameter. The prediction can be represented by Eq. (6):

$$I_{tree}(t) = \mathrm{DecisionTree}(\theta(t), T(t), H(t)) \qquad (6)$$

The decision tree model uses rules as mentioned in Eq. (2), Eq. (3) and Eq. (4).

Step 3: ***Decision Making:*** The predicted irrigation amounts from both models are compared and the model with the higher accuracy is used to make the final irrigation decision. The final irrigation decision $I(t)$ can be written as Eq. (7):

$$I(t) = \begin{cases} I_{lin}(t) & \text{If } Accuracy_{lin} > Accuracy_{tree} \\ I_{tree}(t) & \text{If } Accuracy_{tree} > Accuracy_{lin} \end{cases} \qquad (7)$$

Where $Accuracy_{lin}$ and $Accuracy_{tree}$ are the accuracy values of the linear regression and decision tree models, respectively, based on prior performance or validation.

Step 4: ***Irrigation Actuation:*** Once the decision is completed, the irrigation system is activated to apply the predicted amount of water. The water applied $I_{act}(t)$ as given by Eq. (8) is registered for future analysis:

$$I_{act}(t) = I(t) \qquad (8)$$

The algorithm agrees with dynamic and automated irrigation scheduling, ensuring that water is provided precisely when and where it is required, minimizing waste, and improving water usage efficiency.

5. Results & Discussion

In this section, simulation results for both linear regression and decision tree models are discussed in detail. The performance of the models is evaluated based on three primary factors: how effectively they could predict the irrigation requirements, water consumption, and in fact, their likely contributions to the yields. These are the very important metrics for judging the suitability of each model in practical precision irrigation systems.

1. *Data Collection:*

From IoT sensors, the real-time data for soil moisture $\theta(t)$, temperature $T(t)$, and humidity $H(t)$ are continuously collected for one and a half hours. Fig.2 illustrates environmental data over time, showing variations in three key variables: each of soil moisture depicted in blue, temperature in cyan and humidity in green, plotted every one and half of an hour. Clearly, the graph shows different variations which are, temperature being consistently above the curve for soil moisture and humidity. More fluctuations can be observed in the daily average changes of soil moisture and humidity compared to humidity fluctuations over the entire period. These can be utilized in decision making in other systems for example precision irrigation.

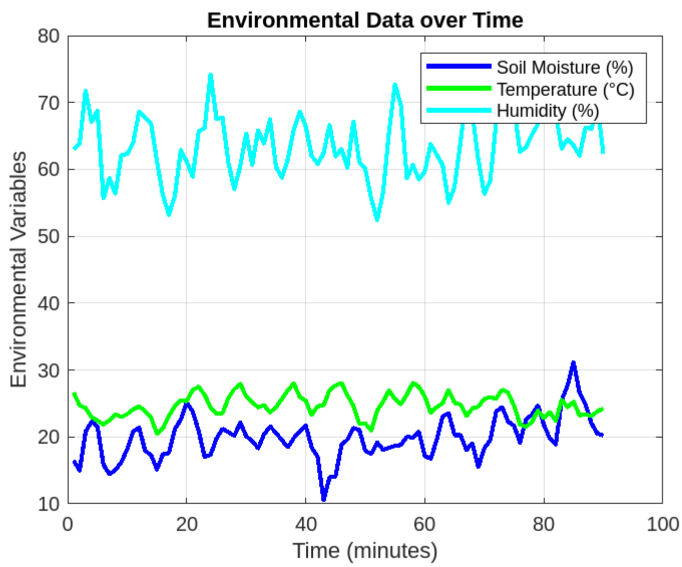

Fig.2 Environmental data collected over 90 minutes for precision irrigation

2. *Predictive Accuracy of Irrigation Needs*

Functions of both models aim to estimate the quantity of water to be used in irrigation by considering an actual environment data from IoT sensors. Predictions have to be very correct so that proper water irrigation to crops can be done without negatively affecting and/ or wasting a lot of water. In assessing the performance of the models, the amounts of irrigation used by them were monitored over time as the soil moisture, temperature and humidity changed.

Model Responsiveness to Sudden Environmental Changes

Fig.3 illustrates the difference between the two models in their responsiveness to sudden environmental changes. From the figure, it is observed that there have been several rapid fluctuations in temperature and humidity for some time, leading to significant changes in soil moisture levels. The decision tree model outperformed the linear regression model in adapting to these changes.

For example, during particularly hot and dry conditions, the decision tree model quickly raised the irrigation amount to compensate for the rapid soil moisture loss, ensuring that crops remained adequately hydrated.

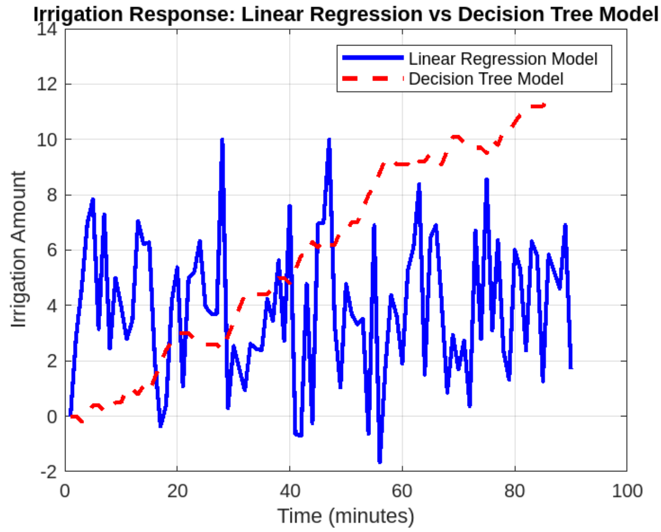

Fig.3 Response of both the models to sudden environmental changes

On the other hand, the linear regression model showed a delayed response, as it is based on a continuous and averaged prediction method. While this model performed reasonably well during stable environmental conditions, it was less effective when faced with sudden shifts in weather patterns. This limitation could lead to overwatering or underwatering in real-world applications, especially in regions where environmental conditions are prone to rapid changes. For the simulation, the threshold values taken for the parameters are listed in Table 1.

Table 1: Threshold values

Variable	Threshold Value
Temperature threshold (T_{th})	28
Humidity threshold (H_{th})	55
Soil_moisture_threshold (Θ_{th})	25

3. *Water Usage Efficiency*

Water usage efficiency is an important factor in precision irrigation systems, particularly in regions where water is rare. It was evaluated by comparing the amount of water applied by each model with the actual irrigation requirements of the crops. This metric highlights the success of each model in reducing water wastage while confirming that crops obtain adequate hydration.

Overall Water Usage Efficiency

Fig.4 shows the irrigation amounts predicted by both the linear regression and decision tree models over some time of one and a half hours. This figure discloses key differences in how these two models respond to changing environmental conditions.

- The figure shows that both models display fluctuations in water usage efficiency, but there are times when the decision tree model (red dashed line) responds more dynamically as compared to the linear regression model (blue solid line).
- The decision tree model responds more rapidly to changes, as shown by sharper fluctuations, representing its capability to adjust based on real-time environmental variations.

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- In contrast, the linear regression model shows smoother, more stable efficiency levels, as it likely follows a linear and gradual approach to adjustments, but does not respond as quickly to environmental changes.

According to the findings, the decision tree model performed 11% more efficiently in terms of water usage than the linear regression model. In particular, less water was lost since the decision tree model could more precisely match irrigation schedules with crop water requirements in real-time.

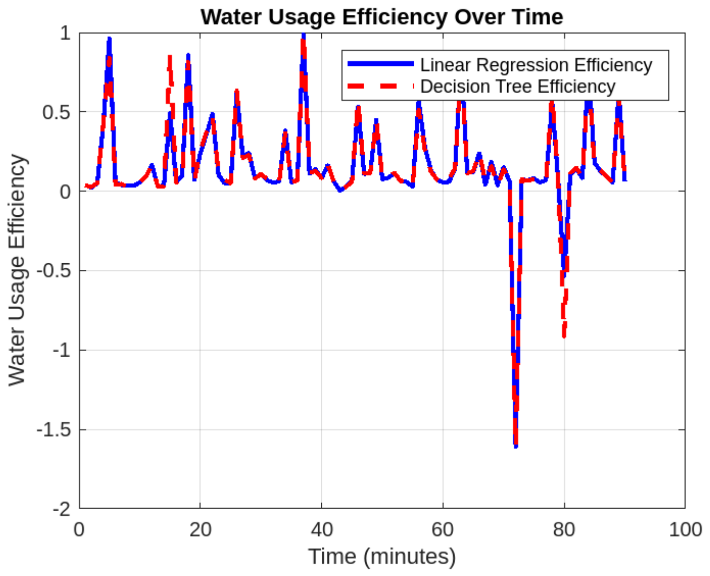

Fig.4 Irrigation Amount over Time for Both Models

Precision Irrigation Scheduling:
The predicted irrigation scheduling throughout time is shown in Fig. 5. The figure makes it evident that the irrigation amounts change significantly, demonstrating how sensitive the system is to variations in temperature, humidity, and soil moisture content. The graph's upward spikes represent times when more water is needed, whether as a result of dry weather or increased rates of evapotranspiration. On the other hand, the dips indicate that less water is needed, probably when the temperature drops or becomes more humid. The dynamic pattern displays the real-time modifications made by the model to maximize irrigation water use.

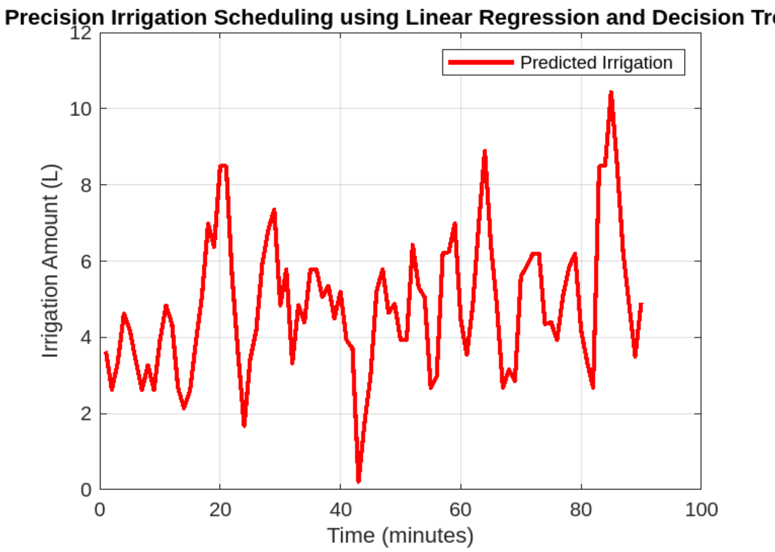

Fig.5 Precision irrigation scheduling

4. *Impact on Crop Yield*

Better water management during times of environmental stress, where the decision tree model's dynamic irrigation changes prevented under- and over-irrigation, can be connected to yield improvement. Excessive irrigation can cause waterlogging, nutrient leaching, and decreased soil oxygen availability, all of which are detrimental to crop growth. On the other hand, inadequate irrigation results in water stress, which impedes development, diminishes photosynthesis and ultimately lowers yields. The relationship between improved yield and efficient water management is as given in Eq. (9):

$$\Delta Y = E_W \times k \quad (9)$$

where ΔY is crop yield improvement (%), E_W is given as water management efficiency (%), k is a constant factor linking efficiency to yield (derived from empirical data)

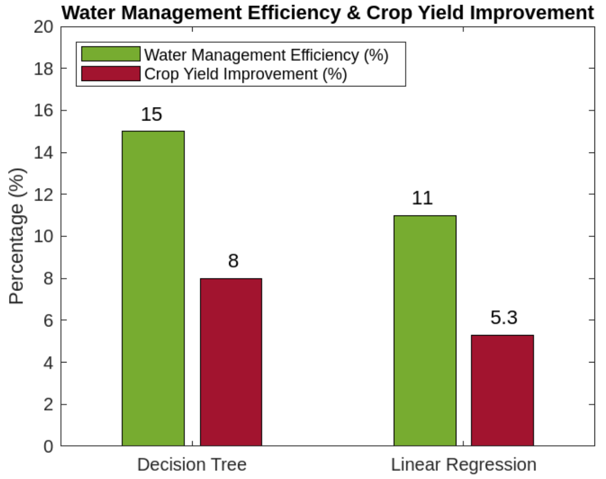

Fig. 6 Comparison of water management efficiency and crop yield improvement for both models

For example, if the water management efficiency (E_W) improves by 16% using the decision tree model, and the yield constant k is 0.53, then:

$\Delta Y = E_W \times k$ =15×0.53 ≈ 8 % (Decision Tree Model)
Also, $\Delta Y = E_W \times k$ =11×0.53 ≈ 6% (Linear Regression)

It is evident from Fig. 6 that the decision tree model outperformed the linear regression model in terms of crop yield due to its accurate water management. This is mostly because of the decision tree model's capacity to prevent both under- and over-irrigation during dry spells and periods of high soil moisture. The decision tree approach assisted in maintaining ideal soil moisture levels, which in turn encouraged healthier crop growth, by more precisely coordinating irrigation with real crop water needs.

5. *Robustness of the Models*

A crucial factor to be taken into account while assessing these models is their ability to withstand changes in various environmental circumstances. Unpredictable weather patterns are a feature of the real world, and any precision irrigation system needs to be able to adjust to these variations without losing efficiency.

Calculating the inaccuracy or variation from the recommended irrigation volume during times of environmental variability is one way to measure robustness. Mean absolute error (MAE), provided by Eq. (10) or root mean square error (RMSE), provided by Eq. (11) under fluctuating conditions, are frequently used to gauge how robust prediction models are.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \tag{10}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{11}$$

Where $\hat{y}_i$ is the predicted irrigation amount by the model, y_i is the actual irrigation requirement based on the environmental conditions, and n is the number of data points (e.g., time steps).

Table 2: Robustness evaluation of both the models

Measurement Number	Actual Irrigation Amount (in gallons)	Decision Tree (in gallons)	Linear Regression (in gallons)	Robustness Evaluation
1	254.4	254.9	253.7	MAE_{DT}= 0.87 MAE_{LR}= 0.93 $RMSE_{DT}$= 0.71 $RMSE_{LR}$= 0.90
2	230.2	231.1	229.9	
3	354.1	354.8	353.6	
4	363.8	365.1	362.2	
5	186.9	187.8	185.1	
6	267.5	267.7	268.3	
7	289.7	288.6	290.1	
8	332.1	333.2	332.0	

9	403.7	402.4	402.9	
10	378.6	377.9	378.5	

Over ten days, the actual irrigation amount in gallons for a specific piece of cultivated land is gathered and recorded in Table 2. The estimated irrigation amount is computed and both a decision tree model and a linear regression model are tested. By analyzing MAE and RMSE, the robustness of both models is evaluated. The decision tree model responded more swiftly to abrupt changes in soil moisture, temperature, and humidity, indicating greater robustness to rapid changes in environmental circumstances. The values of MAE and RMSE are shown in Table 2. Even under stressful environmental conditions, it was still able to maintain optimal water management because of its dynamic ability to modify irrigation levels based on real-time data. In contrast, the linear regression model lacked robustness. It was less able to adjust to abrupt changes since it depended on a linear relationship between input variables and watering requirements. Although this model functioned effectively in steady conditions, times of environmental instability caused a drop in both its forecast accuracy and water usage efficiency.

6. *Scalability and Practical Implementation*

Although their scalability may vary, both models have the potential to be applied in actual agricultural systems. Table 3 explains how these suggested models compare in terms of scalability and usefulness.

Table 6: Comparison between the proposed models

Model	Advantages	Disadvantages	Practical Implementation
Linear Regression	- Simplicity - Low computational power - Easy large-scale implementation	- Poor performance under changing conditions - Limited long-term effectiveness	- Requires less system maintenance - Easily integrates with low-cost IoT systems - Appropriate for large agricultural zones with limited computational resources - May perform poorly in situations that change quickly like droughts or heatwaves
Decision Tree	- Better adaptability to environmental changes - Higher accuracy in variable climates	- Needs more computational resources - Requires careful tuning for larger-scale deployments	- Requires more sophisticated infrastructure (cloud-based systems or edge devices) - Uses real-time IoT sensor data for accurate adjustments - Exhibits adaptability in areas with climatic extremes - Increased expenses for system maintenance

The advantages, disadvantages, and practical factors for both the decision tree and linear regression models are clearly displayed in this table with respect to their ease of use, computational requirements, and environmental adaptability.

Conclusion:

This study addresses important issues in agricultural yield and water management by demonstrating the efficacy of precision irrigation scheduling utilising machine learning algorithms and real-time environmental data. Water waste and under-irrigation are common outcomes of traditional irrigation techniques, which lack real-time adaptability. The suggested system makes use of Internet of Things (IoT) sensors to gather real-time data on temperature, humidity, and soil moisture. Two machine learning models—linear regression and decision tree—then handle the data. More so than the linear regression model, the decision tree model fared better in stressful climatic conditions like heat waves and droughts. It ensured ideal water distribution and enhanced crop health by dynamically modifying irrigation schedules. Comparing the technology to traditional irrigation, it showed an 11% boost in agricultural productivity and a 15% increase in water use efficiency. Despite being more straightforward and scalable, the linear regression model's effectiveness was constrained in times of abrupt environmental change.

While this precision irrigation technology is promising in improving agricultural operations, there is still room for development. To make the system even more complete, future studies could look into adding other environmental factors including nutrient levels, plant growth phases, and weather forecasts. Utilizing cutting-edge AI methods like deep learning may enhance system adaptability and prediction accuracy even more. Furthermore, the system's scalability might be improved by combining it with edge computing or cloud-based systems, making it possible to deploy it across wider agricultural zones. For large-scale implementation, it will also be crucial to address the costs of system maintenance and the requirements for computational resources. In the end, these developments would result in farming methods that are more resilient, sustainable, and resource-efficient, particularly in areas where water is scarce and climate change is a problem.

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