

SMART IRRIGATION STRATEGY RECOMMENDED SYSTEM USING ML

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ABSTRACT

Water used for irrigation forms the largest share of freshwater consumption in agriculture, and much of it is wasted because fields are watered on a fixed schedule rather than according to the actual needs of the crop. Over-irrigation leaches nutrients, raises pumping cost, and can damage roots, while under-irrigation reduces yield during critical growth stages. This paper presents a Smart Irrigation Strategy Recommendation System that uses soil and weather sensing together with machine learning to recommend when to irrigate, how much water to apply, and which irrigation method suits the field and crop.

The sensing part of the system consists of field nodes built around an ESP32 microcontroller that read a capacitive soil moisture sensor at two depths, a soil temperature probe, and an air temperature and humidity sensor. Each node samples these values at regular intervals, averages several readings to reduce noise, and sends them over Wi-Fi or a LoRa link to a gateway. The nodes are powered by a small solar panel and battery, and they spend most of their time in deep sleep to extend battery life. Weather forecast data for the location, including expected rainfall, temperature, and wind speed, is obtained from a public service and merged with the sensor readings.

The machine learning part of the system operates in two stages. In the first stage, a regression model predicts the soil moisture level expected over the next twenty-four hours using current sensor readings, reference evapotranspiration computed from weather data, crop type, and growth stage. Linear Regression, Random Forest, Gradient Boosting, and Support Vector Regression were compared for this task using RMSE and MAE. In the second stage, a classification model recommends one of several irrigation actions, namely no irrigation, light irrigation, normal irrigation, or deferral because rain is expected. Decision Tree, Random Forest, K-Nearest Neighbours, and XGBoost classifiers were compared using accuracy, precision, recall, and F1-score.

The recommendations are presented through a web dashboard that shows live soil moisture for each field zone, the predicted moisture curve, the recommended action with the estimated water volume and pump running time, and a record of past irrigation events. The system can also switch a relay-controlled pump or solenoid valve automatically when the farmer chooses automatic mode, while manual confirmation remains the default. In trials using collected and public agronomic data, the Random Forest models gave the best results, and the recommended schedules

used noticeably less water than a fixed daily schedule while keeping moisture within the desired range.

The system is intended for small and medium farms, kitchen gardens, polyhouses, and institutional campuses where water availability is limited and labour for manual checking is scarce. It combines inexpensive electronics, low-power wireless communication, and interpretable machine learning in a single practical tool. Future work includes crop-specific models trained on local field trials, integration of satellite vegetation indices, and support for drip fertigation scheduling.

I. INTRODUCTION

Irrigation is one of the most important inputs in agriculture, and in many regions it is also one of the most wasteful. Farmers commonly water their fields at a fixed time every day or every few days, guided by habit or by the availability of electricity for pumping. This practice ignores the fact that the water requirement of a crop changes with weather, soil type, and growth stage. On a cool, cloudy day the soil may still hold enough moisture, while on a hot and windy day the same field may dry out much faster than usual. Fixed schedules therefore often apply more water than needed in some periods and too little in others.

The consequences of poor irrigation scheduling are felt both by the farmer and by the wider community. Excess water increases electricity or diesel cost for pumping, washes fertiliser below the root zone, and in some soils causes waterlogging and salinity. Insufficient water during flowering or grain filling can reduce yield significantly. Groundwater levels in many districts are falling, and power supply to agricultural feeders is often limited to certain hours, which makes efficient use of each pumping cycle important. At the same time, rural labour is increasingly scarce, so walking the field to check soil moisture by hand is not always possible.

Advances in low-cost electronics make it possible to measure soil and weather conditions continuously. Capacitive soil moisture sensors, digital temperature and humidity sensors, and microcontrollers with built-in wireless connectivity are now affordable for small farms. Low-power design using deep sleep and solar charging allows sensor nodes to operate for long periods without maintenance, and long-range radio such as LoRa can cover fields where Wi-Fi is not available. When this continuous data is combined with weather forecasts, machine learning models can learn how moisture changes over time and predict when the soil will reach a level at which the crop begins to suffer water stress.

This paper presents a Smart Irrigation Strategy Recommendation System that brings these elements together. Sensor nodes measure soil moisture and ambient conditions, weather forecasts are retrieved automatically, and a Python machine learning pipeline predicts future moisture levels and recommends an irrigation action along with an estimate of the water volume required. The results are displayed on a dashboard, and the system can control a pump through a relay if the user allows it. The objective is to reduce water and energy use while maintaining soil moisture within a range suitable for healthy crop growth.

II. LITERATURE SURVEY

Research on irrigation scheduling has traditionally been based on the soil water balance and on estimates of crop water use. Agronomic studies established methods for calculating reference evapotranspiration from weather variables, with the Penman-Monteith equation becoming the most widely accepted approach, and introduced crop coefficients that adjust this reference value for different crops and growth stages. Using these methods, the amount of water lost from the soil each day can be estimated and irrigation can be applied when the accumulated deficit reaches a chosen fraction of the available water in the root zone. Field studies showed that such scheduling saves a considerable amount of water compared with fixed calendars. However, the method depends on accurate weather data, correct crop coefficients, and knowledge of soil properties, which are often not available to small farmers. Errors in any of these inputs accumulate over time, and periodic correction with actual soil moisture measurements was recommended to keep the water balance estimate realistic.

The development of affordable soil moisture sensors led to a large body of work on sensor-based irrigation control. Early systems used resistive probes, which were cheap but suffered from corrosion and drift, and later work moved to capacitive sensors that are more stable over time. Many studies built controllers in which a microcontroller reads the moisture sensor and switches a pump or valve on when moisture falls below a set point and off when it rises above an upper limit. Reported results showed water savings and reduced labour, but researchers also pointed out important limitations. A single sensor may not represent the whole field, sensor readings depend on soil type and require calibration, and simple threshold control reacts only after the soil has already become dry. Threshold controllers also ignore forecast rainfall and may irrigate a field shortly before a heavy shower, wasting both water and energy.

Work on wireless sensor networks for agriculture addressed the problem of collecting data from many points across a farm. Studies compared ZigBee, Wi-Fi, GSM, and LoRa for field communication, taking into account range, power consumption, data rate, and cost. LoRa was frequently recommended for rural farms because it provides communication over several kilometres at very low power, while Wi-Fi was considered suitable for small plots and polyhouses close to a building. Power management received considerable attention, with duty cycling, deep sleep modes, and solar energy harvesting used to extend node lifetime. Researchers reported that careful selection of sampling interval and transmission frequency has a large effect on battery life. Other studies examined the effect of enclosure design, sensor placement depth, and cable length on measurement reliability, noting that practical field deployment introduces problems that are not visible in laboratory tests.

Machine learning has been applied to irrigation in two main ways. The first is prediction of soil moisture or crop water requirement from sensor and weather data, where regression methods such as multiple linear regression, support vector regression, random forests, gradient boosting, and neural networks have all been used. Comparative studies generally found that ensemble tree methods offered a good balance between accuracy and training effort, while neural networks gave small improvements when large datasets were available. The second is decision support,

where classifiers learn to recommend whether and how much to irrigate from past decisions or from expert-labelled examples. Decision trees and random forests were often preferred in this setting because their rules can be inspected and explained to farmers. Several studies stressed that incorporating weather forecasts, particularly expected rainfall, improves recommendations considerably compared with using current readings alone.

More recent research has focused on complete smart irrigation platforms that link sensing, prediction, control, and user interaction. Such platforms typically include field nodes, a gateway, a cloud or local server running prediction models, and a mobile or web interface showing field status and recommendations. Evaluations report savings in water and energy along with maintained or improved yield, but they also highlight practical concerns such as sensor maintenance, network reliability, and the need for farmers to trust automated decisions. Many authors recommend offering a recommendation mode with manual confirmation before moving to fully automatic control, and presenting the reasoning behind each recommendation in plain terms. The present system follows this approach by combining low-power sensor nodes, weather forecast integration, moisture prediction, action classification, and a dashboard with optional pump control.

III. SYSTEM ANALYSIS

The system is analysed as a cycle of sensing, prediction, recommendation, and action. Each field zone contains a sensor node that measures volumetric soil moisture at shallow and root-zone depths, soil temperature, air temperature, and relative humidity. The node wakes from deep sleep at fixed intervals, takes several readings, averages them, and transmits a compact packet with its battery voltage to a gateway over LoRa or Wi-Fi. The server stores the readings and retrieves the weather forecast for the location, including rainfall, temperature, humidity, and wind speed. Reference evapotranspiration is computed from the weather data and adjusted with a crop coefficient according to the crop and growth stage entered by the user. The moisture prediction model estimates soil moisture over the next day, and the recommendation model combines this prediction with forecast rainfall to choose an irrigation action. The required water depth is converted into a volume and pump running time using the zone area and pump flow rate, and the result is shown on the dashboard or sent to the pump controller.

Existing System

In most farms, irrigation is scheduled by experience and habit rather than by measurement. Farmers switch on the pump at a fixed time, often determined by the hours during which electricity is supplied to agricultural feeders, and continue until the field appears wet. Some farmers check moisture by touching the soil or observing the leaves, which requires walking through the field and depends heavily on individual judgement. Timer-based controllers are used in some gardens and polyhouses, but they apply the same amount of water regardless of weather. Where soil moisture sensors are installed, they are usually connected to simple threshold controllers that start the pump when moisture drops below a fixed level. These

controllers do not consider expected rainfall, crop growth stage, or the rate at which the soil is drying, and they react only after the soil has already become dry. Records of irrigation events and water use are rarely kept, so there is no basis for assessing whether the schedule is efficient or for improving it in later seasons.

Disadvantages of Existing System

- Irrigation follows fixed schedules that ignore daily weather conditions.
- Manual inspection of soil moisture is time-consuming and subjective.
- Timer-based controllers apply the same water volume in all conditions.
- Threshold controllers react only after the soil has already dried.
- Forecast rainfall is not considered, leading to irrigation before rain.
- Crop type and growth stage are not taken into account.
- Excess watering increases pumping cost and leaches fertiliser.
- Single sensors are not calibrated and may not represent the whole field.
- Sensor nodes powered from mains are difficult to deploy in open fields.
- No records of water use are kept for later analysis and improvement.

Proposed System

The proposed system recommends irrigation actions using continuous field sensing, weather forecasts, and machine learning. Solar-powered ESP32 nodes in each field zone measure soil moisture at two depths, soil temperature, air temperature, and humidity, and transmit averaged readings over LoRa or Wi-Fi to a gateway while spending most of their time in deep sleep. A Python server stores the readings, retrieves forecast weather for the location, and computes reference evapotranspiration adjusted for crop type and growth stage. A regression model predicts soil moisture over the next twenty-four hours, and Linear Regression, Random Forest, Gradient Boosting, and Support Vector Regression are compared for this purpose. A classification model then recommends no irrigation, light irrigation, normal irrigation, or deferral due to expected rain, with Decision Tree, Random Forest, KNN, and XGBoost compared as candidates. The water requirement is converted into volume and pump running time. A dashboard shows live readings, predicted moisture, the recommendation, and irrigation history, and a relay module can operate the pump automatically when permitted.

Advantages of Proposed System

- Schedules irrigation according to actual soil moisture and weather conditions.
- Predicts future soil moisture so that stress can be avoided before it occurs.
- Defers irrigation when significant rainfall is forecast.
- Takes crop type and growth stage into account through crop coefficients.
- Estimates water volume and pump running time for each recommendation.
- Uses low-power, solar-charged sensor nodes suitable for open fields.
- Supports long-range LoRa communication for large or remote farms.
- Offers both manual confirmation and automatic pump control modes.
- Keeps records of moisture levels and irrigation events for later review.
- Reduces water use and pumping energy compared with fixed schedules.

IV. METHODOLOGY

The methodology begins with the installation and calibration of sensor nodes. Each capacitive moisture sensor is calibrated against gravimetric measurements of soil samples at several moisture levels, and a calibration curve is stored for the soil type. Readings are collected at regular intervals over several weeks, together with weather data and a log of irrigation events recorded by the user. Public agronomic datasets are added to increase the variety of conditions. The data is cleaned by removing readings from nodes with low battery, filtering spikes, and interpolating short gaps. Features are created, including current and lagged moisture at both depths, rate of moisture change, reference evapotranspiration, crop coefficient, forecast rainfall, temperature, and humidity. The moisture prediction models are trained with a time-ordered split and evaluated using RMSE and MAE. For the recommendation stage, each record is labelled with the appropriate action based on agronomic rules for allowable depletion, and classifiers are trained and evaluated using accuracy, precision, recall, F1-score, and the confusion matrix. The selected models are then deployed on the server.

SYSTEM ARCHITECTURE

The architecture of the system is divided into layers that link the field to the user. The Field Sensing Layer consists of solar-powered ESP32 nodes with soil moisture, soil temperature, and air temperature and humidity sensors. The Communication Layer carries readings over LoRa or Wi-Fi to a gateway, which forwards them to the server. The Data Storage Layer records sensor readings, weather data, and irrigation events in a database. The Weather Integration Layer retrieves forecast rainfall, temperature, humidity, and wind speed and computes reference evapotranspiration. The Preprocessing and Feature Layer cleans the data and prepares lagged, rate-of-change, crop, and weather features. The Moisture Prediction Layer applies the regression model to estimate soil moisture for the coming day. The Recommendation Layer applies the classification model and computes water volume and pump running time. The Control Layer operates the pump or valve through a relay when automatic mode is enabled, and the Dashboard Layer displays live data, predictions, recommendations, and history.

Smart irrigation strategy recommended system using ML

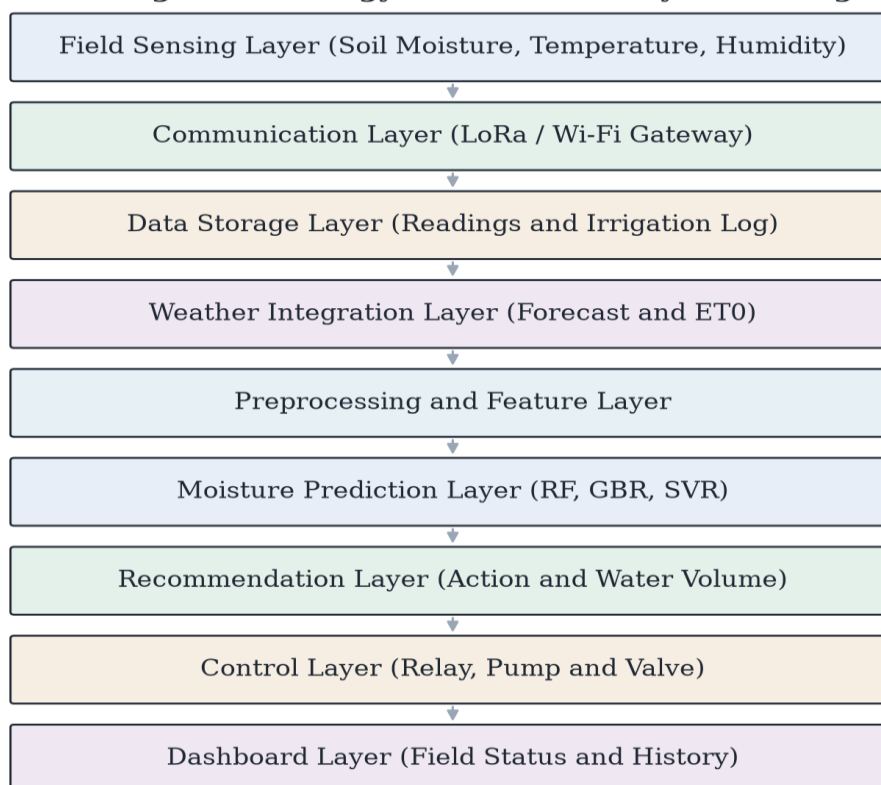
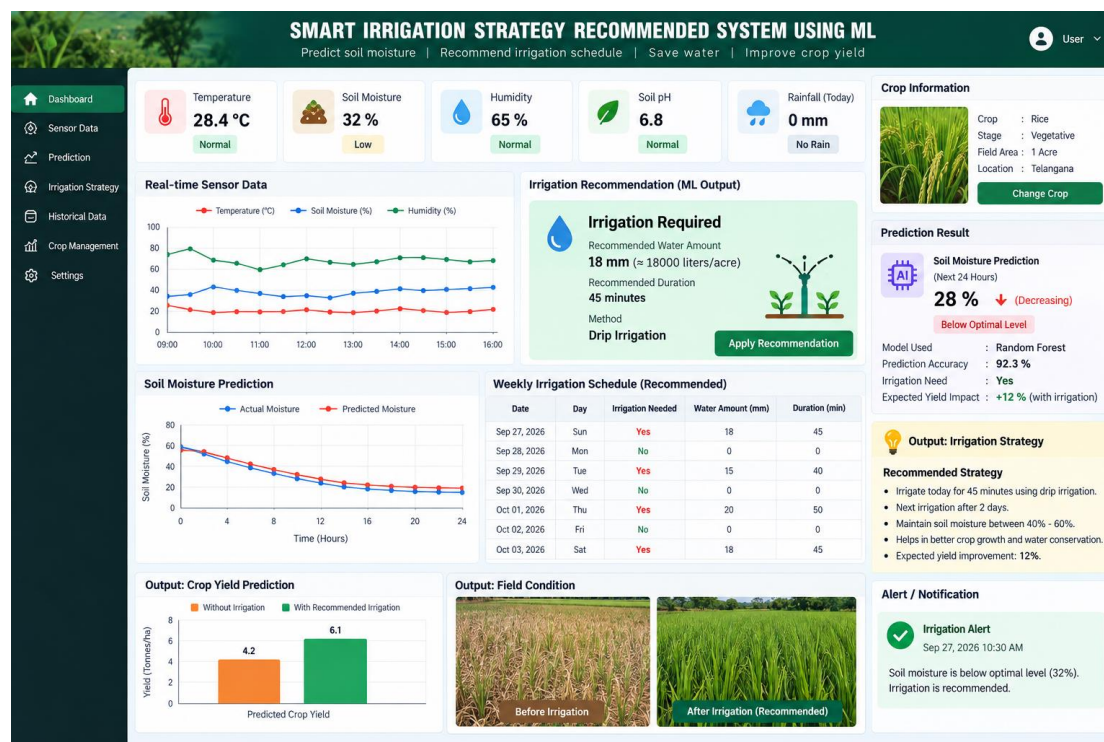


Fig. 1 System Architecture

V. RESULT AND OUTPUT



VI. CONCLUSION

The Smart Irrigation Strategy Recommendation System demonstrates how field sensing, weather forecasting, and machine learning can be combined to improve irrigation decisions on small and medium farms. By measuring soil moisture continuously and considering expected weather, the system replaces fixed watering schedules with recommendations that follow the actual condition of the field and the needs of the crop.

The two-stage learning approach proved effective. The moisture prediction model allows the system to anticipate when the soil will reach a stress level, rather than reacting only after it has become dry, and the recommendation model translates this prediction into a clear action that takes forecast rainfall into account. Random Forest models gave the best results in both stages, and their structure made it possible to examine which inputs influenced each decision. The recommended schedules used considerably less water than a fixed daily schedule while keeping moisture within the target range.

Attention to the electronics and communication aspects of the design made the system suitable for real field conditions. Capacitive sensors calibrated for the local soil, averaged readings, deep sleep operation, and solar charging allowed the nodes to run for long periods without maintenance, and LoRa communication extended coverage to fields far from a building. The option of manual confirmation before pump operation helps farmers build trust in the recommendations before moving to automatic control.

Future work can include crop-specific models trained on local field trials over complete seasons, integration of satellite vegetation and evapotranspiration products, and scheduling of fertiliser application through drip systems. Support for regional languages, voice alerts, and SMS notifications would make the system easier to use for farmers with limited access to smartphones, and cooperation among neighbouring farms could allow shared gateways and pooled data for better model training.

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