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Smart Irrigation Optimization: Leveraging IoT-Driven Soil Moisture Monitoring and Cloud-Based Weather Integration for Sustainable Crop Water Management

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***Abstract*—**Managing water well in farming is a big challenge. Climate change and lack of water worldwide make it hard to manage water well. Both agriculture and agricultural irrigation use machinery designed to give water to plants without any person's intervention, it is possible to do this process using small controlled and huge uncontrolled irrigation. The research proposes a cloud application that uses the Internet of Things (IoT) sensors to monitor soil moisture constantly and fetches related weather data to improve water particularly for outdoor crops. The objective of this research is to assess whether the technology can help save water compared to the conventional method. The project requires gathering soil moisture data using IoT sensors in an open field environment, integrating it with instant weather parameters and developing an algorithm in a cloud platform to specify irrigation schedules. The data will be analyzed for the next four weeks to find out the correlation with the environmental factors of the soil moisture which will help in decision-making for irrigation. The study reveals uses of IoT and Cloud Computing in precision agriculture which helps in saving water, enhancing the health of the crop, and sustainability of farming. This research' findings aim to offer a practical course of action for agriculture sectors to implement smart irrigation and effective management of resources under different environmental conditions.

I. INTRODUCTION

1) Background and Context: The time resolution is limited for estimation of soil moisture by applying the conventional manual process for estimation of soil moisture. Most of the time, it depends on visual inspection only which may not be an optimal condition for applying water. (bwambale2022smart) reported on the indication made possible by the great ad vancement in IoT-enabled sensors which help to continuously and at a high frequency measure volumetric water content on different soil depths on varying soil profiles[1]. Scientists still do not understand how soil texture and moisture condition affect AIs used on sensor models.

Many frameworks for irrigation scheduling do not use dynamic weather input data (rainfall forecast, air temperature and humidity) for schedul ing. The only assessments for decision making are hydrology and climatological [2]. This hampers the crop performance and leads to water resource wastage.

***2) Research Questions and Objectives**:* The following re search questions are addressed:

1) What magnitude of irrigation water savings can be achieved by leveraging a cloud-based platform that inte
grates real-time soil moisture measurements and weather forecasts?

2) In what ways does the integrated IoT–cloud approach outperform conventional manual scheduling in terms of water use efficiency and crop health indicators?

To answer these questions, the investigation objectives are: • Examination of IoT sensor principles for soil moisture detection and cloud computing architectures for data processing in precision agriculture.

• Design of predictive algorithms that fuse soil moisture readings with meteorological data to determine irrigation requirements.

• Quantification of statistical relationships between selected weather variables and soil moisture dynamics.

• Development of a cloud-hosted decision support applica tion for automated irrigation scheduling.

• Validation of algorithmic performance against traditional manual scheduling through a four-week field trial.

II. METHODOLOGY

A. Study Site and Experimental Design

A field testing area was recently established at a station characterized by loamy soil and a subtropical climate *algo rithm* . We filled two pots with the same soil mixture. Each 30 cm diameter pot had six Salanova lettuce seedlings. One pot was the algorithm treatment, while the other pot was the control. The randomized block layout prevents edge effects and guarantees uniform exposure to ambient conditions over a four-week period, including the well-defined data acquisition (two-week) and validation (two-week) phases.

B. Sensor Deployment and Calibration

Four capacitive soil moisture sensors (Section III-A1) were installed at depths of 5cm and 15cm in each pot to capture vertical moisture gradients. Prior to deployment, each sensor underwent laboratory-based calibration against gravimetric soil samples at water contents of 10%, 25%, and 40% by mass. Calibration curves were fitted using second-order polynomial regression to translate raw voltage outputs into volumetric water content. Sensor drift was assessed over a separate seven day period under constant moisture conditions and found to remain within ±2% of reference values.

C. Data Acquisition and Transmission

An ESP32 microcontroller was configured to poll each soil moisture sensor at 15-minute intervals. Firmware implemented in Arduino C++ handled analog-to-digital conversion, error checking, and packet assembly. Concurrently, a RESTful API client module queried a commercial weather service every 15minutes for forecasted and in-situ values of precipitation, air temperature, relative humidity, UV index, cloud cover, and barometric pressure. JSON-formatted payloads containing sensor readings and weather data were transmitted via HTTPS to a cloud endpoint.

D. Cloud Infrastructure and Data Management

A Node.js/Express.js backend received incoming data and enforced schema validation using Joi. Validated records were inserted into PostgreSQL tables partitioned by date for ef ficient querying. A time-series index on timestamp fields enabled rapid extraction of contiguous data segments. Daily automated jobs archived raw data to object storage and gener ated summary statistics. User authentication, rate limiting, and SSL termination were managed by Nginx and Let's Encrypt certificates to ensure data security.

E. Algorithm Development and Implementation

Feature engineering included calculation of hourly soil moisture change rates, rolling averages of weather variables over 1-, 3-, and 6-hour windows, and interaction terms (e.g., precipitation × temperature). A multivariate linear regression model was selected for its interpretability and low compu tational overhead. Coefficients were estimated using ordinary least squares with 5-fold cross-validation to prevent overfitting. The final model equation took the form:

$$\Delta s_m = \beta_0 + \beta_1 w_p + \beta_2 w_t + \beta_3 w_h + \beta_4 w_u .$$

Model parameters were stored in the cloud database and reloaded by a scheduler process, which evaluated real-time inputs every hour to decide on irrigation events when predicted moisture change would drive volumetric content below a 30% threshold.

F. Validation and Performance Assessment

During the two-week validation phase, the algorithm treat ment pot was irrigated only when triggered by the model, while the control pot received a daily fixed volume of 600mL at 18:00hr. Soil moisture in both pots was logged continuously. Key performance indicators included total water applied, event frequency, and moisture retention metrics (e.g., time spent within the 25%–75% "optimal" band). Water savings were calculated as the percentage reduction in cumulative volume relative to the control.

G. Statistical Analysis

In order to clean up the data, the recorded sensor values that lay outside three standard deviations from the moving mean were dropped. Additionally, missing weather readings were also imputed through linear interpolation. The relationship between climate variables and changes in soil moisture was studied. To assess the validity of regression models, R^2, adjusted R^2, root-mean-square error (RMSE), and mean absolute error (MAE) are being used. Residual checks and tests confirmed that there is no autocorrelation or departure from normality. The analyses were done in Python (pandas, statsmodels), using $p < 0.05$ as the threshold for significance.

H. Literature Review

1) IoT Sensors and Their Applications in Agriculture: As water scarcity and climate variability have become common global problems, agricultural precision is increasingly being pressured to optimize water use. Agriculture is responsible for about 71% of freshwater use. The use of wireless sensor networks in farm management systems allows continuous monitoring of soil moisture, temperature, and nutrient status and thus data-driven irrigation and fertilization.

One research study achieved a 46% reduction in water use together with improved plant vigor, as a result of control of the irrigation with IoT and machine learning models [3]. A scalable, low

power architecture suitable for the IoT is designed to relay soil moisture and temperature data from the home-scale farm to the cloud platform so that irrigation can be done efficiently with low power [3]. Pathogen detection, NPK nutrient analysis and automated actuators for irrigation valves have been other areas of application. Deployment difficulties continue to persist [4], including high capital cost, maintenance complexity, a lack of awareness among stakeholders, regulatory and infrastructure barriers.

***2) Cloud Computing and Monitoring in Agriculture**:* Cloud computing platforms have been harnessed to manage and ana lyze large-scale IoT data streams within agricultural networks. An open-source hardware prototype demonstrated the integra tion of motion-detection video surveillance with RESTful data services and a Hadoop-based big-data backend, supporting machine learning modules for crop variety selection, cultiva tion management, and market timing [5]. Maturation of IoT standards has led to compatible transmission protocols and unified software–hardware interfaces for sensing, storage, pro cessing, and control functions [5]. Scalable storage, analytics, and decision support functionalities are provided by cloud services, accessible via web and mobile clients. Equipment administration, data querying, visualization, alerting, and push notifications are supported through RESTful APIs, thereby decoupling infrastructure maintenance from application devel opment and accelerating domain-specific innovation.

3) Biological Aspects of Soil Moisture and Crop Irrigation Needs:

a) The Effect of Soil Moisture on Plant Growth and Yield: The soil moisture availability has a profound effect on physiological responses of the plant affecting growth, yield and product quality [6].

The texture, structure, and organic matter content of the soil determine its water retention capacity which sets the field capacity and permanent wilting point. The water content of soil beyond the field capacity and at the permanent wilting point is that which cannot be extracted by plants anymore. Keeping soil moisture above lower threshold and below upper threshold facilitates water uptake, transport of nutrients and prevents water stress as well as anaerobic conditions in soil. Nutrient solubilization and absorption by the roots depend on moisture. Water logging may cause root diseases because of anaerobic environment and moisture deficiency causes dehydration of cells resulting in metabolic inhibition. This means that a water supply that is just right is essential in order to make the plants use their resources most efficiently.

III. EXPERIMENT

A. Design and Setup

Data collection was conducted in two phases. Two pots were used to grow six salad plants; one for algorithm testing and the other for control. The pots were placed in the open, so that weather conditions and rain and sunlight affect them. An ESP32 microcontroller interfaced with four capacitive soil moisture sensors (Section III-A1) was inserted at equal depths. The scheme is shown in the figure. Sensor readings were sent through wireless transmission to a server on the web and archived in a cloud-database in addition to retrieving meteorological data via an APIFigure ??. I used the collected data to train a machine learning model which would forecast water requirement for irrigation. A web interface helped in visualizing the incoming data streams.(Section III-A2).

1) Sensors: Capacitive moisture sensing technology, which measures changes in soil dielectric properties, was selected due to its high resolution and stability across variable soil matrices [7]. Four distinct sensor models were deployed: one SoilWatch 10 sensor (PINO-TECH) and three Hygrometer Module V1.2 units (AZ-Delivery). The SoilWatch 10 oper ates at 3.3–5 V, outputs 0–3 V analog signals, and resolves volumetric water content between 0 % and 50 % with 0.1 % precision [8].

The Hygrometer Module V1.2 functions at 5 V and provides analogous interface pins (VCC, GND, OUT) at a lower cost. Multiple sensors were deployed to capture spatial heterogeneity and to mitigate individual device drift or failure [9].

2) Data Collection and Analysis: A cloud-based backend was implemented using Node.js and Express.js to expose RESTful endpoints for ESP32 data ingestion. Incoming soil moisture readings and weather API responses were persisted in a PostgreSQL database. A React.js frontend, supplemented by ReCharts, rendered real-time visualizations of sensor and weather metrics (Figure ??). After three weeks of contin uous monitoring, the consolidated dataset was exported for statistical analysis in Python. Linear regression techniques were applied to model the relationship between meteorological predictors and soil moisture change rates.

IV. RESULTS

To ensure data completeness, measurements were contin uously logged from two validated sensors over 21 days, resulting in a total of 3 120 measurements per sensor after exclusion of sensor drift-affected data streams. Six weather variables were recorded using API calls at the same frequency.

The soil moisture dataset (Table I) have mean volumetric contents of 45.2 and 47.5 with an overall coefficient of variation of less than 11

Typical subtropical weather patterns are shown by the met data. On average, precipitation events were 2.5 mm, with maximum daily totals of 7 mm. The day-night temperature difference attained a maximum of 12.8 °C, while relative humidity ranged between 45

Analysis shown in Table III indicated a strong correlation (r=0.74) of hourly soil moisture change with precipitation. A moderate negative correlation ($r = -0.58$), similar to evaporative loss, was evident with temperature. Association between cloud cover and UV index were weak whereas no association shown with pressure.

A precise model was developed to predict the hourly percentage change in soil moisture.

This table shows the performance metrics. R2=0.6 and RMSE=0.045%/hr indicates that the selected meteorological predictors explain the maxi mum variance in the material moisture dynamics. Statistical significance was confirmed (F-test $p < 0.001$) and residuals were homoscedastic.

A cloud-based irrigation scheduler implemented the model. The model-driven irrigation events took place six times over the nine-day validation period. In comparison, the irrigation was performed daily, totaling nine events, under the manual mode. Table V summarizes overall water use and moisture control results. Through the application of the rainwater man agement tool in Tomato cultivation, an 11.1% reduction in water volume was achieved, while the 25% – 75% range of moisture band in the soil was not compromised as against the 30% – 81% under the fixed schedule.

TABLE I
DESCRIPTIVE STATISTICS OF SOIL MOISTURE DATA

Sensor	Mean (%)	Std Dev (%)	Min (%)	Max (%)	N
Sensor 1 (SoilWatch 10)	45.2	5.1	30.4	56.7	3120
Sensor 3 (Hygrometer V1.2)	47.5	4.8	33.1	58.2	3120

TABLE II
DESCRIPTIVE STATISTICS OF METEOROLOGICAL VARIABLES

Variable	Mean	Std Dev	Min	Max
Precipitation (mm)	2.5	1.8	0.0	7.0
Temperature (°C)	24.3	3.5	18.2	31.0
Humidity (%)	68.2	10.4	45.0	89.0
UV Index	5.7	1.2	3.0	8.0
Cloud Cover (%)	40.3	20.1	10.0	90.0
Pressure (hPa)	1012.5	4.2	1005.0	1019.0

TABLE III
PEARSON CORRELATION BETWEEN SOIL MOISTURE CHANGE AND METEOROLOGICAL VARIABLES

	w_p	w_t	w_h	w_u	Cloud	Press
Δs_m	0.74	−0.58	0.69	−0.32	0.28	0.05

Moisture trajectories tracked via automated logging demon strated that thresholds for action (30 % volumetric content) were met precisely before irrigation events, reducing both over- and under-watering incidents. Temporal alignment of rainfall and irrigation further optimized resource application.

Economic implications were assessed using unit water cost assumptions, yielding projected savings of approximately 0.25 € per square meter per week at current sensor and data-service prices. Scalability analyses suggest that LoRa-based sensor networks could extend coverage with minimal additional op erational costs.

Statistical validation across crop phenological stages re mains pending. Nevertheless, the proof-of-concept confirms that IoT–cloud integration can deliver actionable irrigation guidance, setting a foundation for future large-scale trials and advanced non-linear modeling approaches.

V. DISCUSSION

A. Limitations of the Experiment and Possible Improvements

The trial's limited scale (six plants) and short duration (three weeks) constrain the generalizability of the findings. Plant species variability, soil heterogeneity, and extended pheno logical stages were not accounted for. Sensor waterproofing and deployment logistics in open-field conditions warrant further refinement to prevent data loss. Model complexity was restricted to linear regression; non-linear or ensemble methods may enhance predictive accuracy.

B. Future Directions for Research

To further the work, it is suggested to conduct long-term field trials on various crop types and soil types. Deploying on a commercial farm will help tackle practical challenges and eco nomics. We need to examine how to improve sensor networks.

TABLE IV
REGRESSION MODEL PERFORMANCE METRICS

Metric	Value
R^2	0.64
Adjusted R^2	0.63
RMSE (%/hr)	0.045
MAE (%/hr)	0.037
F-statistic p-value	< 0.001

TABLE V
COMPARISON OF IRRIGATION STRATEGIES

Metric Algorithm-driven Manual (time-based) Events 6 9-Total Volume (mL) 4 800 5 400 Average per Event (mL) 800 600 Moisture Range (%) 25–75 30–81 Savings (%) 11.1 –

We can optimize the irrigation method by integrating advanced algorithmic approaches like machine learning ensembles or adaptive control systems. To promote and get the necessary adoption from stakeholders, it will be important to do cost benefit analyses that include yield and saving resources.

VI. CONCLUSION

It was proven the useful of cloud computing resource with regression-based algorithm to predict the irrigation require ment of crops. Enabling the acquisition of meteorological parameters and soil moisture assessment in real-time was demonstrated through a proof of concept on cloud framework, confirming that automated data pipelines can assist decision making.

A contribution to precision agriculture has been made by establishing that low-cost capacitive sensors coupled with cloud services can produce useful irrigation schedules with little human intervention. By automating sensor deployment and data processing workflows, labor demands were reduced, allowing non-expert users to utilize data-driven irrigation management. One key area of extending coverage to entire fields is to scale sensor networks. Wide-area LoRa networks have been identified as a strong candidate.

In the future it will be useful to repeat the experimental trials in commercial units, over more growing seasons and different crop types, to test robustness and generalizability of the system. Including more biophysical variables like crop growth stage, canopy cover, and soil texture with the satellite based moisture indices is expected to improve model accuracy. Making use of ensemble models and deep learning models maybe a good idea to capture complex non-linear associations in the data. Researchers, farmers and agricultural organizations can form data-sharing consortia to jointly refine and region alize different models. In conclusion, it is vital to conduct economic assessments that measure the water saving, energy saving and yield effects of sustainable irrigation technologies to facilitate investment and inform policy incentives.

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