ISBN: 978-628-96613-1-6. ISSN: 2414-6390. Digital Object Identifier: https://dx.doi.org/10.18687/LACCEI2025.1.1.905

Development of Software to Improve Water Management in Irrigation Systems for Rice Fields Using the Internet of Things and Machine Learning

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***Abstract*—Rice cultivation demands a significant amount of water for irrigation, particularly in the Piura region of Peru, where water supplies are limited. Currently, the region lacks effective systems to conserve water resources, which could increase the risk of water scarcity in the future. To address this challenge, an integrated technological solution is proposed, focusing on the development of a web and mobile application that leverages the capabilities of the Internet of Things (IoT) for device control and monitoring. This solution employs LoRa connectivity for data transmission to the receiver, which utilizes the MQTT protocol to send information to the Arduino IoT Cloud via 4G LTE. Additionally, machine learning (ML), specifically the Long Short-Term Memory (LSTM) algorithm, is integrated to predict water consumption for irrigation. These predictions are based on data from IoT devices and meteorological information obtained through the OpenWeatherMap API. The research results indicate a 56.8% reduction in water consumption when using this IoT solution compared to the traditional flood irrigation method, optimizing resource usage without impacting crop health. The water consumption prediction model, evaluated with a root mean square error (RMSE) of 1.33998, confirms the tool's effectiveness in accurately forecasting water needs. This technological solution provides an efficient and sustainable tool to improve water management in rice cultivation in Piura and mitigate the effects of future water scarcity.**

***Index Terms*—Internet of Things (IoT), Machine Learning (ML), Rice Cultivation, Long Short-Term Memory (LSTM)**

I. INTRODUCCIÓN

In Peru, agriculture consumes approximately 80% of water resources [1]. This is mainly due to climatic variations, such as the "Fenómeno de El Niño" which significantly impacts food productivity [2]. Excess or deficit in rainfall, as well as high temperatures, hinder optimal crop growth. Regarding rice cultivation, it ranks among the top three crops with the highest blue water demand, as its production is concentrated mainly in the arid regions of the northern part of the country [3]. Furthermore, a population growth of 6 million inhabitants is projected by 2050 [4], which will require an increase in water resources and the adoption of smart irrigation techniques to prevent excessive water use by considering water needs at each stage of rice growth, including the vegetative, reproductive, and maturation phases [5].

Flood irrigation, typical in rice cultivation, involves covering the soil with a layer of water but shows low efficiency due to losses from evaporation and infiltration. Alternatively, advanced irrigation methods, such as drip or sprinkler irrigation, allow for controlled and precise water application, reducing losses and increasing efficiency. Additionally, these systems can be integrated with IoT devices to automate and monitor irrigation in real-time, optimizing water resource use in areas with limited availability.

Currently, in Peru, some funded research initiatives, such as ECOSMART RICE, use remote sensors for a sustainable production system in the Lambayeque region [6]; however, this project does not include an ML model, and the regions employing such IoT solutions are limited. For instance, the Piura region uses drones for crop fertilization but lacks IoT sensors. Thus, by employing an LSTM model for water consumption forecasting and IoT devices, this research aims to improve water management in rice fields remotely and with user-friendly accessibility.

For the selection of the LSTM model, the studies by [7], which compared ANN and LSTM models, and [8], which compared RNN and LSTM models, were taken into account. Both studies presented favorable results for the LSTM model in terms of water consumption prediction. Additionally, [9] also demonstrates that the LSTM model provides high performance for water demand prediction.

Various studies contribute to water management. For example, [10] provides real-time data visualization through the Blynk platform, associating it with an ESP32 connected to a soil moisture sensor and water pump. Other studies, such as [11], propose a Fiware service to capture data from devices for each plot in the field. These devices have a wireless connection. Additionally, the work of [12], which offers notifications and early alerts for farmers, was referenced. Various ML models were also examined, resulting in an LSTM model for predicting water consumption in agriculture with an Mean Squared Error (MSE) of 1.0930 using an 80% training set and a 20% test set [13]. Furthermore, [14] conducted a study on automated rice irrigation using a fuzzy controller and weather forecasting, achieving a 15% reduction in water consumption and, under unfavorable conditions, up to 33%.

The proposed project aims to implement a web and mobile application that uses IoT and ML technologies to optimize water management in irrigation systems used for rice cultivation. Additionally, it seeks to contribute to the achievement of SDG No. 6 on clean water and sanitation, specifically Target 6.4, which sets the goal of increasing water-use efficiency across all sectors by 2030.

This article proposes a technological solution for farmers in rice cultivation. The mobile application allows remote control of the water pump and monitoring of sensors through the Arduino IoT Cloud platform, which collects data on soil moisture, relative humidity, ambient temperature, and water flow by sending data via the MQTT protocol. Additionally, it displays water consumption forecasts generated by the LSTM model, based on meteorological data from the OpenWeatherMap API and sensor readings. Furthermore, the web application enables visualization of the historical data records and management of ESP32 devices for fault detection.

This work is organized into five sections. Section 2 discusses previous research related to the use of IoT technologies, middleware platforms, and ML models used for the control, monitoring, and prediction of irrigation. Section 3 presents the methodology used for connectivity between IoT sensors and water consumption prediction in irrigation. Section 4 presents the validation and results of the case study. Finally, Section 5 presents the conclusions and ideas for future research.

II. Related Works

Some solutions for monitoring rice crops to improve water management using IoT and ML technologies are presented below:

In the work of [15], it is demonstrated and results show that the automatic irrigation system in rice fields, compared to manual irrigation, contributes to a significant reduction in water consumption and has a high cost-benefit for its implementation. Since the research is conducted in flood irrigation, a submersible depth sensor is used.

In the study of [12], an IoT solution is presented by calculating the evapotranspiration indicator, and its MCU collects data from the water level sensor, which is characterized by having an NB-IoT connection and a solar panel power source.

The study of [16] offers real-time monitoring of low-cost sensor connections using WiFi, which alerts the farmer if the collected values fall below the optimal threshold.

In the study of [14], a fuzzy logic is used for intelligent control of rice crops. It also considers weather forecasting to improve irrigation decision-making. Finally, its intelligent control can achieve energy efficiency gains and significantly reduce water capture.

In the work of [10], an IoT irrigation system for sustainable agriculture is created by associating the ESP32 microcontroller with the Blynk platform for controlling and monitoring temperature and humidity sensors.

The study of [17] calculates dryness levels with an Arduino Uno to decide whether to activate the water motor or not depending on the required threshold, which is adjusted with a potentiometer. This MCU needs a GSM module to connect to the internet.

In the study of [11], an Orion-LD Context Broker is used to connect the different microservices components into a single API. It also uses QuantumLeap for the temporal persistence of sensor data in a real-time database. It calculates a soil water balance model based on data from connected LPWAN sensors.

The MOPECO model proposed by [18] addresses the challenge of managing water supply validated in Spain, Tunisia, and Lebanon for different plant types. One of its irrigation programs focuses on estimating irrigation needs by collecting soil water data using soil moisture sensors and considering each plant phase.

In the study of [19], the global problem of food insufficiency is effectively addressed by proposing an autonomous irrigation system based on cutting-edge technologies, such as AI and 6G connectivity. The AI is mounted on the microprocessor and analyzes rainfall patterns and climate changes for the system's autonomy. It also considers soil moisture to provide the precise amount of water to the crop.

According to [20], the study focuses on calibrating and evaluating thermal sensors in unmanned aerial vehicles (UAVs) to detect water stress in crops, especially in sorghum fields.

According to [21], the study uses digital twin technology to replicate physical environments in precision agriculture but with real data to evaluate and improve various water-saving techniques, such as weather forecasts, UAV images, and others.

Reference [22] emphasizes the importance of applying technologies like IoT and AI to improve decision-making, crop monitoring, water management, and pest detection. Two approaches, MACO-DQN and RL-DQN, are presented, combining optimization techniques and deep learning to optimize agricultural tasks.

The research project by [23] proposes a two-level approach using a k-NN classification model to estimate soil quality and an ELM-mBOA model to predict crop yield, implemented with real-time IoT sensor data.

Reference [24] addresses security vulnerabilities that may occur during data collection in IoT devices by employing SCAE for data encryption and thus developing an effective intrusion detection system.

This study by [25] attempts to reduce the cost percentage and potential damage under global warming in different rotating irrigation systems, such as traditional flood irrigation, intermittent irrigation, and dryland transplantation.

According to [26], it addresses the need to optimize tomato production in multi-truss crop systems in greenhouses. It contributes significantly to the sector by demonstrating that partial root zone alternating irrigation can improve both production and tomato quality, particularly in terms of sugar content, lutein, and vitamin C.

In the study by [27], it proposes addressing the challenging problem of inefficient irrigation management in agriculture, particularly in the context of growing water scarcity. Through a combination of remote sensing technology, ET0 estimation models (TSEB-PTS2+S3 and Penman-Monteith), and a vineyard digital twin, the study offers innovative solutions to optimize agricultural irrigation and promote sustainability in the sector.

In the work of [28], the management of the water system and energy optimization is handled using time series forecasting in irrigation, such as GBT, LSTM, and Spearman's rank correlation in banana crops in southern India. It uses a 12-hour time interval. It employs ZigBee wireless communication for sensor nodes.

According to [29], it highlights the importance of precision agriculture supported by IoT technologies and wireless sensor networks to address this issue, optimizing agricultural production, reducing the use of natural resources, and improving crop quality by using sensors, fuzzy logic-based controllers, and a web-based user interface. The processing unit is provided by a Raspberry Pi.

According to [30], it proposes the EERAA algorithm and demonstrates its effectiveness through simulations, making it a significant advancement for resource management in smart irrigation systems. This irrigation is based on cognitive sensor networks (radio technologies).

III. Technological Solution Proposal

This study proposes a technological solution called "AgroTech" (an acronym for Agriculture and Technology) to measure the water flow to be used in the crop field according to the values of the parameters found by IoT devices in real-time and meteorological data from OpenWeatherMap to forecast irrigation water consumption with an LSTM model, advantageous for time-series tasks [28]. Arduino IoT Cloud is used for the control and monitoring of IoT devices. The platform's API is used to obtain data and create a personalized mobile and web application for the farmer.

A. *Arquitecture*

This IoT system is monitored by the Arduino IoT Cloud platform, and its historical data is stored within the Cloud service on Microsoft Azure. The MySQL database manages all the data sent from the emitters to the receiver, as they are connected to the humidity and temperature sensors, soil moisture, and flow sensors. Each emitter represents a plot of the rice field, so the goal is for the receiver to send all the data from each plot via 4G LTE to the Arduino IoT Cloud. The communication between the emitter-receiver (Embedded App - Edge Server App) is through LoRa communication, which is ideal for wireless communication in rural areas with a coverage range of 10-40 km, but with a maximum payload length of 243 bytes [21]. The solution was developed using Domain-Driven Design to manage the complexity of the business domain and implemented in a microservices architecture with Docker to ensure scalability and efficient deployment. Finally, this data is displayed to the user via a web and mobile application. (Figure 1)

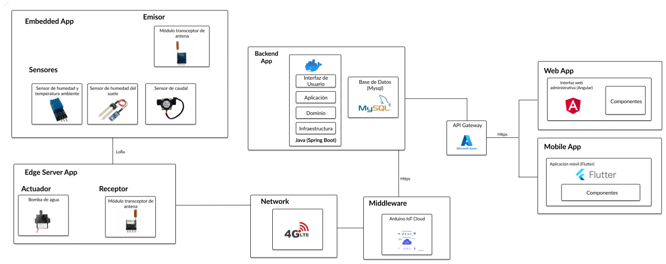


Fig. 1: Description of the Architecture Components

According to Figure 2, the application will send a notification to the farmer whether the irrigation is active or not, based on the soil moisture value recorded. The Edge Server App will decide whether to activate or deactivate the water pump based on the expected threshold (80% for the seedling phase).

Cuadro 7: REQUERIMIENTOS TERMICOS E HIDRICOS DEL CULTIVO DE ARROZ

REQUERIMIENTOS TERMICOS E HIDRICOS DEL CULTIVO	FASES DEL CULTIVO DE ARROZ									
	Emergencia	Plántula	Macollaje	Elongación de tallo	Inicio de la Panoja	Desarrollo de panoja	Floración	Maduración Lechosa	Maduración pastosa	Maduración córnea
Temperatura óptima	25 -30° C	22 - 30 °C	22 - 30 °C	22 - 30 °C	22 - 30 °C	22 - 30 °C	22 - 30 °C	22 - 30 °C	22 - 30 °C	22 - 30 °C
Temperatura crítica	>12° C	10 - 35 °C	10 - 35 °C	10 - 35 °C	10 - 35 °C	10 - 35 °C	10 - 35 °C	10 - 35 °C	10 - 35 °C	10 - 35 °C
Humedad óptima	suelos con humedad del 70 al 80% de saturación	suelos con humedad del 70 al 80% de saturación	suelos con humedad del 70 al 80% de saturación	suelos con humedad del 70 al 80% de saturación	suelos con humedad del 70 al 80% de saturación	suelos con humedad del 70 al 80% de saturación	suelos con humedad del 70 al 80% de saturación	Sin agua	Sin agua	Sin agua
	Agua profunda	Agua profunda	Agua media	Agua somera	Agua profunda	Agua profunda	Agua profunda			
Periodo Vegetativo*	3	10	15	70	17		15	10	10	8
Cultivo en desarrollo*	1 - 3 enero	4 -13 enero	14 -28 enero	29ene - 8 abril	9 - 25 abril		26abrl-10may	11-20 mayo	21-30 mayo	31may-07jun

*Tomado del Banco de dato fenológico DGA-SENAMHI. Cultivo de arroz NIR-1. Mallares - Piura.

Fig. 2: Optimal Ranges for Each Phase of Rice Crop. Prepared by [5].

Figures 3 and 4 show the design for the construction of the emitter and receiver, respectively. Each of them uses an ESP32 and a voltage regulator to provide the correct power input to the circuit.

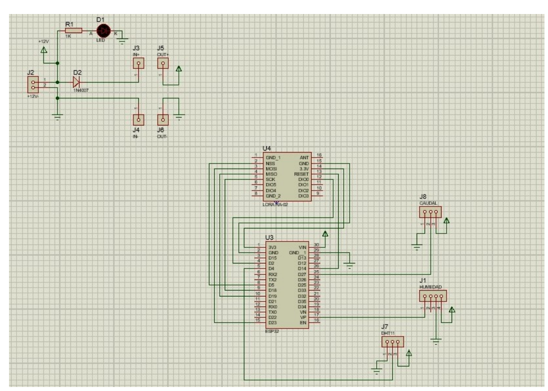


Fig. 3: Design of the Emitter Components

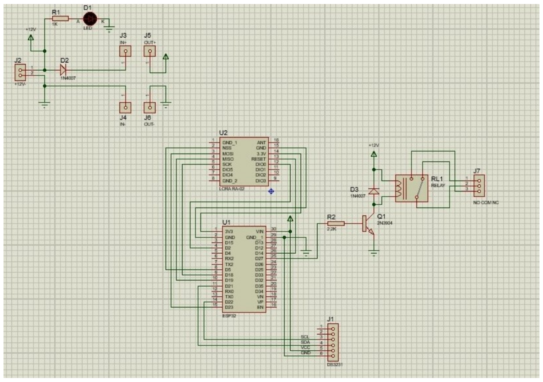


Fig. 4: Design of the Receiver Components

B. IoT System

The following presents low-cost materials to build an IoT system that allows the collection of important data within the rice crop, as shown in the figure 5.

Fig. 5: Components of the IoT System for Water Management

The main materials for the project are:

- **Humidity and temperature sensor (DHT-11) x2**: Measures the percentage of humidity in the air and the ambient temperature in degrees Celsius, with a precision of ±5RH and ±2°C.
- **Soil moisture sensor (HW-390) x2**: Measures the percentage of soil moisture in a range of 0-100%.
- **Flow sensor (YF-S201) x2**: Measures the water flow to distribute it to each plot in liters, with a range of 1-30L/min and a precision of ±10%.
- **Water pump x1**: Allows the water to be released.
- **Relay (HW-084) x1**: Allows the water pump to be controlled remotely and automatically via the microcontroller.
- **ESP32 microcontroller (ESP-WROOM-32) x3**: Contains the program to perform the corresponding actions for irrigation scheduling.
- **Antenna transceiver module (Ra-01) x3**: Enables communication via LoRa wireless communication.
- **Voltage regulator x3**
- **LED x3**: To indicate to the farmer that the device is powered on.
- **6V Batteries x3**: To power the devices.
- **Resistors**
- **Wires**
- **Safety enclosures**

As shown in Figures 6 and 7, the installation of the monitoring devices in the rice field and the water distribution system can be observed. The first figure illustrates the device installed on a support structure, secured to monitor the conditions in the plot, while the second figure shows the piping used to distribute water to the different areas of the crop. Flood irrigation for the seedling phase has a water layer of 10cm.

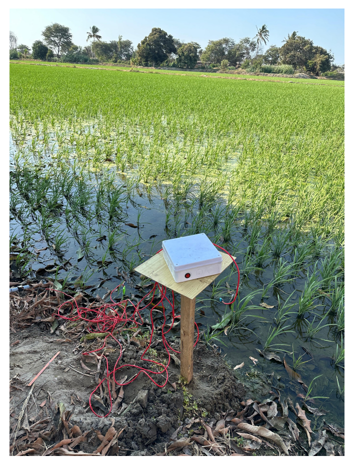


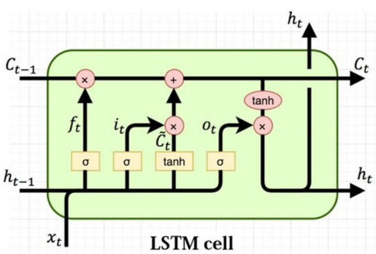
Fig. 6: Installation of the IoT Devices

Fig. 7: Installation of the Water Distribution

C. LSTM Model

The LSTM is a type of recurrent neural network designed to process long-term and short-term remembered data in order to predict the sequence of data indicating the prediction of irrigation water consumption based on weather data to make a decision at the time of irrigation. This model consists of an input gate, output gate, and forget gate, which use mathematical equations of a sigmoid function and hyperbolic tangent [28]. The cell state and hidden state represent long-term memory and short-term memory, respectively. For this research, a time interval of every 24 hours has been considered, following the reference from [9]. (Figure 8)

The LSTM network employed in this study was built using the Keras library with a TensorFlow backend. The architecture includes an input layer that receives five climatic and sensor-related variables (precipitation, wind speed, relative humidity, ambient temperature, and historical water consumption), followed by two LSTM layers with 50 units each, using tanh activation and a dropout regularization rate of 0.2 to prevent overfitting. A fully connected dense layer is then added, with a single output neuron and a linear activation function for predicting the number of liters of water to be used. The network was trained over 100 epochs using the Adam optimizer and a loss function based on MSE.



$$i_t = \sigma\left(x_t U^i + h_{t-1} W^i\right)$$
$$f_t = \sigma\left(x_t U^f + h_{t-1} W^f\right)$$
$$o_t = \sigma\left(x_t U^o + h_{t-1} W^o\right)$$
$$\tilde{C}_t = \tanh\left(x_t U^g + h_{t-1} W^g\right)$$
$$C_t = \sigma\left(f_t * C_{t-1} + i_t * \tilde{C}_t\right)$$
$$h_t = \tanh(C_t) * o_t$$

Fig. 8: tructure of the LSTM Model

The dataset with the variables to be used for the water consumption forecast includes:

- **Date**: Day and time when the data was recorded.
- **Precipitation**: The rainfall depth in mm.
- **Wind speed**: Measured in km/h.
- **Air humidity**: Measured as a percentage.
- **Air temperature**: Measured in degrees Celsius.
- **Water consumption**: The amount of water consumed by the rice crop field in liters.

D. Mobile Application

Next, we will present the security, notification, weather, manual irrigation, irrigation scheduling, sensor data visualization by parcel, and water consumption forecast modules in relation to the mobile application.

In Figure 9, the authentication of the farmer for monitoring and controlling the rice crop to which they belong is shown.

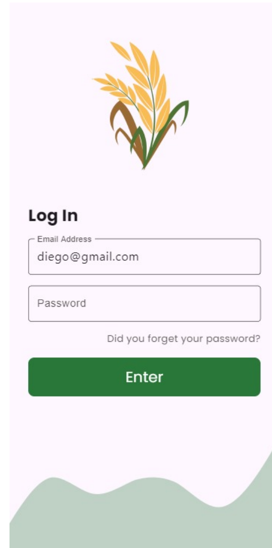


Fig. 9: Mobile Application Security Module

In Figure 10, the manual irrigation module is shown, where the farmer has the option to activate irrigation at any time and shows the days elapsed since the last irrigation. Additionally, it shows the weather data and the water consumption forecast.

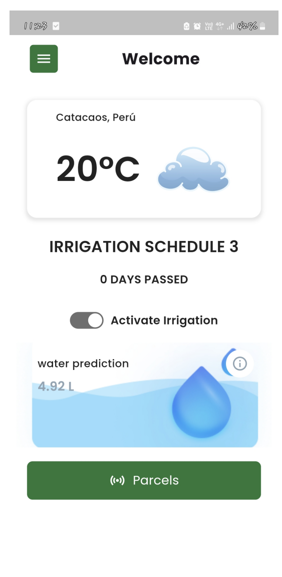


Fig. 10: Manual Irrigation Module

In Figure 11, the irrigation scheduling module is shown, where the farmer can schedule the irrigation time, and the devices analyze the time and optimal conditions for irrigation.

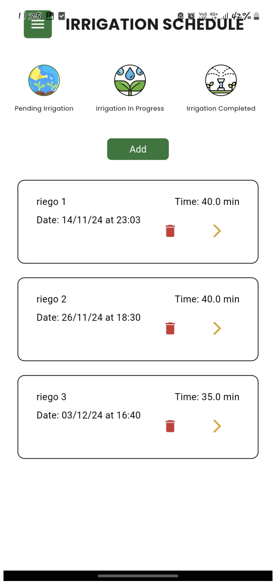


Fig. 11: Irrigation Scheduling Module

In Figure 12, the module for the sensor data captured for each parcel is shown. This allows the farmer to know the water needs of their parcel.

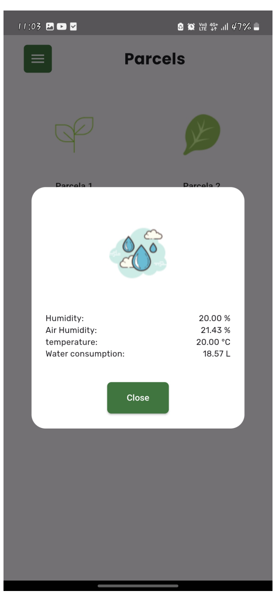


Fig. 12: Sensor Data by Parcel Module

In Figure 13, the notifications module is shown, which allows the user to be notified when irrigation is activated or deactivated.

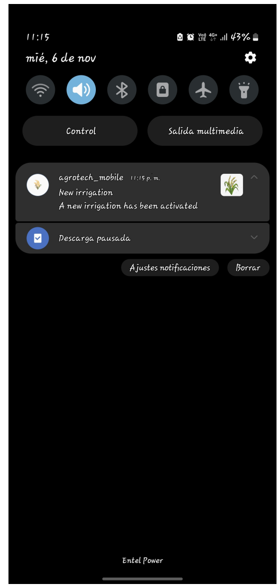


Fig. 13: Notifications Module

E. Web Application

Next, we will present the security, notifications, control panel, device management, and statistical graphics modules for the data captured by IoT devices in relation to the web application.

In Figure 14, the authentication of the farmer for monitoring and controlling the rice crop to which they belong is shown.

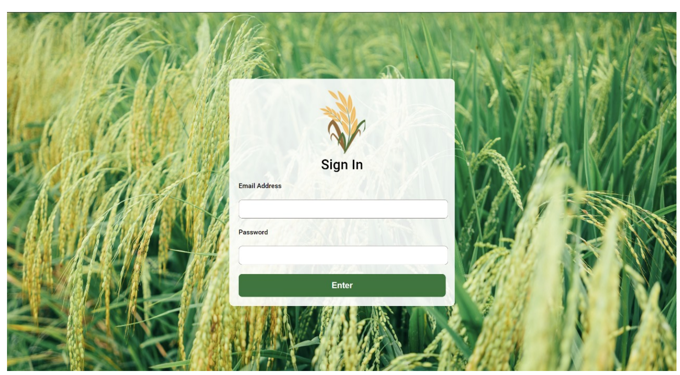


Fig. 14: Web Application Security Module

In Figure 15, the control panel module is shown, where the farmer can not only view weather data but also see sensor data for the past 5 hours, device management, and notifications.

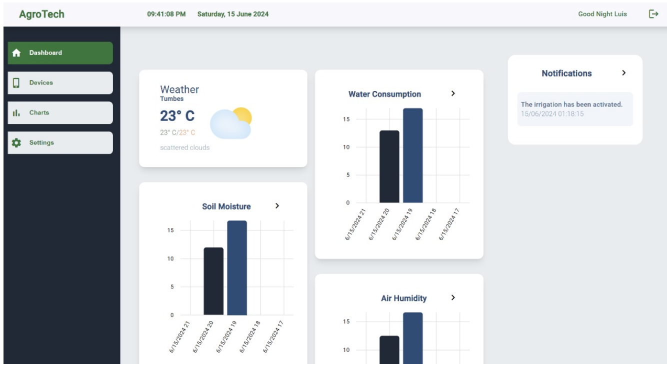


Fig. 15: Control Panel Module

In Figure 16, the device management module is shown, which helps the farmer check the status of their devices: activated, deactivated, or faulty. Each device displays its main data, such as the sensors it has and the parcel it belongs to.

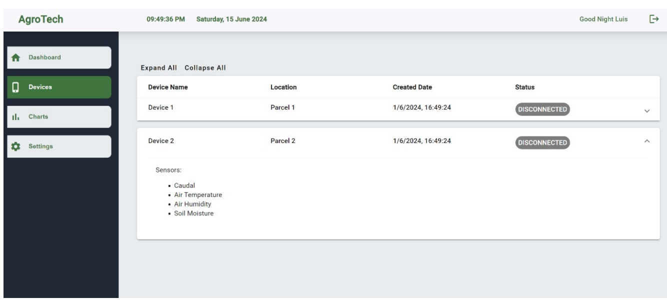


Fig. 16: Device Management Module

In Figure 17, the historical data graphics module is shown, filtered by the same day, last week, or last month, and also filtered by location, either generally or by specific parcel registered.

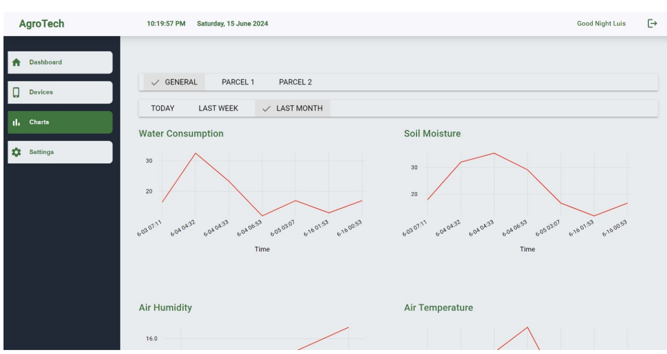


Fig. 17: Historical IoT Sensor Data Graphics Module

IV. Validation and Results

A. Experimentation Design

The study was developed in Catacaos, Piura. The tool used for experimentation was the *Experiment Card*, within the context of Experiment-Driven Product Development, to validate the hypothesis and make decisions based on evidence, allowing risks to be reduced by implementing controlled changes and evaluating results based on objective metrics. The *Experiment Card* designed is described in Table I.

TABLE I: Description of the Experiment Card

Item	Description
Question	How can the effectiveness of the automated IoT-based irrigation system be measured compared to traditional methods?
Why	Optimize water use to reduce costs and improve sustainability.
What	Monitor real-time water consumption using flow and humidity sensors.
Hypothesis	The automated IoT-based irrigation system will reduce water usage by 20%.
Metrics	Water usage reduction (%).
Goal	Reduce water usage by 20% or more.

B. Monitoring and Control of IoT Devices

The following presents the control and monitoring provided by the Arduino IoT Cloud service. It was selected due to its native compatibility with ESP32 devices and its architecture based on lightweight protocols such as MQTT, enabling efficient integration in low-connectivity environments. The visual interface of Arduino Cloud Things facilitates the rapid creation of customizable dashboards that display real-time sensor status and water consumption, accessible from any browser or mobile application. Additionally, the Arduino Cloud REST API was leveraged to synchronize data with the developed web and mobile applications, allowing not only real-time monitoring but also the automation of events (such as activating irrigation when soil moisture falls below a predefined threshold) through predefined triggers—without the need for direct human intervention. This functionality renders the system a scalable and autonomous solution, ideally suited for agricultural regions with limited access to advanced technological infrastructure. In addition to the sensor values recorded by date, it is also possible to control the activation of the water pump. This platform offers data communication via MQTT, which facilitates data transfer due to its low overhead and high scalability through its publish/subscribe model. Data collection has been carried out using soil moisture, relative humidity, ambient temperature, and flow rate sensors.

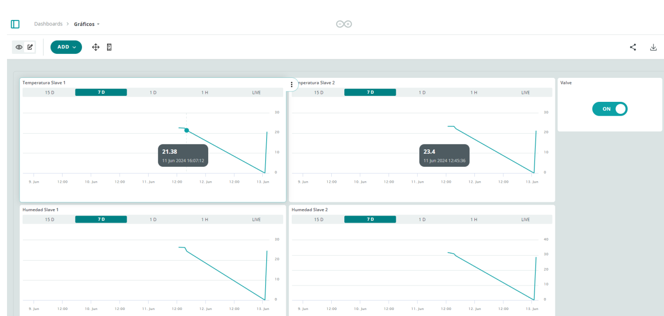


Fig. 18: Arduino IoT Cloud Control Panel

The data is sent to a web application for processing and visualization in real-time graphs (see Figures 19, 20, and 21).

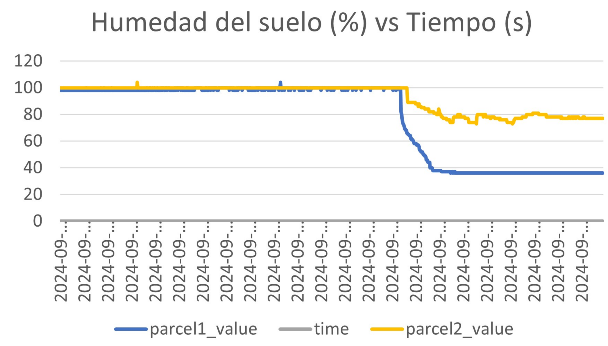


Fig. 19: Soil Moisture vs Time Graph

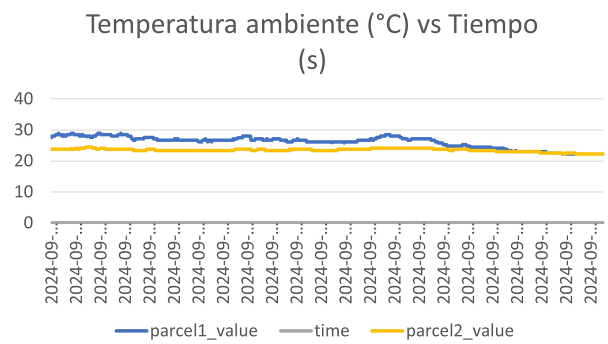


Fig. 20: Ambient Temperature vs Time Graph

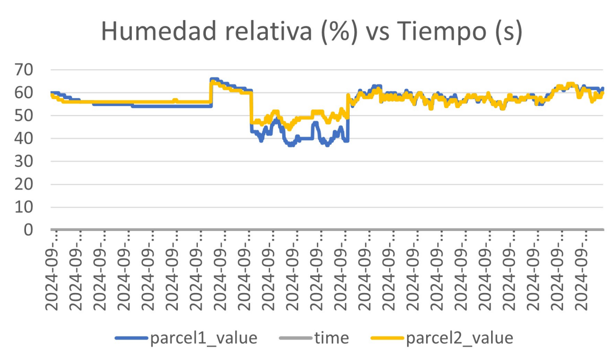


Fig. 21: Relative Humidity vs Time Graph

C. *Projection of Water Consumption Reduction*

Two irrigation methods are presented: the traditional method and the automated method based on IoT.

1) Data from the Traditional Method:

- Cultivation area: 1 hectare
- Irrigation height: 0.10 m
- Calculated volume: 1,000,000 liters

Water Volume Traditional Method:

$$\text{Volume} = \text{Area} \times \text{Height} \tag{1}$$

$$\text{Volume} = 1 \text{ ha} \times 0.10 \text{ m} = 1{,}000 \text{ m}^3 \tag{2}$$

Convert from m^3 to liters

$$\text{liters} = 1{,}000 \text{ m}^3 \times 1000 \frac{\text{liters}}{\text{m}^3} \tag{3}$$

$$\text{liters} = 1{,}000{,}000 \text{ liters} \tag{4}$$

2) Data from the IoT Method:

- Flow rate: 0.5 L/s
- Continuous monitoring: 24 hours
- Irrigation period: 10 days
- Calculated volume: 432,000 liters

Water Volume of the IoT Solution:

$$\text{Volume} = \text{water per day} \times \text{number of days} \tag{5}$$

$$\text{Volume} = 0.5 \frac{\text{L}}{\text{s}} \times 3600 \frac{\text{s}}{\text{h}} \times 24 \frac{\text{h}}{\text{day}} \times 10 \text{ days} = 432{,}000 \text{ liters} \tag{6}$$

3) Water Consumption Reduction Calculation: The comparison shows a 56.8% reduction in water consumption when using IoT, optimizing the resource without compromising plant health. The following calculation yields the Water Savings Percentage (WSP).

$$\text{WSP} = \left(\frac{\text{water in liters traditional method} - \text{water in liters IoT method}}{\text{water in liters traditional method}} \times 100\% \right) \tag{7}$$

$$\text{WSP} = \left(\frac{1{,}000{,}000 - 432{,}000}{1{,}000{,}000} \times 100\% \right) = \mathbf{56.8\%} \tag{8}$$

D. *Water Consumption Forecasting*

Also, the correlation of test data between actual and predicted values can be observed in Figure 22. On the Y-axis, the water consumption values in liters are displayed, and on the X-axis, the accumulated time interval values are shown for better observation of the trend in the graph.

The performance of the prediction model has been analyzed using the RMSE of the test data. The forecast of water consumption was 1.33998 when using 80% of the training set and 20% of the test set.

In addition to the RMSE (1.34), the performance of the LSTM model was evaluated using complementary metrics derived from the test set. The predicted values were compared with the actual ones using standard functions from the sklearn.metrics library, applying the calculation of the MSE and the Coefficient of Determination (R^2). The resulting MSE was 1.80, indicating a moderate average squared error between the predictions and the actual values. The R^2 score was 0.31, suggesting that the model is able to explain approximately 31% of the variability in actual water consumption. While this level of accuracy is moderate, it is consistent with the complexity of the phenomenon and the inherent variability of water consumption data. These metrics suggest that the model exhibits acceptable performance for supporting decision-making tasks in irrigation planning, with potential for improvement through the inclusion of additional climatic and agronomic variables.

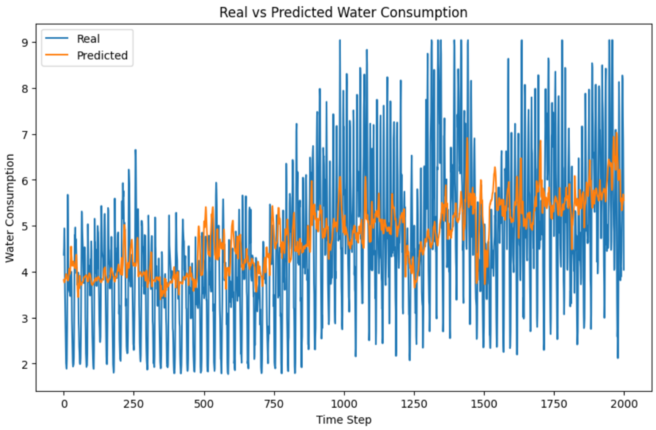


Fig. 22: Water Consumption vs Time Interval Graph

V. Discussion/Conclusions

This work proposes an IoT and ML solution to improve water management in rice cultivation fields. As a result, 56.8% prediction of water savings was achieved, together with an optimal outcome in the water consumption forecast, with an RMSE of 1.34, an MSE of 1.80 and an R^2 of 0.31. This water reduction significantly outperforms the 15-33% reduction reported by Uberti et al. [14], which also applied smart irrigation techniques to rice fields. This substantial improvement can be attributed to our integrated approach combining real-time IoT monitoring with predictive ML modeling. Our LSTM model's prediction accuracy is comparable to that reported in similar time-series forecasting applications [28], demonstrating the robustness of our modeling approach across agricultural contexts. The development of a mobile application for sensor monitoring and water pump control, as well as the development of a web application to manage devices and visualize the data collected in real time, promotes water sustainability in agriculture.

Previous agricultural IoT solutions have primarily focused on either monitoring capabilities [10, 16, 17] or prediction models [7, 8, 9], but rarely integrate both aspects effectively. Additionally, most existing solutions have been deployed in regions with well-developed infrastructure rather than addressing the unique challenges of water-scarce regions with limited technological access. Our solution addresses both limitations by providing an integrated monitoring-prediction system specifically designed for deployment in regions like Piura, Peru, where water conservation in rice cultivation is critical for sustainable agricultural practices. The combination of LoRa technology for rural connectivity, MQTT protocol for efficient data transfer, and a user-friendly interface designed for farmers with varying levels of technological literacy makes this solution particularly suitable for implementation in developing agricultural regions.

The experiment was carried out on a crop traditionally associated with high water consumption. By developing an intelligent irrigation system based on IoT and ML, the need for continuous flooding is reduced, which decreases methane emissions, a potent greenhouse gas, and improves water quality. Additionally, the developed prediction model allows for real-time irrigation adjustments based on the crop's needs, contributing to more efficient management of water resources.

For future work, the aim is to add more important variables to the LSTM model, such as soil moisture, land area, and considering different stages of the rice cycle. Furthermore, it is proposed to evaluate the energy consumption of IoT devices.

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