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Energy performance analysis of an edge-AI irrigation system for cocoa production in rural Colombia

Rocio Cazes Ortega[1]*, Aldo Pardo Garcia[2], Jorge Saul Fandiño Pelayo[3], C. L. Sandoval-Rodrıguez[4]
[1,3,4] Department of Natural Sciences and Engineering, Unidades Tecnólogicas de Santander (UTS), Bucaramanga, Colombia
[2] Department of Engineering and Architecture, Universidad de Pamplona, Pamplona, Colombia

*Corresponding author E-mail: rcazes@correo.uts.edu.co

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Abstract

This study presents the design and energy performance evaluation of a low-cost intelligent irrigation system tailored for cocoa (Theobroma cacao) agroforestry in tropical Colombia. The system integrates DHT11 temperature and humidity sensors, as well as analog soil hygrometers, with a Raspberry Pi 4 for edge computing. A multilayer perceptron (MLP) model, trained using Edge Impulse, was deployed on an Arduino Uno to enable real-time, autonomous irrigation control. Field validation was carried out over nine weeks in Piedecuesta, Colombia, with environmental variables recorded at 60-second intervals. Compared to conventional timer-based systems, the proposed solution reduced water consumption by 25%, while maintaining soil moisture consistently within the agronomic threshold of 70–85%. Post-irrigation measurements revealed stable microclimatic conditions, with relative humidity maintained between 81% and 87%. In terms of energy performance, the system operated at an average daily consumption of 204 Wh, powered entirely by a standalone solar photovoltaic unit. The deployed neural network model achieved 82% classification accuracy in predicting irrigation states based on sensor data. These results underscore the system's potential as a scalable, energy-autonomous solution for smallholder agriculture in infrastructure-limited tropical settings.

Keywords: Smart irrigation, Edge AI, Cocoa production, Soil moisture sensing, Energy efficiency, Microcontroller-based systems, Embedded neural networks

1. Introduction

Cocoa (Theobroma cacao) is a perennial tropical crop of significant economic value, particularly in Latin American countries such as Colombia, where smallholder production predominates [1, 2]. In 2022, Santander was the leading cocoa-producing department in Colombia, with over 29,000 tons harvested, accounting for approximately 40% of the national output. Despite its importance, production efficiency remains limited by climatic variability, soil degradation, and the lack of adequate irrigation infrastructure [3].

In tropical agroforestry systems, irregular rainfall patterns and high evapotranspiration rates significantly affect soil moisture stability—one of the most critical factors for optimal cocoa development [4, 5]. Research has shown that maintaining soil moisture within the 70–85% range is essential to prevent pod loss, root stress, and disease proliferation. Nevertheless, in the absence of automated systems, smallholder farms often rely on fixed-time irrigation or manual practices, leading to inefficient water use and unnecessary energy expenditure [3, 6].

Recent developments in smart irrigation have enabled the use of environmental sensors, microcontrollers, and decision-making algorithms to automate water application based on real-time data. Internet of Things (IoT) architectures, combined with artificial intelligence (AI) models, have demonstrated promising results in crops such as grapes, citrus, and wheat [7, 8, 9]. However, most of these systems depend on stable cloud connectivity, which is rarely available in remote cocoa-growing regions [10, 11].

Edge computing has emerged as a viable alternative, allowing local data processing and inference on embedded devices such as Raspberry Pi or microcontrollers [6, 12]. Additionally, recent studies in Côte d'Ivoire have shown that machine learning applications can improve irrigation scheduling and disease management in cocoa systems [13]. In Brazil, a linear programming model applied under water stress conditions successfully optimized cocoa biomass allocation, increasing water-use efficiency by up to 15% [14]. These examples underscore the potential of AI-driven tools in managing tropical perennial crops, although field-based validations in Latin America remain scarce.

Furthermore, studies have shown that integrating smart irrigation technologies into agroforestry systems can improve water-use efficiency, support climate adaptation strategies, and enhance overall system productivity [15, 16]. These benefits are aligned with global sustainability frameworks, including Sustainable Development Goals 6 (Clean Water and Sanitation), 12 (Responsible Consumption and Production), and 13 (Climate Action) [17].

In this context, the present study introduces the design, implementation, and field validation of a low-cost, AI-enabled smart irrigation system tailored for smallholder cocoa producers in northeastern Colombia. The system integrates soil moisture and environmental sensing, neural network inference at the edge, and solar-powered actuation. In addition to assessing its agronomic effectiveness and energy performance, the proposed system aims to contribute to efficient water management and improved decision-making in cocoa cultivation under field conditions.

2. Research method

2.1. Soil sampling and analysis

To assess the initial soil conditions, samples were collected using a standard diagonal compositing technique to account for field heterogeneity. Five composite samples per zone were extracted at a depth of 30 cm. Laboratory analyses were performed at Ganacampo (Bucaramanga, Colombia), yielding the following characteristics: pH of 6.68, organic matter at 2.83%, elevated levels of phosphorus, potassium, calcium, and magnesium, normal sodium, high iron and zinc, adequate copper, and deficiencies in manganese, boron, and aluminum. These findings informed the decision to implement a drip irrigation system, minimizing leaching risks and preserving soil structure under controlled electrical conductivity and sodium adsorption ratio (SAR) conditions [18].

2.2. System architecture and deployment

The proposed intelligent irrigation system consists of five integrated modules: sensing, processing, power management, actuation, and decision control. Environmental parameters (temperature and humidity) were monitored using DHT11 sensors, while soil moisture was measured with FC-28 YL-69 soil hygrometers strategically positioned throughout the field. Two Arduino Uno boards were used to collect and transmit sensor data to a central processing unit (Raspberry Pi 4), chosen for its compatibility and cost-effectiveness in agricultural IoT applications [12].

A hybrid edge–cloud architecture was implemented. The Raspberry Pi processes real-time data locally and synchronizes it with a Firebase cloud database for remote access and historical analysis [11]. The system operates autonomously via a photovoltaic energy supply comprising solar panels, a charge controller, deep-cycle batteries, and an inverter, ensuring operational continuity in off-grid conditions [19].

Irrigation actuation is handled using solenoid valves, relay modules, and a dimmer to modulate pump intensity. A rain sensor is integrated to interrupt irrigation events during or after rainfall, aligning with best practices in water-saving strategies under variable weather conditions [8].

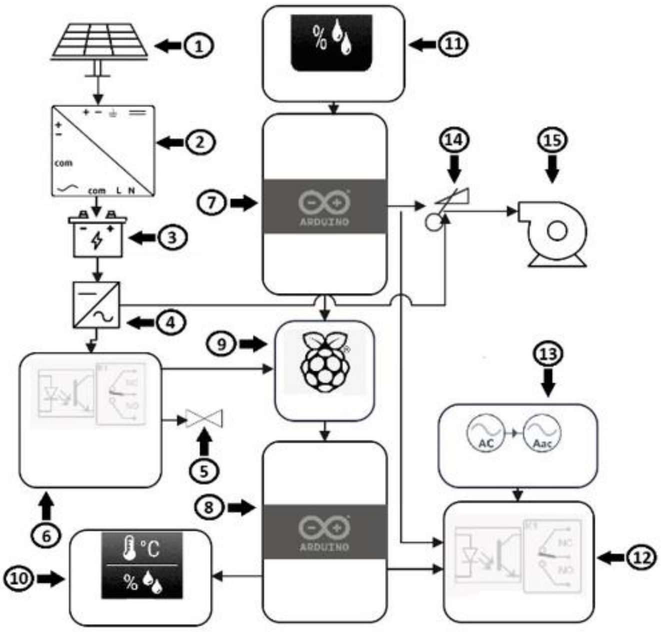


Figure 1. System architecture for AI-enabled irrigation: (1) solar panel, (2) charge controller, (3) battery, (4) inverter, (5) solenoid valves, (6) relay modules, (7) Arduino for pump control, (8) Arduino for sensors/valves, (9) Raspberry Pi 4, (10) rain sensor, (11) soil moisture sensors (DHT11 and FC-28 YL-69), (12) secondary relay, (13) current sensor, (14) dimmer, (15) pump

2.3. Artificial intelligence-based control

A multilayer perceptron (MLP) neural network was trained using 5,000 labeled samples that combined environmental and soil moisture data. The dataset was split into training (80%) and testing (20%), and model performance was evaluated using 5-fold cross-validation. The model was built on the Edge Impulse platform and deployed on the Arduino Uno for real-time edge inference.

The neural network architecture comprised two hidden layers with 20 and 10 neurons, respectively, using the ReLU activation function:

$$f(x) = \max(0, x) \qquad (1)$$

The output layer used a Softmax function to classify the input into three states: irrigate, delay, and inhibit

$$P(y_i) = \frac{e^{z_i}}{\sum_j e^{zj}} \qquad (2)$$

Volumetric soil moisture (Hs) was calculated using:

$$H(s) = \frac{V_w}{V_t} \times 100 \qquad (3)$$

Where Vw is the volume of water and Vt is the total volume of the soil sample.

A simple linear regression model was also implemented to predict rainfall based on temperature (T) and humidity (H):

$$P_r = \alpha T + \beta H + \gamma \qquad (4)$$

This approach follows established practices in agroclimatic modeling, where temperature and relative humidity are often used as reliable predictors of short-term precipitation trends under tropical conditions. The combination of this model-based prediction with rule-based control allowed for adaptive irrigation management in response to both current and forecasted environmental conditions [20].

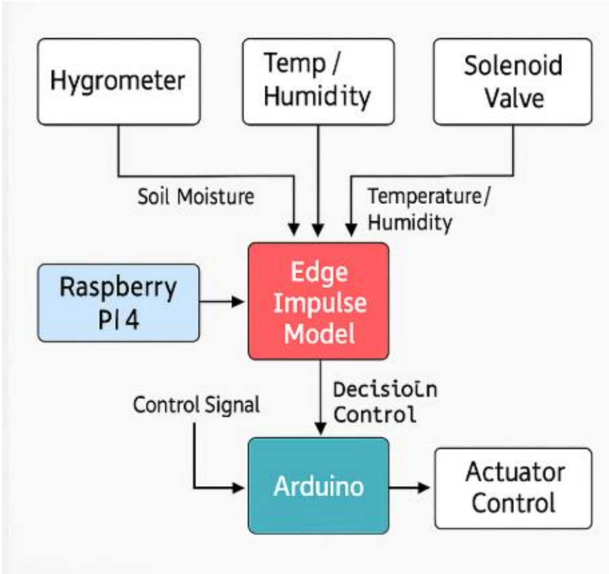


Figure 2. Functional block diagram of the intelligent irrigation system integrating real-time sensing, edge inference, and actuation

2.4. Data acquisition and preprocessing

Data acquisition was conducted over a nine-week period at a smallholder cocoa farm in Piedecuesta, Colombia. Temperature, humidity, and soil moisture measurements were captured every 60 seconds using the installed sensors. Data were transmitted via serial communication from the Arduino boards to the Raspberry Pi, where they were stored locally in CSV format and subsequently uploaded to Firebase for redundancy and visualization.

Preprocessing was carried out using Edge Impulse tools. Noise reduction, interpolation of missing values, and labeling into four categories were applied: HIGROHUMEDAD, HIGROSINHUMEDAD, CONLLUVIA, and SINLLUVIA. Stratified sampling was used to ensure balanced representation across classes in both the training and validation datasets.

2.5. Training configuration and model deployment

The MLP model was trained using the Adam optimizer with a learning rate of 0.001, batch size of 32, and early stopping to prevent overfitting.

The loss function was categorical cross-entropy, appropriate for multi-class classification problems.

Upon completion, the model was quantized into the '.eim' format and deployed to the Arduino Uno using the Edge Impulse CLI.

Inference was executed every 10 seconds, enabling responsive and autonomous irrigation decisions based on the current environmental and soil conditions.

3. Results

3.1. Soil moisture dynamics without irrigation

Figure 3 presents soil moisture levels recorded over a 7-day period in which the irrigation system remained deactivated. The volumetric water content declined steadily from approximately 68% to 12%, exhibiting a clear stepwise reduction pattern across days. This behavior corresponds to progressive water loss due to evaporation and drainage, especially in sandy loam soils. The absence of rainfall during the period confirms that the sensors accurately reflected natural depletion. These measurements validate the system's ability to monitor critical thresholds and support automation strategies for water conservation.

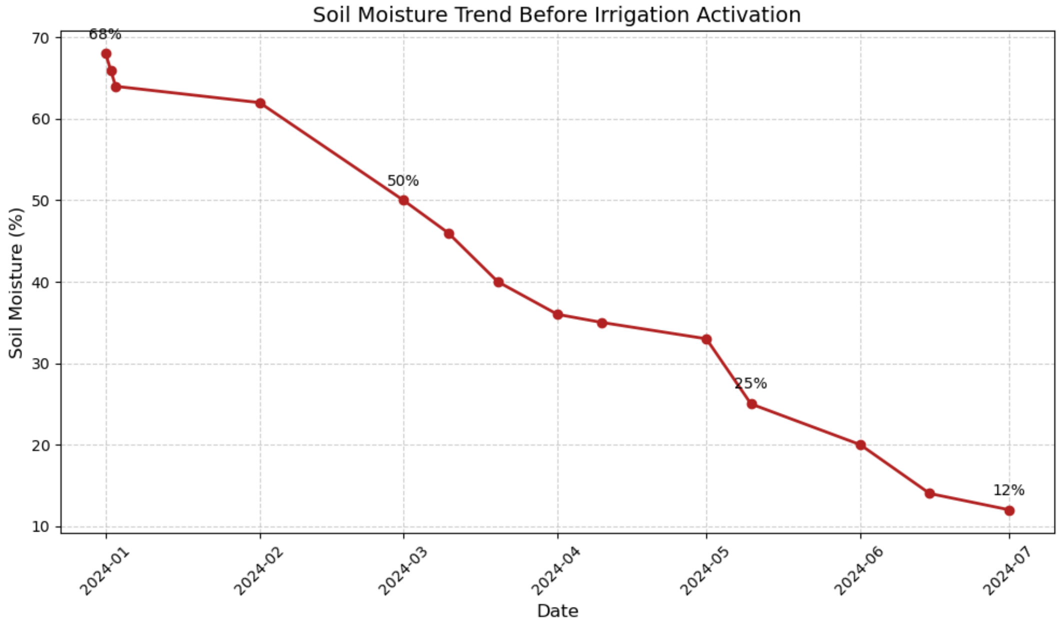


Figure 3. Soil moisture percentage over 7 days without irrigation system activation

3.2. Post-activation humidity response

Following system activation, ambient relative humidity was monitored over a 10-minute window. As shown in Figure 4, relative humidity stabilized within a narrow band between 81% and 87%, falling within the predefined optimal range (82–88%). This controlled microclimatic behavior suggests the system effectively mitigated evaporative losses. The observed environmental stability underscores the relevance of precision irrigation in enhancing local field conditions, particularly under tropical agroforestry settings.

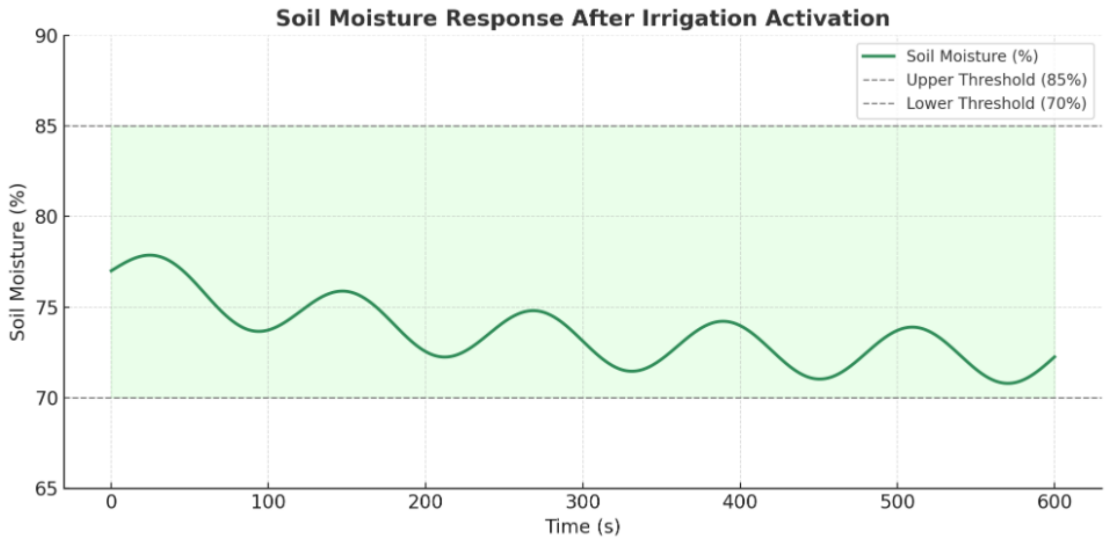


Figure 4. Relative humidity levels recorded after system activation, demonstrating environmental stabilization

3.3. Correlation between humidity and soil moisture

Figure 5 displays a time-series comparison of ambient relative humidity (DHT11 sensor) and soil moisture (hygrometer). A strong temporal association is evident: peaks in ambient humidity are followed by corresponding increases in soil moisture. This synchrony confirms that the irrigation logic—driven by atmospheric and subsurface conditions—achieves coordinated actuation. The observed response illustrates the system's capacity to adapt to changing environmental conditions, ensuring efficient water distribution within agronomic thresholds.

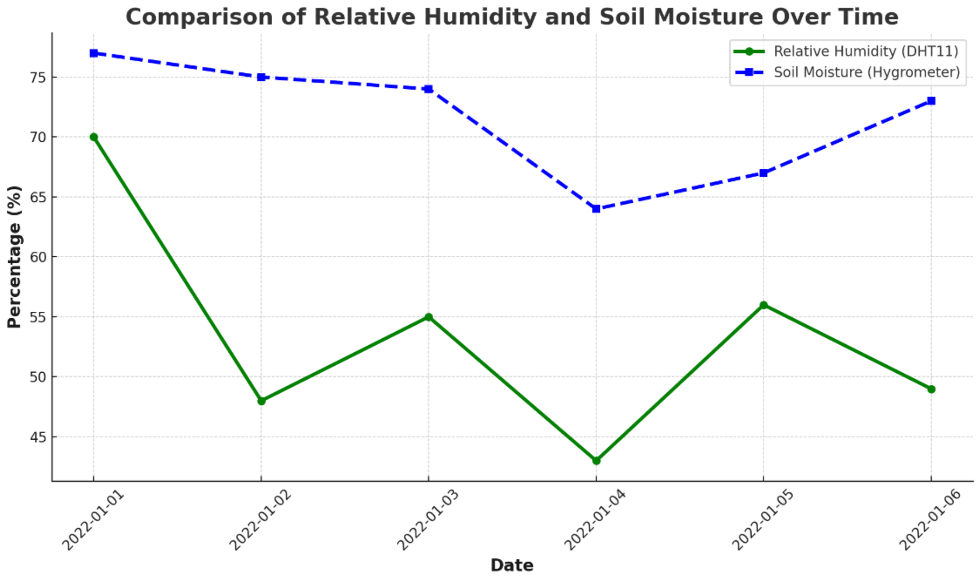
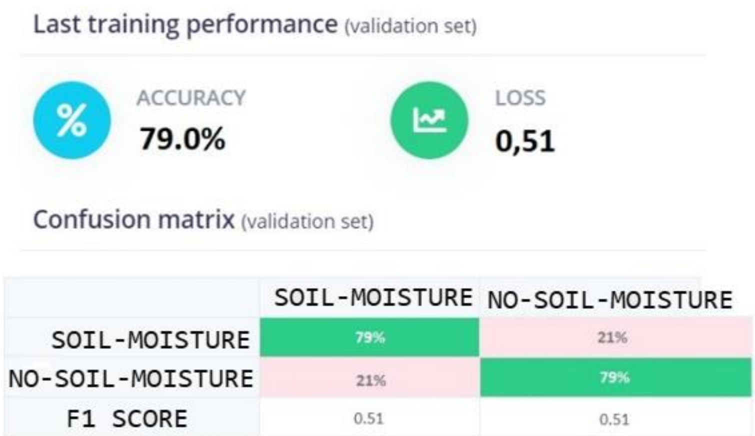


Figure 5. Time-series comparison of ambient humidity and soil moisture content

3.4. Classification performance of neural network models

The neural network models were developed and trained using labeled datasets derived from both hygrometer and DHT11 sensors. Model implementation was carried out using the Edge Impulse platform. Figures 6 and 7 present the resulting confusion matrices. The model based on soil moisture data yielded a classification accuracy of 79% with an F1 SCORE of 0.51. It achieved symmetric true positive rates of 79% for the classes SOIL-MOISTURE and NO-SOIL-MOISTURE. However, a 21% misclassification rate highlights moderate separability under field conditions, possibly due to sensor noise and overlapping class distributions.

By contrast, the model based on the DHT11 sensor input outperformed the previous configuration. It achieved an overall accuracy of 82% and an F1 SCORE of 0.82. The classifier demonstrated reliable discrimination between the RAIN and NO-RAIN labels, with a misclassification rate of only 18%. These results indicate that ambient humidity is a more robust and stable feature for real-time irrigation state prediction in tropical environments.



	SOIL-MOISTURE	NO-SOIL-MOISTURE
SOIL-MOISTURE	79%	21%
NO-SOIL-MOISTURE	21%	79%
F1 SCORE	0.51	0.51

Figure 6. Confusion matrix of the classifier using soil moisture (hygrometer) input. Accuracy: 79%, F1 score: 0.51

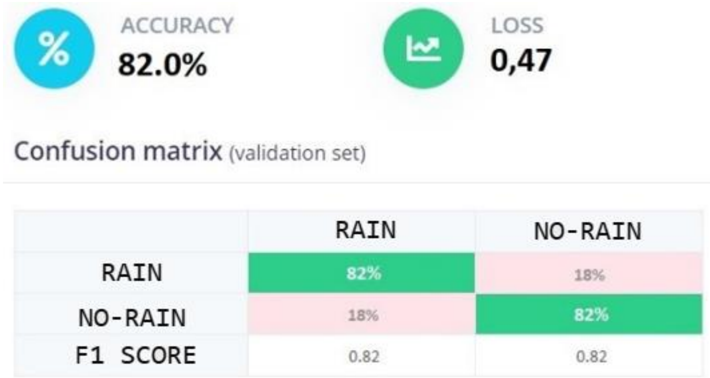


Figure 7. Confusion matrix of the classifier using ambient humidity (DHT11) input. Accuracy: 82%, F1 score: 0.82

4. Conclusions and discussion

This study demonstrated the successful development and field validation of a low-cost, intelligent irrigation system tailored for cocoa agroforestry in tropical conditions. By integrating edge computing, real-time environmental sensing, and embedded neural networks, the system autonomously regulates irrigation events in response to dynamic field conditions, supporting efficient water use in infrastructure-limited settings.

In this study, soil moisture measurements were obtained using two low-cost sensors: the DHT11 sensor and the FC-28 YL-69 soil hygrometer. While both sensors have nominal measurement tolerances—DHT11 with ±2–5% RH and FC-28 YL-69 with ±3–5% soil moisture—these levels of precision proved sufficient for the predictive model, which achieved 82% irrigation accuracy over the 9-week field trial. The sensors provided reliable data to maintain optimal soil moisture levels (70–85%) in the cocoa agroforestry plots. Future studies could consider higher-precision sensors to further improve model accuracy in areas with highly variable microclimates, although the current configuration demonstrates a cost-effective and practical solution for smallholder farmers.

Field observations revealed that, in the absence of intervention, soil moisture decreased from agronomic optimums (68%) to severely depleted levels (12%), reinforcing the necessity of automated water control in rain-fed tropical systems. Upon system activation, moisture levels were consistently maintained within the optimal range (70–85%), effectively reducing drought stress and stabilizing water availability—key factors for cocoa, a crop with narrow humidity tolerance thresholds [4].

Environmental sensing with the DHT11 sensor indicated stable relative humidity values (81–87%) after irrigation events, suggesting a localized microclimatic buffer effect. This aligns with prior evidence on the ecological value of microclimate regulation in agroforestry and its contribution to climate resilience [8, 16, 21].

Neural network classification models achieved high predictive accuracy, particularly when based on ambient humidity data. The DHT11-based model achieved 82% accuracy and an F1 score of 0.82, outperforming the hygrometer-based model (79% accuracy, F1 score 0.51).

Compared to previously reported smart irrigation systems, such as the solar-powered system by Abdelhamid et al. [19], our approach integrates edge AI with low-cost sensors (DHT11) and a modular solar-powered architecture, maintaining optimal soil moisture levels (70–85%) with 82% predictive accuracy. Unlike the system in [19], which relies on continuous connectivity and higher-cost sensors, our design provides operational autonomy in infrastructure-limited conditions, facilitating adoption by smallholder cocoa farmers in rural tropical areas. These distinctions highlight the feasibility of implementing scalable and cost-effective smart irrigation solutions tailored for agroforestry contexts.

These results suggest that atmospheric variables may serve as more stable predictors in short-term irrigation decisions, especially under conditions of fluctuating soil moisture. Furthermore, the successful deployment of edge AI models on microcontroller platforms confirmed the technical viability of embedded intelligence in remote, resource-constrained agricultural environments [22, 23].

The modular design and solar-powered architecture provided operational autonomy, scalability, and reduced dependence on external infrastructure. Real-time data logging and cloud integration enabled remote supervision, features particularly beneficial for smallholder farmers lacking continuous technical assistance. These attributes address long-standing barriers in tropical agriculture, including high system costs, intermittent connectivity, and labor shortages [7, 12].

Nonetheless, several limitations were identified. The DHT11 sensor, despite its affordability, exhibits moderate accuracy and could be replaced by more precise alternatives in future iterations. Similarly, the binary classification logic, while functional for prototype deployment, may oversimplify the complex dynamics of tropical agroecosystems. Enhancing the model with larger, seasonally varied datasets and incorporating meteorological forecasts could improve generalizability and robustness.

In addition, the relatively short duration of field experiments constrains conclusions regarding long-term impacts on crop productivity, root-zone moisture dynamics, and soil health. Future studies should extend evaluations across multiple phenological stages and diverse climatic scenarios to validate sustained agronomic performance.

Further improvements may include the integration of evapotranspiration models, localized weather forecasts, and decision support systems. Incorporating low-power communication technologies such as LoRaWAN could expand system coverage while minimizing energy consumption. Moreover, mobile dashboards and farmer-friendly interfaces can enhance usability and adoption in community-managed settings [15].

In summary, this work presents a replicable, scalable, and energy-autonomous irrigation solution aligned with the needs of smallholder cocoa producers in tropical agroforestry contexts. By addressing both environmental constraints and technological gaps, the system contributes to the achievement of Sustainable Development Goals 2 (Zero Hunger), 6 (Clean Water and Sanitation), and 13 (Climate Action).

The approach reinforces the role of edge AI in advancing digital agriculture and climate-smart land management in the Global South.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

R. Cazes Ortega: conceptualization, system design, experimental implementation, and manuscript drafting; A. Pardo García: methodology support and data analysis;
J. S. Fandiño Pelayo: methodology, analysis of results, and manuscript refinement;
C. L. Sandoval-Rodríguez: data validation and technical input during final manuscript revision.
All authors reviewed and approved the final version of the manuscript.

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