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Preliminary results of irrigation management for mango using LSTM neural networks and IoT
Resultados preliminares de gestión de riego para mango con redes neuronales LSTM e IoT

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KEYWORDS
IoT; irrigation management; LSTM neural networks; mango cultivation; trends forecasting.
Cultivo de mango; gestión del riego; pronóstico de tendencias; redes neuronales LSTM; IoT.

ABSTRACT: Mango cultivation in Colombia faces the impact of regional climate variability. To improve fruit development and minimize environmental and economic effects, it is necessary to implement efficient irrigation and appropriate water management technologies. In this study, we developed a trend forecasting system based on an LSTM neural network and technologies such as ThingsBoard, LoRA, and MQTT. The aim was to improve mango irrigation practices through informed decisions based on monitoring and predicting matric potential and evapotranspiration variables. This article describes the development and application of the system for mango irrigation management. Results validate the effectiveness of the proposed system for mango cultivation, with RMSE indices of 1.56 and 0.0019 and determination coefficients (R^2) of 0.9989 and 0.9971 for matric potential and evapotranspiration, respectively. These findings support enhancing growth conditions and promoting sustainable practices. Despite data availability limitations, the system's efficacy in prediction and irrigation management demonstrates significant potential to maximize productivity and reduce the environmental and economic impacts of inadequate water management.

RESUMEN: El mango (Mangifera indica L.) es un fruto tropical ampliamente comercializado en varios continentes y el cultivo de mango en Colombia se ve afectado por la variabilidad climática regional. Para mejorar el desarrollo del fruto y minimizar los impactos ambientales y económicos, se requiere un riego eficiente y tecnologías de manejo del agua adecuadas. En este estudio, se desarrolló un sistema de pronóstico de tendencias basado en una red neuronal LSTM y tecnologías como ThingsBoard, LoRA y

MQTT. El objetivo fue mejorar las prácticas de riego en el cultivo de mango mediante decisiones informadas, basadas en el monitoreo y la predicción de las variables de potencial mátrico y evapotranspiración. Este artículo describe el desarrollo y aplicación de dicho sistema en el manejo del riego del cultivo de mango. Los resultados validaron la efectividad del sistema propuesto para el cultivo de mango, con índices de RMSE de 1.56 y 0.0019, y coeficientes de determinación (R^2) de 0.9989 y 0,9971 para el potencial mátrico y la evapotranspiración, respectivamente. Estos hallazgos respaldan la mejora de las condiciones de crecimiento y la promoción de prácticas sostenibles. Aunque se reconoce la limitación de datos, la eficacia del sistema en la predicción y la gestión de riego ofrece un potencial significativo para maximizar la productividad y reducir los impactos ambientales y económicos asociados a una gestión inadecuada del agua.

1. Introduction

Mango is a widely valued and popular tropical fruit worldwide due to its sweet flavor and exotic aroma. It is extensively cultivated in over 100 countries across Asia, South America, North America, and Africa. According to statistics, the global production of mango is estimated at 50.64 million metric tons [1], [2].

In 2021, the mango sector in Colombia recorded a total of 26,158 hectares of cultivated mango, with a production of 279,886 tons during that period. Within the Colombian context, the Cesar department stands out as one of the top 10 mango producers in the country, with 1,223 hectares of cultivated mango. In 2021, a production of 7,576 tons was achieved, resulting in an average yield of 11.4 tons of mango per hectare planted [3].

In Colombia, inadequate soil and water management are among the various technical factors affecting the efficiency and sustainability of mango production [4]. In the current context, irrigation application is determined without considering the plants' agroclimatic conditions and actual water needs. This can result in excessive or insufficient irrigation, affecting crop productivity and quality, and resource and raw material consumption [5].

Efficient water management in mango cultivation is crucial to maximize production and ensure fruit quality while reducing water scarcity's environmental and economic impacts. Despite numerous studies to improve irrigation practices in mango cultivation, the inadequacy of suitable water management technologies for this activity has been highlighted [1, 6-8].

The present study proposes leveraging the IoT paradigm for efficient water management in mango cultivation. This would enable real-time monitoring and control of irrigation systems while enhancing traceability and security [9]. Additionally, integrating LSTM neural networks improves accuracy by addressing missing and anomalous sensor data, fostering sustainable agricultural practices through better insights and predictions [10].

Mango cultivation has been the subject of numerous studies worldwide, with research focusing on irrigation management systems. For instance, an alternative infiltration irrigation system was introduced in China, which improved the photosynthetic characteristics and water use efficiency in mango plants [11]. This system employed a homemade irrigation device consisting of a water storage bottle, a switch, a rubber hose, and a porous emitter, effectively reducing irrigation by 30% to 50%. Furthermore, an automated micro-sprinkler irrigation system was developed in China, incorporating a soil moisture sensor at a depth of 30 cm from the mango tree trunks and an automated agrometeorological station for recording climatic data [12]. The results demonstrated significant increases in average fruit weight, diameter, and length, as well as soluble protein and titratable acidity. In summary, the present system relies on monitoring soil and climatic variables using Long Short-Term Memory (LSTM) neural networks to enhance irrigation management in mango cultivation and achieve more efficient water utilization.

In addition to the advancements in irrigation management, recent research has focused on enhancing the security and traceability of agricultural products through IoT-based systems. For instance, a proposed hardware architecture integrates Blockchain technology into IoT devices, explicitly targeting food traceability systems [13]. This hardware design, implemented on FPGA Altera DE0-Nano, enables IoT devices to participate as miners in the blockchain network, addressing security issues related to data integrity and traceability within the food certification process. Similarly, another study presents a greenhouse traceability model based on IoT for tracking and monitoring seedlings and agricultural products [14]. This model facilitates the automated control of greenhouse environments and internal traceability of products, promoting sound farming practices and ensuring quality and safety throughout the agricultural value chain. Integrating these advancements with innovative irrigation management systems can further enhance the productivity and sustainability of mango cultivation practices.

Irrigation is fundamental to ensuring crop production and meeting the demand for water resources worldwide. As agriculture is crucial to feeding the global population, irrigation is essential to increasing production and improving food availability [15].

In Mango cultivation, irrigation is essential for plant growth and development, ensuring the necessary water balance for optimal growth and fruit quality. Furthermore, proper irrigation can enhance the fruit's quality and yield by providing an adequate water supply during critical stages of the cultivation cycle, such as flowering and fruit formation. Therefore, it is essential to implement an efficient and well-planned irrigation program in mango cultivation to maximize productivity and profitability [4].

Integrating IoT-based systems and LSTM neural networks is central to the present study, offering enhanced precision in mango irrigation management. This approach enables real-time monitoring of irrigation systems and allows for tailored water delivery to meet the specific needs of mango plants. Consequently, it leads to improved efficiency, sustainability, and yield outcomes compared to conventional methods. Notably, the versatility of this solution suggests its potential applicability across various agricultural domains, highlighting its broader impact beyond mango cultivation.

The present article is structured as follows: Section 1 addresses the introduction and related works, Section 2 describes the architecture of the monitoring system and the LSTM neural networks, Section 3 presents the detailed results of the monitoring system, and finally, Section 4 presents the conclusions of this work.

2. Materials and Methods

The present study is based on applied field research employing a data collection approach using devices and sensors in the study area. The research is classified as quantitative and aims to train a Long Short-Term Memory (LSTM) neural network model to develop a trend forecasting system. This system will provide information for decision-making in mango crop irrigation, utilizing the data collected by the sensors.

The monitoring and forecasting system relied on automatic data collection in the field crops. The LSTM neural network deployed on a Virtual Private Server (VPS) stored, transmitted, and analyzed the collected data. Subsequently, the processed and analyzed data was sent and represented on a web platform for visualization and understanding by the end-users (see Figure 1).

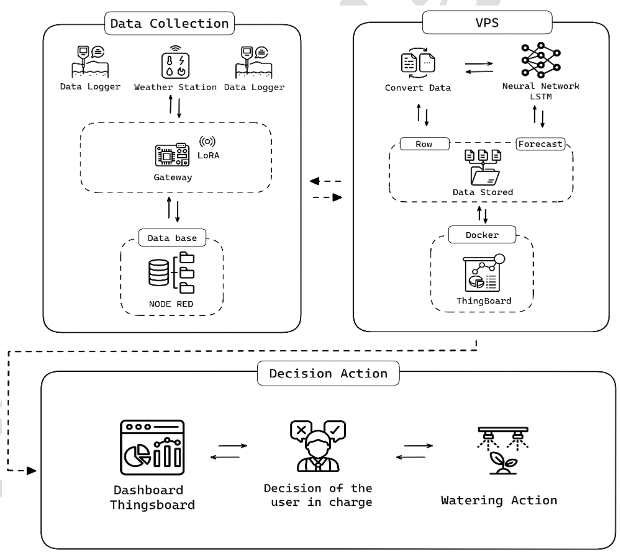

Figure 1 General graphical description of the system.

2.1. Study area

The study was conducted on a farm in the municipality of Chimichagua, located in the department of Cesar, Colombia. The farm is situated at geographic coordinates 9° 16' 0.8688" N, 73° 50' 40.2684" W, and has an area of 120,000 m^2 (see Figure 2). The Cesar River runs through several municipalities, including Chimichagua, in this Caribbean region. It plays a vital role as a water supply source and in economic activities such as agriculture, fishing, and livestock farming [16]. Additionally, the area is characterized by diverse thermal floors and climates, with temperatures ranging from 38 °C to below four °C [17].

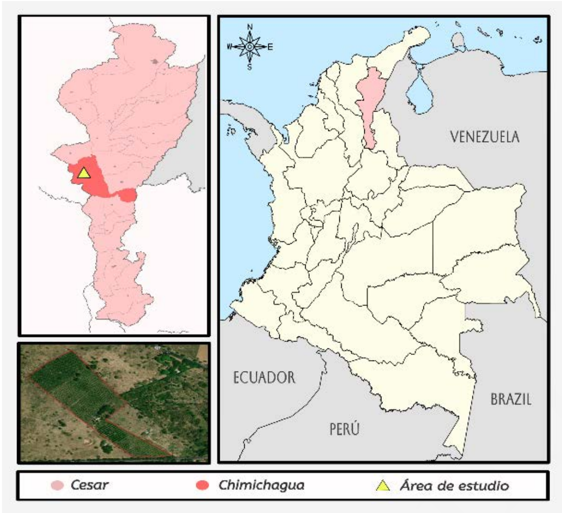

Figure 2 Farm location: Chimichagua, Cesar, Colombia.

2.2. Data collection

In the study area, two types of devices were used for data collection: the data logger, which measured matric potential, and the weather station, which monitored climatic variables such as solar radiation, UV index, humidity, wind direction and speed, and precipitation. A Gateway device was also employed as an intermediary device that communicated with the input devices, transmitting the sensed variables via the Long Range (LoRa) protocol. These variables were then sent and stored in a Node-Red database and their corresponding time series (see Figure 3).

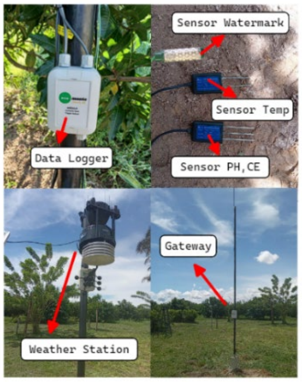

Figure 3 Data collection devices installed in the field.

2.2.1 Input variables

The monitored variables represented in the Internet of Things (IoT) platform were as follows: evapotranspiration, calculated from the values captured by wind speed, direction, solar radiation, UV index, and precipitation sensors of the weather station. These data played a crucial role in adjusting the irrigation needs of the mango crop. In addition, matric potential sensors located in the data logger were used to measure soil moisture levels. Data collection occurred every 15 minutes throughout the day, resulting in a sampling frequency of 96 daily values. Subsequently, the data were graphically represented on the ThingsBoard platform for comparison with the values predicted by the LSTM model. Finally, a technician was responsible for validating the forecasted trends and deciding whether to activate the irrigation system.

2.3. Specifications of the computing device

The computing setup consisted of a Ryzen 5 3500U processor and 12 GB of RAM, running on the ArchLinux x86-64 operating system with Linux kernel 6.1. The study was conducted on a VPS with a 2-core processor, 8 GB of RAM, and the Ubuntu Server 22.04 operating system.

2.4. Virtual Private Server (VPS)

The processing system and IoT platform were deployed in the Virtual Private Server. This system was divided into sections, from data transformation to JavaScript Object Notation (JSON) format. This format was chosen for its text structure, which facilitates communication between various technologies and languages and enables agile and efficient information exchange. The transformed data was sent as inputs to both the ThingsBoard platform and the neural network (see Figure 1).

2.5. IoT tools

ThingsBoard is an open-source platform used in the project for IoT device management. This platform facilitated device connectivity and management, real-time data collection and visualization, alert configuration, and automation of actions. Its intuitive and user-friendly web interface enabled users to manage and monitor IoT devices at scale efficiently. Additionally, the platform offered a wide range of built-in tools and services that assisted users in developing custom IoT applications and creating solutions for diverse use cases [18]. Given its advantages and features, this platform was the ideal choice for graphically representing the collected and analyzed variables in the field.

For the transfer of information between the sensor data processing applications and the ThingsBoard platform, the Message Queuing Telemetry Transport (MQTT) communication protocol was chosen. This protocol, created and published in 1999 and standardized by the OASIS consortium under the ISO/IEC 20922 number, stood out for being lightweight, simple, and reliable for IoT devices. An important and positive aspect of this protocol is its open nature, which means that companies or developers do not need to acquire a license or pay copyright fees for its use in their systems and applications [4].

On the other hand, the LoRa protocol was used for internal communication with the input devices installed in the field, facilitating the transfer of variables to the Gateway. The Gateway sent the information to the Node-Red database (Figure 1). LoRa is a long-range, low-power wireless technology designed to connect IoT devices with energy efficiency and extended battery life over long distances. It enables data transmission over several kilometers, making it suitable for applications in smart cities, agriculture, environmental monitoring, and security [5].

2.6. Evapotranspiration

Evapotranspiration is crucial in water management in agriculture as it determines the amount of water required for crop growth and development. This complex process depends on temperature, relative humidity, wind speed, solar radiation, soil characteristics, and vegetation. Measuring and estimating evapotranspiration is essential for planning and managing crop irrigation [21, 22]. The calculation of reference evapotranspiration (ET0) is performed using the FAO Penman-Monteith standard method developed by the Food and Agriculture Organization of the United Nations (FAO) [21, 22]. This method allows for estimating the value of ET0 for various vegetation conditions using Equation (1), as shown below.

$$ET_0 = \frac{0.408 * \Delta * (R_n - G) + \gamma * \frac{900}{T + 273} * u_2 * (e_s - e_a)}{\Delta + \gamma * (1 + 0.34 * u_2)} \quad \mathbf{(1)}$$

In Equation (1), the following terms are defined: ET_o is the reference evapotranspiration (mm day^{-1}), R_n is the net radiation at the crop surface (MJ mm^{-2} day^{-1}), G is the soil heat flux density (MJ mm^{-2} day^{-1}), T is the average daily air temperature at 2 meters height (ºC), u_2 is the wind speed at two meters height ($\mathrm{m/s}^{-1}$), e_s is the saturation vapor pressure (kPa), e_a is the actual vapor pressure (kPa), Δ is the slope of the vapor pressure curve ($\mathrm{kPa/ºC}^{-1}$), and γ is a psychrometric constant ($\mathrm{kPa/ºC}^{-1}$).

2.7. Artificial Neural Networks

In recent years, neural networks have garnered significant attention in computing, drawing inspiration from biological models. Defined as mathematical models composed of multiple processing elements organized in levels, these networks are characterized by their computational complexity and dynamic response to external stimuli [23].

Artificial neural networks, mimicking the biological nervous system [23], play a crucial role in agroclimatic prediction and agricultural production optimization. They facilitate improved productivity, weather forecasting, and plant image classification in precision agriculture. These technologies, including convolutional and recurrent neural networks, enable real-time monitoring of agricultural parameters through IoT, enhancing decision-making tools [24],[25].

While neural networks have been a subject of research in computing, it's notable that more recent architectures like LSTM neural networks are currently being investigated for various applications [26].

2.7.1 Long Short-Term Memory (LSTM) Artificial Neural Networks

LSTM artificial neural networks are recurrent architectures for processing sequential data, such as natural language or time series. Recurrent neural networks (RNNs) are widely employed in deep learning for dynamic modeling due to their ability to retain information in their internal memory. However, RNNs face significant challenges, such as the vanishing or exploding gradient problem during training [27]. The uniqueness of LSTM artificial networks lies in their gate structure, which enables them to effectively capture sequential information and address the issue of vanishing or exploding gradients in RNNs [28].

2.8. Development of the LSTM Artificial Neural Network in Python

This study utilized Python libraries such as JSON, Numpy, Pandas, Keras, and Sklearn.

2.8.1 Data input

The input data was collected by reading JSON-format files provided by the process of converting the information recorded by the in-situ devices. Once the input data was gathered, it was converted to data frames using Pandas, a high-performance library for data manipulation and analysis. Subsequently, the input variables were separated from their time series index to normalize the data for each variable using Sklearn, a library of tools for classification, regression, clustering, and data processing (see Figure 4).

2.8.2 Sequential model

For the implementation of the model, the LSTM structure was used through the integration of Keras, a library designed for building and training artificial neural networks. Once the neural network structure was established, the Numpy library was implemented, which allows efficient work with multidimensional arrays and vectors and was used to adjust the dimensions of the matrices suitable for the model (see Figure 4).

After completing the aforementioned processes, the model was trained, followed by input of the desired forecast input values to obtain predictions from the trained model (see Figure 4).

2.8.3 Prediction Compilation

Once the LSTM artificial neural network model predictions were obtained, the data normalization process was performed on the model's output. The data was transformed back to its original scale before being sent to the IoT platform ThingsBoard (see Figure 4).

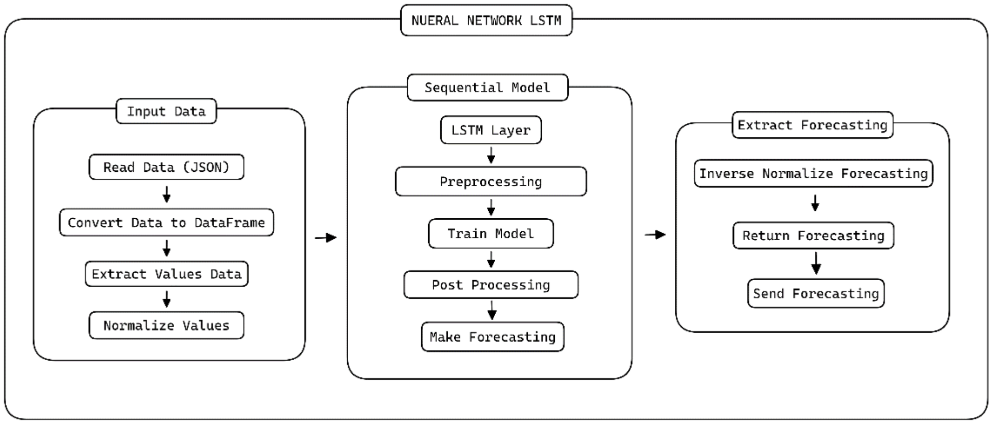

Figure 4 Structure of the LSTM Artificial Neural Network in Python.

118 data samples per variable were used for training and testing the model. During the training stage, 65% of the data (77 samples per variable) was employed from December 21, 2022, to March 16, 2023. The remaining 35% (41 samples per variable) was used to verify the model and make predictions from March 17, 2023, to May 14, 2023, for each field input variable, including evapotranspiration and humidity in the matric potential logger. The data and the neural network results were sent to the ThingsBoard platform, where the historical and graphical trends of the variables were visualized. It is worth noting that 106 data points were filtered out and not considered for graphical analysis due to technical failures in the sensors and communication devices.

2.8. Data visualization

The data visualization was performed using the IoT platform ThingsBoard, allowing real-time graphical observation of the data captured by the sensors. In each graph corresponding to the monitored variables, namely evapotranspiration and matric potential, sensor measurements were presented alongside the predictions generated by the neural network. This facilitated result comparison and model performance evaluation for both variables. Graphs depicting the calculation of evapotranspiration and matric potential, along with the outputs provided by the neural network, were displayed, providing a clear insight into the behavior of both variables over time. The visualization proved helpful in comprehending and analyzing the relationship between actual measurements and model-generated predictions (see Figure 5).

Figure 5 Monitoring Panel in ThingsBoard.

2.9. Model Evaluation

To evaluate the performance of the LSTM artificial neural network model, the root mean square error (RMSE) [29] was utilized as a measure of discrepancies between predicted and observed values. A lower RMSE value indicated higher prediction accuracy, making it a valuable metric for assessing model performance. The calculation of RMSE was performed using Equation (2):

$$RMSE = \sqrt{\sum_{i=1}^{N}\left(\frac{\widehat{y_i} - y_i}{N}\right)^2} \quad (2)$$

Where N is the number of samples, $\widehat{y_i}$ represents the predicted values, and y_i corresponds to the observed data.

Finally, the sensor data and neural network results were exported from the ThingsBoard platform in JSON format. Subsequently, these data were converted to the .xlsx format for processing in Microsoft Excel. The coefficient of determination (R^2) was calculated by analyzing the linear regression between the observed and predicted values using a graph generated in Microsoft Excel.

3. Results

In the present study, the LSTM artificial neural network was employed to perform prediction in the context of efficient water management in mango cultivation. The effectiveness of the neural network was validated using 41 data points collected during the last two months of monitoring. In this study, monitoring and predictions were conducted for matric potential and evapotranspiration variables, as shown in Figures 6 and 7.

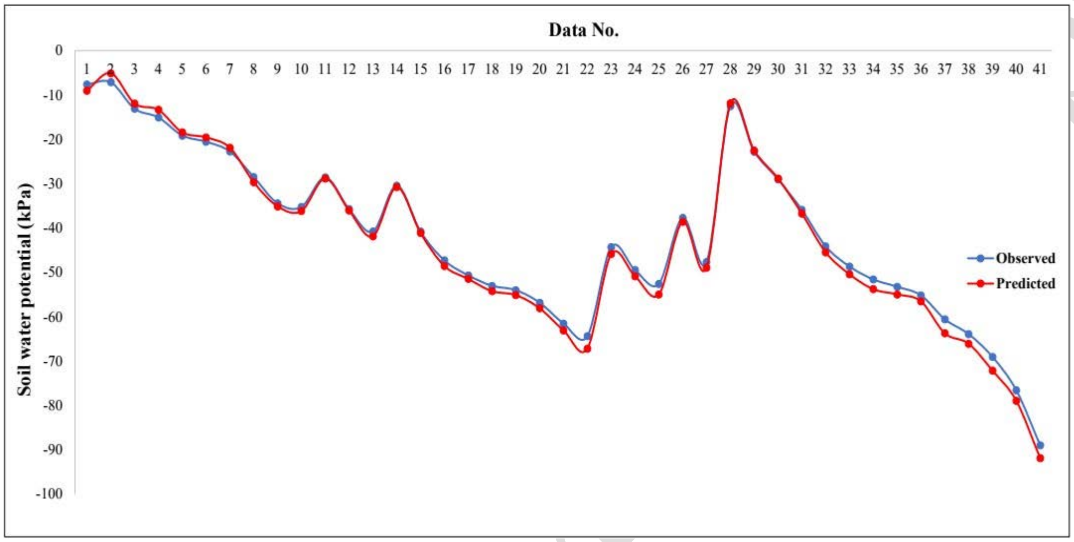

Figure 6 Comparison of predicted and observed matric potential.

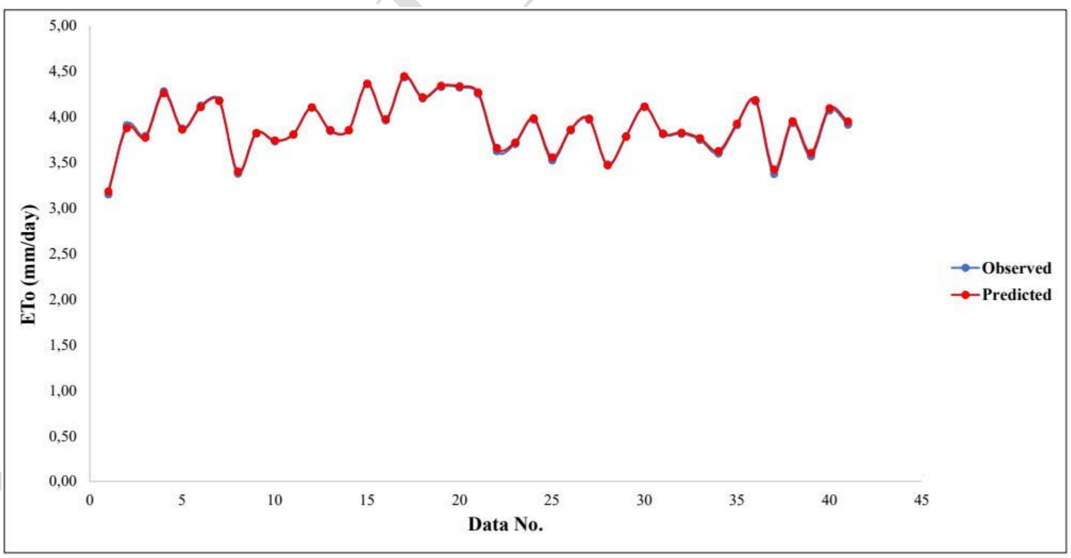

Figure 7 Comparison of predicted and observed evapotranspiration.

The results obtained for the matric potential showed an RMSE index of 1.56 with 41 validation data points and a coefficient of determination (R^2) of 0.9989. A graphical representation of the observed and predicted values was performed, enabling the derivation of linear regression with an R^2 value of 0.9989 (see Figure 8).

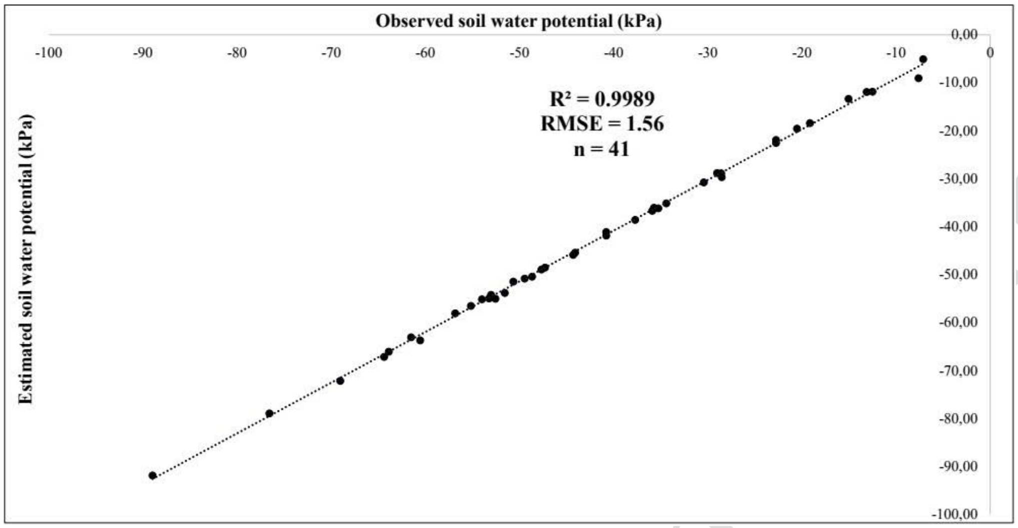

Figure 8 The trend of matric potential in mango cultivation.

On the other hand, evapotranspiration obtained an RMSE index of 0,0019 with 41 validation data points and an R^2 of 0.9971. Similarly to the matric potential case, a graph representing the observed and predicted values was constructed, resulting in a linear regression with an R^2 value of 0.9971, see Figure 9.

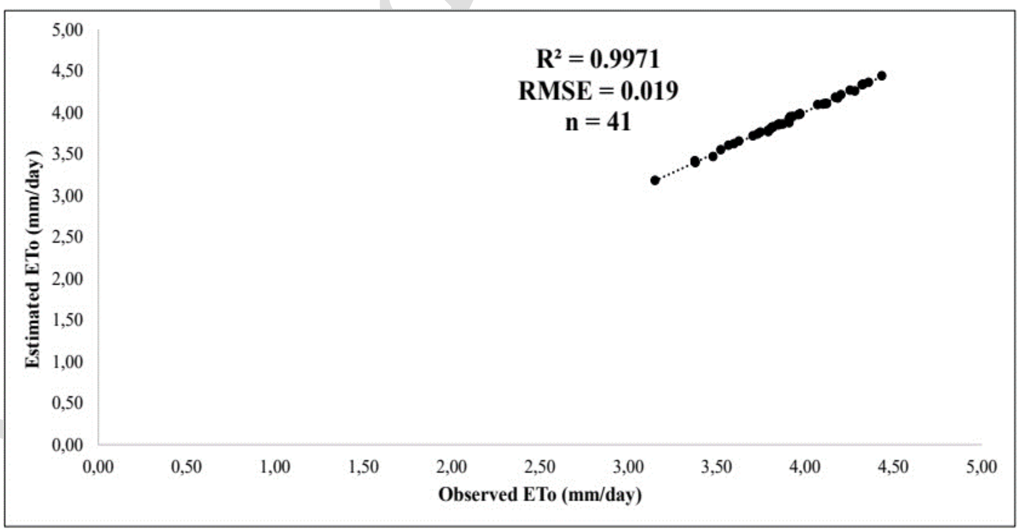

Figure 9 The trend of evapotranspiration in mango cultivation.

It is important to highlight that the LSTM artificial neural network's training process was carried out over 9,000 iterations. This allowed for model adjustments and improvement in its predictive capacity.

The validation of the obtained results emphasizes their validity and contribution. As Table 1 shows, the RMSE values indicate the accuracy of the predictions made by the LSTM artificial neural network, while the R2 values reflect the model's ability to explain the data's variability.

Table 1. Results for soil water potential and evapotranspiration Prediction

Metric	Soil water potential	Evapotranspiration
RMSE index	1.56	0.0019
Validation data points	41	41
R^2 Value	0.9989	0.9971

The obtained results are highly satisfactory in terms of precision and predictive capacity. The linear regression obtained for both variables indicates a strong relationship between the observed and predicted values.

These overall findings and conclusions support the study's main objective, which is to enhance growth and development conditions in mango cultivation through irrigation-based decision-making. Furthermore, this approach is expected to contribute to reducing environmental impact and promoting economic development among farmers through the adoption of innovative agricultural technologies.

Despite the encouraging results, it is essential to acknowledge the study's limitation, which lies in the limited availability of data for validation and the possibility of other unconsidered factors that could influence the monitored variables.

Therefore, the obtained results demonstrate the effectiveness of the LSTM artificial neural network in predicting the matric potential and evapotranspiration in mango cultivation. These findings support implementing an efficient and well-planned irrigation program for this crop to maximize productivity and profitability while reducing inadequate water management's environmental and economic impacts.

4. Conclusions

This study addressed the importance of efficient water management in mango cultivation and highlighted the need for suitable technologies to achieve effective management. It was demonstrated that agricultural irrigation plays a crucial role in mango crop production by contributing to the necessary water balance for optimal plant development and fruit yield.

Implementing a monitoring and forecasting system based on LSTM artificial neural networks has significantly improved decision-making related to mango irrigation. The results demonstrate high precision in the predictions made by the neural network model, supported by low RMSE values (1.56 for matric potential and 0.0019 for evapotranspiration) and high R^2 values (0.9989 and 0.9971, respectively).

The validation of these results emphasizes their validity and contribution, where RMSE values indicate prediction accuracy and R^2 values reflect the model's ability to explain data variability.

Implementing innovative agricultural technologies, such as precision agriculture, can enhance crop efficiency and sustainability, reduce costs, and minimize environmental impact. This study contributes to this objective by providing accurate and accessible irrigation and nutrition tools for farmers, potentially resulting in increased productivity and profitability in mango cultivation.

However, it is essential to consider the limitations of this study, such as the limited availability of data for validation and the possibility of other unconsidered factors that could influence the monitored variables. Despite these limitations, the results support implementing an efficient and well-planned irrigation program in mango cultivation to maximize productivity and profitability while reducing the environmental and economic impacts of inadequate water management.

The work enhances efficiency and irrigation planning in mango cultivation by providing tools and methods to improve water management, but its real impact depends on technology availability and field support. While results show the proposed techniques work, external factors like technological infrastructure and logistical support could hinder their practical use.

5. Declaration of competing interest

We declare that we have no significant competing interests, including financial or non-financial, professional, or personal interests, that interfere with the complete and objective presentation of the work described in this manuscript.

6. Acknowledgments

We thank Ecomonte Colombia S.A.S. for allowing us to conduct this study on their farm and for providing the necessary technological infrastructure. Additionally, we thank the Universidad Cooperativa de Colombia and the Ministry of Science and Technology of Colombia for their support in this research.

7. Funding

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8. Author contributions

Jose Noguera designed and evaluated the LSTM neural network model. Aldo Daconte contributed to the neural network's analysis and drafted the document. Jose Moreu, Camilo Linero, and Ronald Munera collected the data and implemented the LSTM neural network in Python. They also created visualizations of the network's predicted data on ThingBoard. Additionally, they contributed to the documentation and drafting of the manuscript. Furthermore, Pablo César Guevara Barbosa contributed to elaborating and analyzing system results in the agronomic aspect and technical feasibility of the system.

9. Data availability statement

The data supporting the system's implementation was obtained from the technological infrastructure (sensors and IoT) installed on the company Ecomonte S.A.S's farm.

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