



Integration of Internet of Things (IoT) and Machine Learning for Management of Ground Water Banks in Drought-prone Areas: A Case Study from Imjai Organic Garden, Thailand

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Abstract

This study presents an innovative approach integrating Internet of Things (IoT) and machine learning for optimized water management in precision agriculture, focusing on jasmine, date and pomelo farming in a drought-prone area where Imjai Organic Garden is located (Chachoengsao, Thailand). The research addresses a critical need for efficient water use in agriculture, particularly in regions facing spells of both drought and flooding. Using a multi-depth and multi-sensor IoT setup, the real-time data from soil moisture, temperature and water levels at the site were collected and transmitted via NB-IoT technology. The data facilitated the development of virtual soil moisture sensors through machine learning models, specifically Linear Regression, Random Forest, Support Vector Regression (SVR) and Long Short-Term Memory (LSTM) networks. Such models demonstrated a high accuracy in predicting soil moisture levels, thus reducing the need for frequent physical sensor maintenance. The study's novelty lies in its comprehensive approach combining IoT and advanced machine learning to provide actionable insights for water management, thus enhancing both agricultural productivity and sustainability. Quantitatively, the integration of machine learning models improved water usage efficiency by 37% for jasmine flowers, 28% for date palms, and 19% for pomelo trees. This research contributes to the body of knowledge in precision agriculture, and it also offers practical solutions for sustainable water resource management in Thailand's agricultural sector.

Keywords: Ground water banking; Drought area; Water resources management; IoT; Machine learning; Irrigation requirements; Precision agriculture.

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1. Introduction

Rapid population growth, urbanization, industrial expansion, and the impacts of climate change are exerting unprecedented pressures on global water resources, escalating concerns over water scarcity and necessitating innovative water management strategies. Projections by the United Nations estimate that the world's population will exceed 9 billion by 2050. This

population growth will further intensify demands for water across various sectors (United Nations, 2019).^[1] Additionally, an estimated 1.6 to 2.3 billion people, or half of the global urban population, are expected to live in water-scarce areas by 2050.^[2] Groundwater, with its vast reserves, has emerged as an increasingly vital source of potable water, irrigation, and industrial water supply, accounting for approximately 30%, 40%, and 20% of global usage, respectively.^[3,4] However, the over-exploitation of nearly 20% of the world's aquifers has led to significant declines in groundwater levels, emphasizing the critical need for effective water resource management.^[5]

To address water scarcity challenges, Groundwater Banking (GWB) systems have emerged as an alternative solution for enhancing water security and resilience. These systems, including closed-loop groundwater banking, aquifer storage and recovery (ASR), and managed aquifer recharge (MAR), are designed to capture and store excess water underground during periods of abundance for later use during

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droughts or seasonal fluctuations.^[6-10] GWB involves recharging aquifers with surface water, such as rainfall, river water, or treated wastewater, which can then be extracted and used during periods of water scarcity. GWB can offer advantages such as lower costs, a smaller environmental footprint, and reduced evaporation losses compared to traditional surface water storage methods.^[11,12] GWB also enhances the resilience of urban water systems by providing operational flexibility and expanding the water supply portfolio.^[13-16] Likewise, GWB helps mitigate the impacts of drought, supports sustainable water management, and enhances water security by replenishing depleted aquifers.^[8]

Closed underground water banks are another type of GWB specifically designed to store and manage water resources in a controlled and confined manner.^[17,18] Unlike open recharging systems, closed underground water banks inject water directly into sealed aquifers or specially constructed underground storage facilities, thus minimizing water loss and contamination risks. This method is particularly effective in regions with variable rainfall patterns and limited surface water storage options. It plays a vital role in supplementing water supplies, reducing dependence on surface water sources, and sustaining groundwater resources.^[19] In both urban and rural settings, closed underground water banks can help mitigate issues such as flooding, wastewater management, and water shortages while maintaining moisture in farming lands.^[20]

In the last decades, Southeast Asia has faced unique challenges in water resource management, including high seasonal variability in water availability and increasing demand due to rapid urbanization and industrialization. Countries like Thailand have adopted closed underground water banks to mitigate these issues. These water banks have enhanced water storage capacity and ensured a reliable water supply during droughts or extended dry seasons. These systems store excess surface water in underground aquifers, which can then be retrieved when needed. This method helps in managing water scarcity and it also reduces the risk of flooding by capturing runoff during heavy rains. Despite their huge potential, the effectiveness of these water banks depends heavily on robust monitoring and management practices to prevent issues such as groundwater contamination and over-extraction.

In recent years, the Thai government has shown significant interest in developing closed underground water banks to promote more sustainable agricultural practices. According to data from the Local Administration Information Center, as of June 29, 2023, there were approximately 9,200 closed underground water bank projects managed by local organizations across Thailand. This number is expected to increase steadily in the foreseeable future, reflecting the growing emphasis on water resource management and sustainability in the agricultural sector.

In modern agricultural management, the use of IoT through wireless sensor networks (WSNs) has become more common.

Numerous research studies have focused on collecting IoT sensor data to critically assess agriculture processes.^[21-23] The collected data is often processed using machine learning (ML) methods to predict soil contents,^[24-25] crop yield,^[26] diseases^[27] or irrigation requirements.^[28] One widely used method for determining irrigation requirements is the estimation of reference evapotranspiration (ET_0) using the Penman-Monteith equation. This equation is the standard approach for calculating ET_0 , as it integrates various climatic factors such as temperature, humidity, solar radiation, and wind speed, thus providing accurate estimates of crop water needs.^[29] Whilst the climate data can be measured using sensors, some sensors present practical challenges related to high costs, complicated installation, low reliability, and need for calibration. For instance, soil moisture sensors that collect data from the root zone must be periodically maintained. Soil moisture sensors play a crucial role in precision agriculture by providing real-time data on soil water content. These sensors operate based on various principles, such as dielectric constant, time-domain reflectometry (TDR), and capacitance. More recent advancements in soil moisture sensor technology have led to improved accuracy, reduced costs, and enhanced integration with IoT systems, allowing for more effective monitoring and management of irrigation.^[30] Moreover, innovations in sensor calibration and wireless transmission have increased the reliability of soil moisture data in diverse environmental conditions, thus contributing to optimized water use and crop yield prediction.^[31] More recently, the adoption of a deep learning (DL) approach using long short-term memory (LSTM) networks was proposed to create virtual soil moisture sensors. These virtual sensors utilize data from other transducers on the node to predict soil moisture levels, which demonstrated significant accuracy and reliability.^[32] The soil moisture level can be used to calculate the crop irrigation requirements which are critical for ensuring optimal crop growth, yield, and water use efficiency. These requirements are determined by various methodologies that integrate soil moisture monitoring,^[30] weather-based methods,^[32] and crop-specific factors.^[33]

Soil moisture sensors, tensiometers, and evapotranspiration (ET) models are widely utilized to assess and forecast crop water requirements. Evapotranspiration is the combined process of evaporation and transpiration, which occur simultaneously. The ET rate, typically measured in millimeters per unit time, represents the amount of water lost from a cropped surface.^[34] The ET method, particularly the Penman-Monteith equation, is widely utilized to estimate the reference evapotranspiration (ET_0) from weather data, which is then adjusted using crop coefficients (K_c) to derive crop evapotranspiration (ET_c). These coefficients account for the specific water needs of different crops at various growth stages, thus providing a tailored irrigation schedule. Additionally, advanced irrigation scheduling tools and decision support systems (DSS) can be adopted to integrate real-time data and predictive models to optimize irrigation practices, thereby promoting sustainable water use and enhancing agricultural

productivity. The integration of IoT and ML in water management, particularly in drought-prone agricultural areas, has yet to be comprehensively explored. Existing studies often focus on either technological advancements or traditional water management techniques, but rarely on a combined approach. This research gap highlights the necessity for innovative solutions to enhance water use efficiency and sustainability.

This study addresses critical aspects of water management through three interconnected parts: a monitoring system for closed underground water bank, the development of virtual soil moisture sensors, and the determination of irrigation requirements. The first part focuses on using IoT technologies to monitor soil moisture, water levels, and temperature, providing real-time data on the aquifer conditions and the efficiency of water banking processes. This data are crucial for informed decision-making and for ensuring the long-term sustainability of groundwater resources in Thailand. The second part aims to solve issues related to the maintenance and recalibration of soil moisture sensors by developing ML models that predict soil moisture accurately, thereby reducing the need for frequent physical maintenance. Finally, the third part involves determining the irrigation requirements for crops such as jasmine flower, date palms, and pomelo fruit using Imjai Organic Garden (Chachoengsao, Thailand) as a real-world case study. The approach integrates crop coefficients with the Penman-Monteith method, optimized water usage, and enhanced agricultural productivity. Through this approach, the study aims to advance precision agriculture and promote more sustainable water management practices in Southeast Asia.

2. Research background and methodology

2.1 Conventional Ground Water Banking (GWB) Systems in Thailand

Thailand, an agrarian nation with approximately 45% of its land dedicated to agriculture, has consistently pursued sustainable agricultural development. For decades, the country has faced recurring issues with both flooding and drought spells, leading to innovative water management solutions inspired by King Rama IX's philosophy of a self-sufficient economy and natural water resources' development. In alignment with this philosophy, the use of groundwater banking, particularly closed underground water banks, has been extensively adopted across the country.

The significant growth of underground water banks in Thailand started in 2020 when local organizations received special grants for the construction, improvement, and management of GWB systems. These projects have focused on capturing and storing excess surface water in strategic locations where water typically accumulates throughout the year. The implementation of closed underground water banks involves the construction of cylindrical or square pits with diameters of 50-60 cm or dimensions of 50×50 cm, and depths ranging from 1.2 to 1.5 m, depending on site-specific

conditions. Each pit is designed to facilitate the infiltration of stagnant surface water into the soil, which maximizes groundwater recharge. The cost of constructing each water bank is approximately \$280 USD (see procedure for GWB construction with IoT system in Supporting information). Figs. 1a-b illustrate conventional GWB systems in Thailand, depicting both open and closed sections with human-made wells. The open section (Fig. 1a) shows a typical well exposed to the environment, relying on natural infiltration processes to recharge groundwater. This traditional approach is simple and cost-effective, but it is susceptible to contamination and significant water loss through evaporation. In contrast, the closed section (Fig. 1b) utilizes high porous materials, which enhances the infiltration process while mitigating the risks associated with surface water contamination and evaporation. This method demonstrates a more controlled and efficient means of recharging groundwater, particularly in regions with variable rainfall patterns and limited surface water storage options.

The integration of high porous materials in closed underground water banks presents a significant advantage in water management technology. These materials facilitate rapid infiltration and storage of excess surface water, ensuring a reliable water supply during dry seasons. Moreover, the closed system minimizes the risk of contamination, thereby maintaining the quality of the stored water. Empirical studies indicate that these water banks can significantly enhance agricultural productivity by providing a stable and clean water source. Figs. 1a-b effectively contrast the two approaches, highlighting the advantages of closed systems in promoting sustainable water resource management. Despite their benefits, the implementation of closed underground water banks in Thailand faces several challenges. One major gap is the lack of comprehensive monitoring systems post-construction for management. Moreover, while significant funding is allocated for the construction of these water banks, there is limited financial support for ongoing monitoring and evaluation. As a result, owners have to bear such subsequent costs. The cost-effective management of these systems requires continuous data collection and analysis, which is often hindered by insufficient resources and technical expertise.

2.2 Groundwater banking systems integrated with IoT

The integration of IoT technologies within GWB systems represents a transformative approach for a more sustainable water management. By implementing IoT-based monitoring systems, it is possible to collect real-time data which ensures continuous monitoring and immediate data transmission, thus facilitating timely interventions and informed decision-making in water collection and usage. A typical IoT system for GWB includes various sensors installed at different depths to measure soil moisture, temperature, and water levels. These sensors transmit data to a central database via Narrowband Internet of Things (NB-IoT) technology, known for its wide coverage and low power consumption and therefore ideal for

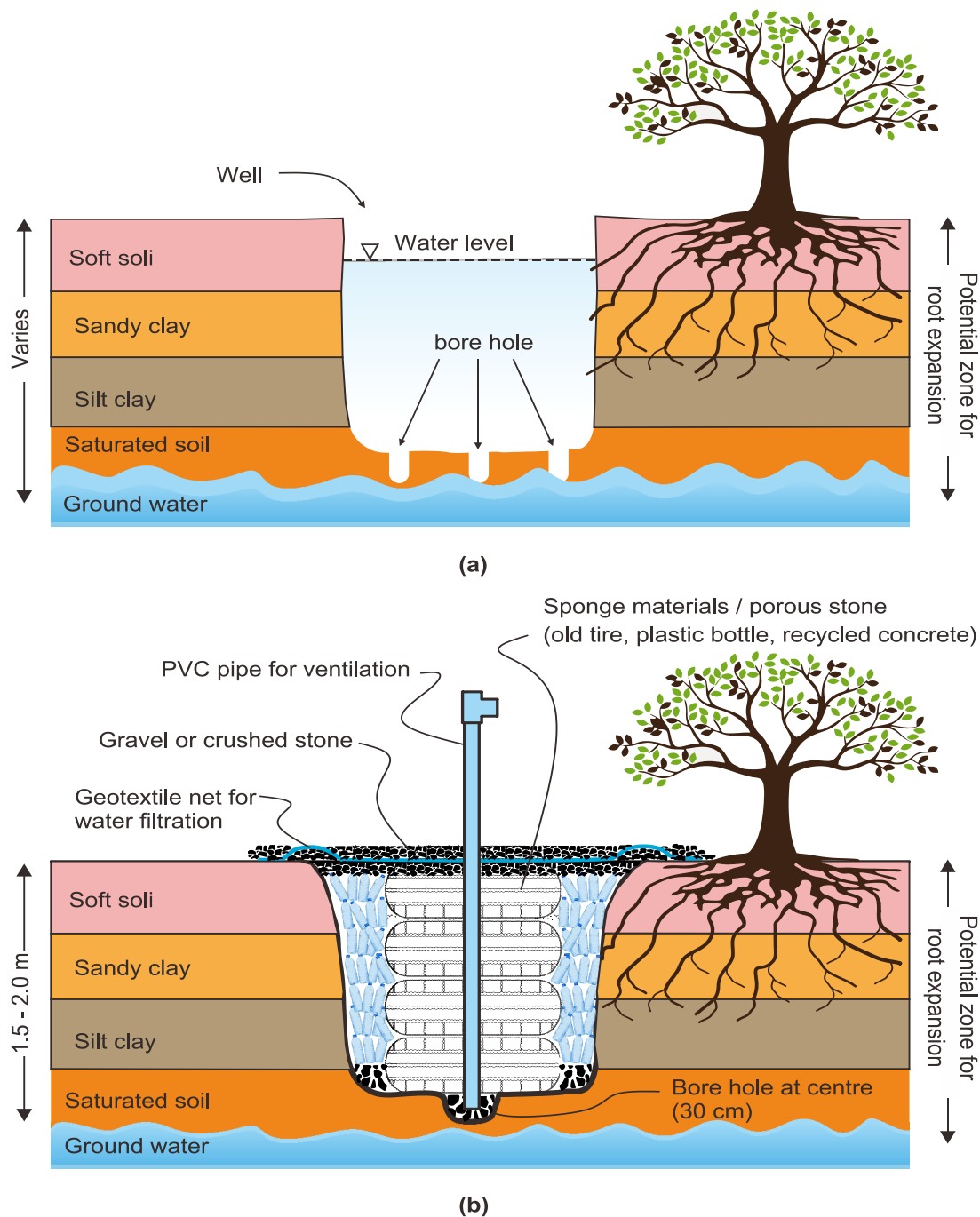


Fig. 1 Conventional GWB systems in Thailand: (a) open section with human-made well, and (b) closed section with human-made well with high porous materials.

remote agricultural settings. The collected data are processed and analyzed to provide real-time insights into the status of the groundwater banks. This integration also allows for the development of virtual soil moisture sensors using ML models such as Linear Regression, Random Forest, and Long Short-Term Memory (LSTM) networks. These models predict soil moisture levels accurately, reducing the need for frequent sensor maintenance and enhancing overall system reliability.

The implementation of an IoT-integrated GWB system can offer numerous benefits. It provides a reliable water source during dry seasons, mitigates flooding by capturing excess rainwater, and reduces water evaporation losses. Additionally,

the system ensures cleaner water supply by preventing surface water contamination. Empirical studies have demonstrated that such systems can significantly improve agricultural productivity and support sustainable water management practices. However, challenges remain, particularly regarding the ongoing monitoring and maintenance of the system. Effective management requires continuous data collection and analysis, which can be hindered by limited resources and technical expertise. Overcoming these challenges is crucial for maximizing the benefits of IoT-integrated groundwater banking systems.

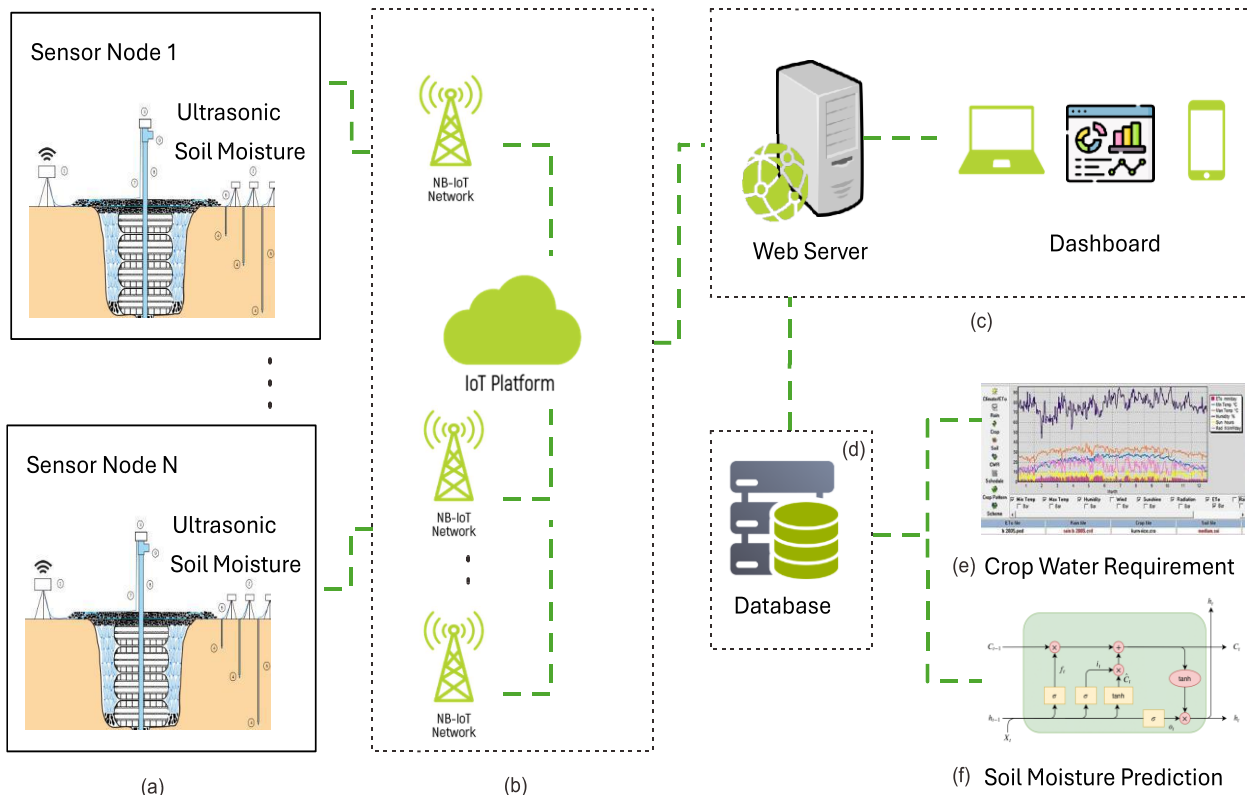


Fig. 2 Research methodology framework of GWB integrated with IoT system optimized via machine learning (ML): (a) underground water bank with IoT sensor, (b) NB-IoT platform, (c) web monitoring system, (d) online database, (e) irrigation requirement, and (f) virtual moisture sensor.

2.3 Design of methodology

2.3.1 Conceptual framework

The conceptual framework adopted to monitor closed underground water banks using advanced sensors and data modeling is shown in Fig. 2. This framework ensures accurate, real-time data collection, analysis, and predictive modeling to enhance water resource management.

The first step involves selecting specific closed underground water banks for monitoring based on strategic criteria such as regional water scarcity, agricultural importance, and existing infrastructure. Each selected water bank has to undergo comprehensive monitoring to gather detailed insights into its performance and effectiveness.

To achieve a robust monitoring, a variety of sensors are installed at each closed underground water bank, including ultrasonic sensors for water level measurement, temperature sensors, and soil moisture sensors. The specific installation details and configurations adopted in this study are outlined in Appendix A. The calibration of soil moisture sensors is then performed to ensure accuracy. Following its installation, each water bank and its associated sensors are registered into a central database. Sensor data are transmitted to the NB-cloud using Narrowband Internet of Things (NB-IoT) technology, which offers superior coverage in Thailand compared to LoRaWAN. This ensures reliable and continuous data transmission even in remote areas. The NB-IoT network facilitates efficient data collection by leveraging its extensive coverage and low power consumption. Collected sensor data

are processed to calculate key variables such as temperature, water level, and soil moisture at various depths. These data points are stored in a central database, enabling real-time monitoring and analysis through a dedicated website. The website interface provides managers with accessible and actionable insights into water bank performance. Finally, a model to predict crop irrigation requirement is developed. This model integrates soil moisture data, soil content properties, raindrop rate, and crop-specific water needs to optimize irrigation practices. By aligning water supply with specific crop demands, the model aims to enhance agricultural productivity and sustainability.

2.3.2 IoT Sensors and field instrumentation

The GWB and IoT installation layout are depicted in Fig. 3a. The measurement devices and the smart measuring system installed in the study area are shown in Figs. 3b-c. Three sensor types are installed, including ultrasonic sensors to measure the water level in the underground water bank, temperature sensors to measure temperature in the experiment site, and soil moisture sensors to measure the soil moisture at different depths. Each sensor is connected to a node device (number 2) which wirelessly communicates with the gateway or master node. This sends out all collected sensor information to the NB-IoT cloud platform. All nodes are powered by solar cells. These data are stored in the cloud system provided by automatic identification systems (AIS). The web server retrieves all sensor information from the cloud and stores it on

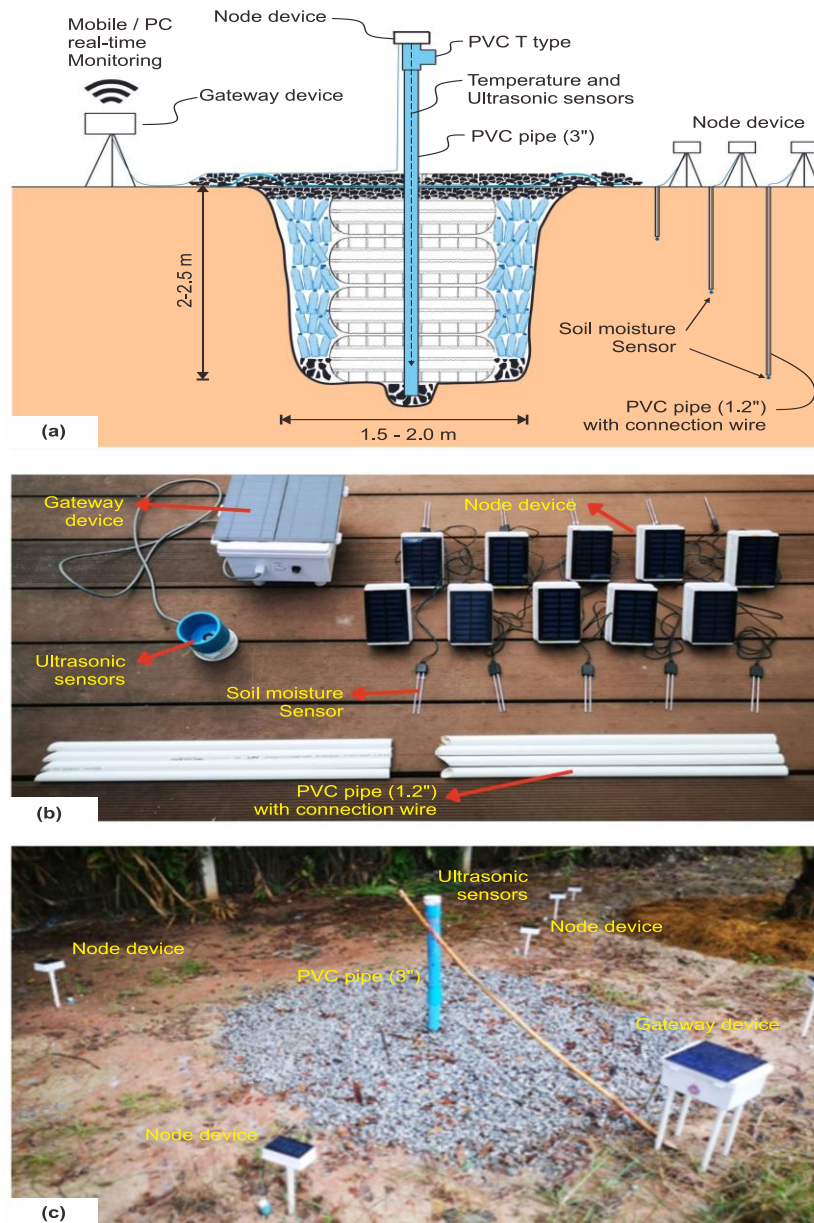


Fig. 3 Example IoT monitoring setup at the site (a) IoT data collecting set, (b) GWB with installed IoT set (Photo taken from Imjai Organic Garden, Chachoengsao, Thailand).

the online database. Users or farmers can monitor the underground water bank information through a web monitoring system.

In scenarios where detailed soil characteristics are not readily available, an alternative approach involves calibrating soil moisture sensors directly based on real-world measurements compared with standard laboratory equipment. This method circumvents the need for extensive soil characterization and instead relies on empirical data collected from field sensors and laboratory equipment. The calibration process begins with the collection of soil moisture data from both the soil moisture sensors deployed in the field and reference laboratory instruments. Field sensors are strategically placed across the study area to capture variations in soil moisture levels at different depths and locations. Simultaneously, standard laboratory equipment, such as

gravimetric or TDR (Time Domain Reflectometry) instruments, is employed to obtain accurate soil moisture measurements for validation purposes.

2.4 Machine learning methods

In this study, various machine learning methods are explored to predict soil moisture levels at different depths, as described below.

2.4.1 Linear regression

Linear regression is a simple and commonly used supervised learning algorithm used for predicting a continuous target variable based on one or more input features. It assumes a linear relationship between the input features and the target variable, as shown in equation 1.

$$\hat{y} = w_0 + w_1x_1 + w_2x_2 + \dots + w_nx_n \quad (1)$$

where \hat{y} is the predicted value, $w_0, w_1, w_2, \dots, w_n$ are the coefficients, and $x_0, x_1, x_2, \dots, x_n$ are the input features. [35]

2.4.2 Random forest

It is an ensemble learning method that constructs a multitude of decision trees during training and outputs the mean prediction of the individual trees. It is robust to overfitting and performs well in a variety of settings, as shown in equation 2.

$$\hat{y} = \frac{1}{N} \sum_{i=1}^N T_i(x) \tag{2}$$

where $T_i(x)$ is the prediction of the i^{th} decision tree. [36]

2.4.3 Support vector regression (SVR)

It is a type of Support Vector Machine (SVM) algorithm used for regression tasks. It works by mapping input features to a higher-dimensional space and finding the hyperplane that maximizes the margin while minimizing errors, as shown in equation 3.

$$\hat{y} = \sum_{i=1}^N \alpha_i \cdot K(x_i, x) + b \tag{3}$$

where α_i are the Lagrange multipliers, $K(x_i, x)$ is the kernel function, and b is the bias term. [37]

2.4.4 Long-short term memory

LSTM is a type of recurrent neural network (RNN) architecture specifically designed to address the vanishing gradient problem in traditional RNNs. It is well-suited for sequence prediction tasks and can capture long-term dependencies in sequential data.

The LSTM architecture comprises multiple layers designed to process sequential data and predict soil moisture at varying depths within the soil profile. The input data consisted of multivariate time series, where each sample represents a sequence of environmental variables observed over a defined period. [37].

The model architecture adopted in this research is shown in Fig. 4.

• **LSTM Layer:** The core of the LSTM model comprises a layer with 50 memory cells or units. These units are augmented with Rectified Linear Unit (ReLU) activation functions, introducing non-linearity into the model and facilitating the capture of intricate temporal patterns inherent in the soil moisture dynamics. The mathematical model of an LSTM cell is defined by the following equations 4-8:

Forget gate decides which information should be discarded from the cell state.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{4}$$

The input gate updates the cell state with new information.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{5}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{6}$$

The output gate controls the cell's output.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{7}$$

$$h_t = o_t \cdot \tanh(C_t) \tag{8}$$

where W_f, W_i, W_C, W_o are the weight matrices, b_f, b_i, b_C, b_o are the bias terms, h_{t-1} is the previous hidden state, and x_t is the input at time step t .

• **Dropout Regularization:** To mitigate overfitting and enhance generalization, a dropout layer with a dropout rate of 0.2 is incorporated following the LSTM layer. This layer randomly drops 20% of the LSTM units during each training epoch, thus promoting robustness and preventing the model from relying too heavily on specific neurons. Mathematically, if y is the output of a layer, the dropout mechanism randomly sets certain outputs to zero as shown in equation 9.

$$\hat{y} = y \cdot m \tag{9}$$

where m is a mask vector where each element is drawn from a Bernoulli distribution with probability $p = 0.8$.

• **Output Layer:** The output layer is implemented as a dense layer comprising 3 units, corresponding to the prediction of soil moisture at depths of 50 cm, 100 cm, and 150 cm. No additional activation function is applied to the output layer, allowing the model to output continuous values directly without imposing further non-linearity. The dense layer computes the following equation 10 for each unit.

$$\hat{y} = W_o \cdot h_t + b_o \tag{10}$$

where \hat{y} is the predicted output, W_o is the weight matrix, and b_o is the bias term.

The LSTM model is trained using the Mean Squared Error (MSE) loss function and then optimized using the Adam optimizer. During training, the model iteratively learns from the input data to minimize the prediction error and improve its ability to forecast soil moisture levels across different depths.

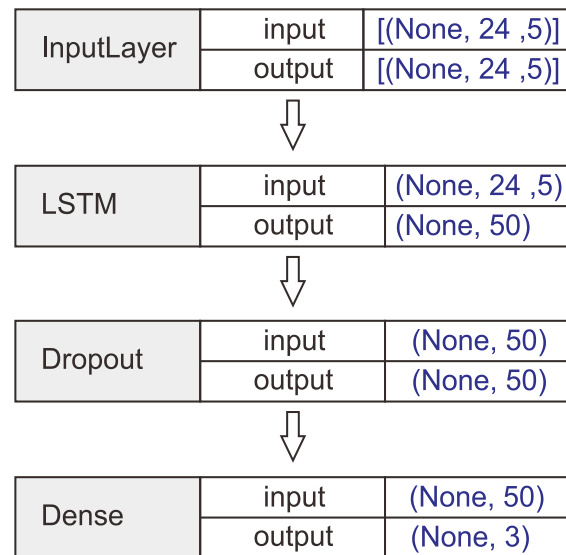


Fig. 4 LSTM model architecture used in this study.

2.5 Model evaluation methods

The following performance metrics are computed for both training and testing phases to gauge the ML models' accuracy, generalization ability, and goodness of fit.

2.5.1 Mean Squared Error (MSE)

MSE measures the average squared difference between the predicted values and the actual values. It provides a measure of the quality of the model's predictions, with lower values indicating better performance. It is calculated as the average

of the squared differences between the predicted \hat{y}_i and actual y_i values for n observations, as shown in equation 11.^[38]

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (11)$$

2.5.2 Root Mean Squared Error (RMSE)

RMSE is the square root of the MSE and provides a measure of the average magnitude of the errors in the predicted values. It is in the same unit as the target variable, making it easier to interpret. It is calculated as the square root of the MSE, as shown in equation 12.^[38]

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (12)$$

2.5.3 R-squared (R^2)

R^2 is a measure of how well the regression model explains the variability in the target variable. It indicates the proportion of the variance in the dependent variable that is predictable from the independent variables. It is calculated as the ratio of the explained variance to the total variance as shown in equation 13.^[38]

$$R^2 = \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (13)$$

where \bar{y} is the mean of the observed values.

2.6 Water requirements estimation

Calculating water requirements for crops based on temperature and soil moisture is a critical aspect of agricultural management. One widely used method for determining these requirements is the Evapotranspiration (ET) method, specifically Reference Evapotranspiration (ET_0).^[34] The FAO's Penman-Monteith and FAO-56 dual crop coefficient method are popular and widely accepted approaches.^[29,39] The Simplified Soil Water Balance Method is used to calculate the water requirement by accounting for the balance between incoming and outgoing water in the soil. This approach considers soil moisture, crop evapotranspiration (ET_c), effective rainfall (P_e) and irrigation requirement (IR).^[29,39] The steps to calculate the water requirement includes:

- (i) Extraterrestrial radiation (R_a) is calculated using the latitude and date.
- (ii) Reference Evapotranspiration (ET_0) is calculated using the Hargreaves-Samani equation, which is suitable for limited data environments. The equation incorporates the mean, maximum, and minimum temperatures along with extraterrestrial radiation as shown in equation 14.

$$ET_0 = 0.0023 \times (T_{mean} + 17.8) \times (T_{max} + T_{min})^{0.5} \times R_a \quad (14)$$

where ET_0 is the reference evapotranspiration (mm/day), T_{mean} is the mean daily temperature, T_{max} is the maximum daily temperature, T_{min} is the minimum daily temperature and R_a is the extraterrestrial radiation (MJ/m²/day).

- (iii) Crop Evapotranspiration (ET_c) is derived by multiplying ET_0 with the crop coefficient (K_c). The K_c values vary with crop type and growth stage as shown in equation 15.

$$ET_c = ET_0 \times K_c \quad (15)$$

where ET_c is the crop evapotranspiration (mm/day), and K_c is the crop coefficient.

- (iv) Effective Rainfall (P_e) is the portion of total rainfall that is available for crop use after accounting for losses such as runoff and deep percolation. Various methods can be used to estimate effective rainfall, including fixed percentage methods, empirical formulas, and more complex hydrological models. Examples of popular methods include USDA's Soil Conservation Service (SCS) and FAO/AGLW Methods. Nonetheless, the use of a fixed percentage, like 80%, is a simplified approach often used in practical applications as shown in equation 16.

$$P_e = P_{total} \times 0.8 \quad (16)$$

where P_e is the effective rainfall (mm), and P_{total} is the total rainfall (mm).

- (v) Soil Water Deficit (SWD) is the amount of water needed to bring soil moisture up to field capacity (FC). To measure FC, it is possible to saturate a soil sample with water, cover it to prevent evaporation, and let it drain for 2-3 days before measuring the moisture content. The permanent wilting point (PWP) is determined by letting the soil dry naturally until plants permanently wilt, then measuring the moisture content of the soil. Alternatively, FC and PWP can be determined using a pressure plate apparatus: FC with a pressure of 0.1 to 0.33 bars, and PWP with a pressure of 15 bars. Then SWD is calculated based on the current soil moisture level, field capacity, and wilting point as shown in equation 17.

$$SWD = \frac{FC - SM}{FC - WP} \quad (17)$$

where SWD is the soil water deficit (dimensionless), FC is the soil moisture content at field capacity (%), SM is the current soil moisture content (%), and WP is the soil moisture content at the wilting point (%)

- (vi) Irrigation Requirement (IR) is calculated by accounting for crop evapotranspiration, effective rainfall, and soil water deficit over the root zone depth, as shown in equation 18.

$$IR = ET_c - P_e + (SWD \times RZ) \quad (18)$$

where IR is the irrigation requirement (mm) and RZ is the depth at which plant roots actively grow and absorb water and nutrients. (mm).

3. Practical implications and performance study

3.1 Study region and drought areas

The primary objective of this study is to implement and monitor groundwater banks utilizing empirical measurement

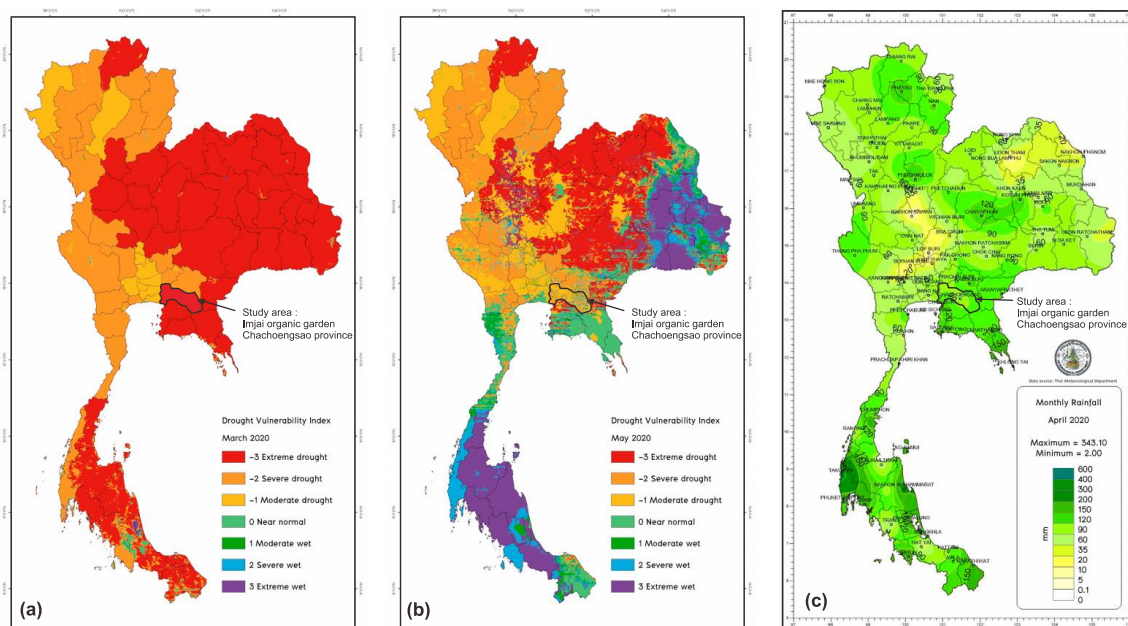


Fig. 5 Thailand's maps from Geo-Informatics and Space Technology Development (a) drought map, (b) flood areas, and (c) monthly rainfall (from website in April 2020: <https://gistda.or.th/>)

data collected from agricultural plots at Imjai Organic Garden in Chachoengsao, Thailand. This region is particularly significant due to its dual challenges of drought and flooding as shown in Figs. 5a-c, making it an ideal location for studying the effectiveness of groundwater banking systems. Chachoengsao has a total area of 3,344,375 rai, of which 2,368,815 rai (70.85%) is agricultural land as of March 2023. Major crops in Chachoengsao include rice, rubber, cassava, oil palm, longan, pineapple, mango, and young coconut.

Imjai Organic Garden, located in Sanam Chai Khet District, Chachoengsao, spans a total area of 15 acres and is renowned for its fully organic cultivation practices (Fig. 6a). The garden is home to three primary crops: jasmine (Fig. 6b), date (Fig. 6c), and pomelo (Fig. 6d). Jasmine occupies 4 acres of the garden, with plants that have been growing for over 7 years. Similarly, dates also cover 4 acres, with a cultivation history of over 7 years. Pomelo, a relatively newer addition to the garden, covers 6 acres and has been cultivated for 3 years (Fig. 6). The garden's organic status and its diverse crop cultivation have made it a popular tourist attraction in Chachoengsao Province. Imjai Organic Garden faces typical agricultural challenges, including variable rainfall, seasonal droughts, and occasional flooding typical of the province.

Chachoengsao Province is located in eastern Thailand. Situated at 19° 11' 31.31" N latitude and 99° 52' 43.79" E longitude, it has an altitude of 380 m above sea level. The province experiences a long rainy season from March to January, but with notable annual rainfall variations. To minimize the effect of these variations, the garden has implemented a Ground Water Bank system integrated with IoT sensors and machine learning models. This advanced system helps in optimizing soil moisture levels, reducing water waste, and ensuring a consistent water supply for the crops all year

round. Annual maximum temperatures in the area range from 33 to 35 °C and minimum temperatures from 21 to 24 °C.

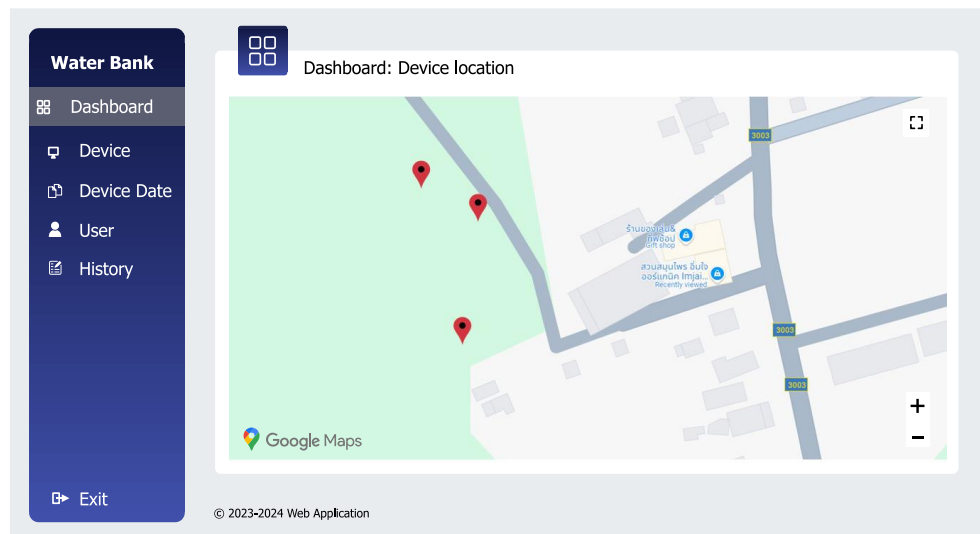
3.2 Soil moisture monitoring and prediction

One of the aims this study is to identify the most suitable ML model for soil moisture content prediction in a GWB located in Imjai Organic Garden. To achieve this, data collected from January 2023 to March 2023 are used here. These data include temperature, water level, and soil moisture measurements.

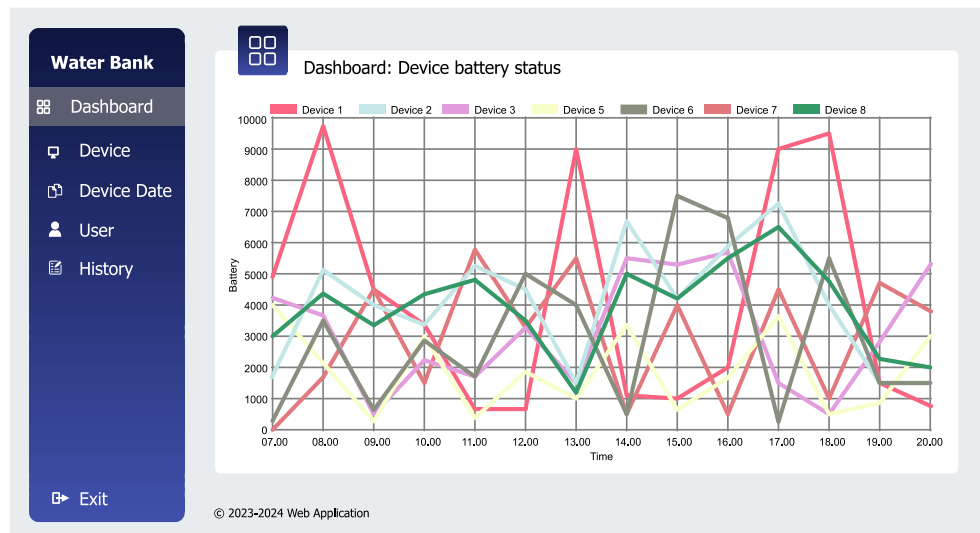
To ensure precise monitoring and data collection, sensors were deployed as reported in Appendix A. These sensors measured temperature, water level, and soil moisture at depths of 50 cm, 100 cm, and 150 cm. At each depth, three soil moisture sensors were also installed to improve measurement accuracy and reliability. This multi-depth and multi-sensor approach is crucial for capturing soil moisture variations across different soil layers, which is essential for effective water management in agriculture. Each sensor node transmits data to a gateway node, which then sends the information to an IoT cloud. This setup facilitates real-time data collection and transmission, ensuring timely and actionable insights. The collected raw sensor and weather data underwent preprocessing to ensure consistency, accuracy, and compatibility with the modeling algorithms. The monitoring system aggregates sensor values by averaging all readings from the three sensors at the same depth into a single value. This method provides a robust and consistent measure of soil moisture levels.

3.2.1 Web-based monitoring system for groundwater banks

The web-based monitoring system implemented in this study is designed to provide real-time and historical data analysis



(a)



(b)

Fig. 7 Web-based dashboard for GWB: (a) device location, and (b) typical real-time monitoring data.

Table 1. Sample data extracted data from online database including ambient temperature, water level in the closed GWB system, soil moisture at different depths.

Time stamp	Temperature (°C)	Water level (cm)	Soil moisture at different depth (%)		
			@ 50cm	@ 100 cm	@ 150 cm
7/9/2023 0:00	27	0	19	24	28
7/9/2023 0:30	28	25	19	24	28
7/9/2023 1:00	28	45	19	24	27
7/9/2023 1:30	27	70	20	25	30
7/9/2023 2:00	27	51	19	25	30
7/9/2023 2:30	27	32	20	24	28
7/9/2023 3:00	27	13	19	25	28
7/9/2023 3:30	27	0	19	24	28
7/9/2023 4:00	27	22	19	24	28
7/9/2023 4:30	26	44	19	25	28
7/9/2023 5:00	26	66	19	26	29
7/9/2023 5:30	27	86	18	24	28

through a user-friendly interface. The sample data stored in the monitoring system, as shown in Table 1, offers valuable insights into the effectiveness of groundwater banks in managing water resources in Chachoengsao. This system can be accessed through a dashboard, as shown in Figs. 7a-b. The dashboard functionality has been thoroughly tested and verified to ensure its reliability and user accessibility. It allows users to view current sensor data and select specific time frames, such as one day, one week, one month, or one year. This feature enables a good understanding of the temperature, water level, and soil moisture variations at the experimental site. By providing both real-time and historical data, the monitoring system facilitates informed decision-making for water resource management.

The dashboard's ability to display data over different periods helps in identifying patterns and trends that are crucial for evaluating the performance of the GWB system in Imjai Organic Garden. Users can easily switch between different data views, gaining insights into short-term fluctuations and long-term trends in environmental conditions. This approach ensures accurate and consistent monitoring of soil moisture, temperature, and water level, allowing for efficient management and assessment of GWB's performance. The robust data collection and visualization capabilities make this system a powerful tool for researchers and practitioners aiming to optimize groundwater management strategies in agriculture.

3.2.2 Soil moisture prediction

Four distinct regression algorithms were considered, as described in section 2.4: Linear Regression, Random Forest,

Support Vector Regression (SVR), and Long Short-Term Memory (LSTM) networks. The study utilizes an 80-20 split approach, where 80% of the preprocessed dataset is used to train the regression models, and the remaining 20% is reserved for testing. This split ensures that the models are trained on a sufficiently large dataset while also providing an independent dataset for evaluating their generalization performance. Each model is trained and tested using the split dataset, with the target variable being soil moisture at depths of 50 cm, 100 cm, and 150 cm.

Performance metrics (see section 2.5) such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2) are computed for both training and testing phases to gauge the models' accuracy, generalization ability, and goodness of fit. The evaluation is conducted separately for each depth to analyze the models' performance across different soil layers.

The performance of these models is shown in Table 2. It is shown that the soil moisture models developed using the collected sensor data demonstrated significant accuracy and reliability in predicting soil moisture levels. The actual sensor data and the virtual sensor calculations from each model are compared in Figs. 8a-d.

The results in Figs. 8a-d indicate that the LSTM network consistently outperforms other models across all depths in terms of MSE, RMSE, and R^2 on both the training and test datasets. Specifically, the LSTM model achieves lower MSE and RMSE values, indicating better predictive accuracy, and higher R^2 values, thus suggesting a better goodness-of-fit to the data compared to Linear Regression, Random Forest, and SVR models. The Random Forest Regressor also

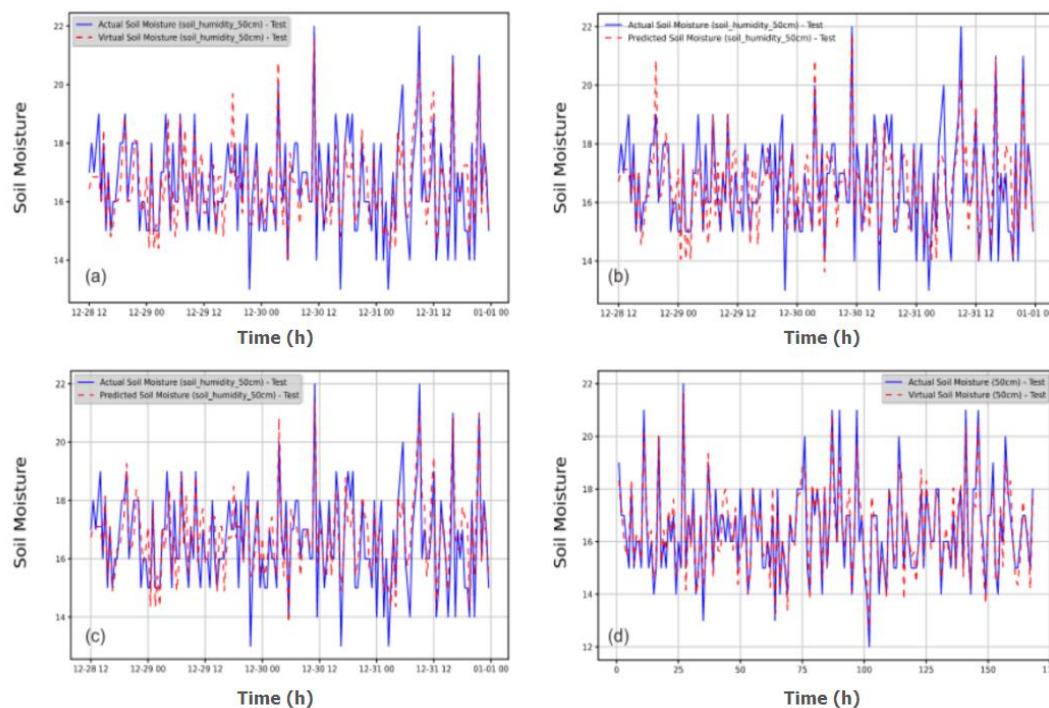


Fig. 8 Comparison of actual and predicted soil moisture at 50 cm depth (a) Linear Regression, (b) Random Forest Regressor, (c) SVR, and (d) LSTM.

Table 2. Comparison of measured soil moisture and predicted values from ML models.

Algorithm	Depth (cm)	Training Dataset			Testing Dataset		
		MSE	RMSE	R^2	MSE	RMSE	R^2
Linear Regression	50	0.0069	0.0832	0.6985	0.0071	0.0843	0.6831
	100	0.0071	0.0841	0.7149	0.0074	0.0859	0.6956
	150	0.0079	0.0888	0.6907	0.0081	0.0901	0.6717
Random Forest	50	0.0051	0.0714	0.7783	0.0056	0.0748	0.7503
	100	0.0049	0.0696	0.8045	0.0053	0.0730	0.7800
	150	0.0054	0.0737	0.7871	0.0059	0.0769	0.7608
Support Vector Regression (SVR)	50	0.0057	0.0752	0.7536	0.0058	0.0758	0.7434
	100	0.0055	0.0741	0.7784	0.0056	0.0750	0.7676
	150	0.0060	0.0776	0.7639	0.0062	0.0786	0.7503
Long Short-Term Memory (LSTM)	50	0.0024	0.0481	0.9032	0.0023	0.0480	0.9038
	100	0.0020	0.443	0.9244	0.0019	0.0439	0.9259
	150	0.0022	0.467	0.9173	0.0021	0.0462	0.9188

demonstrates competitive performance across all metrics, highlighting its robustness in handling non-linear relationships and interactions within the data.

While Linear Regression and SVR exhibit moderate predictive accuracy, they are outperformed by LSTM and Random Forest Regressor in most cases. These findings suggest that the inherent complexities of soil moisture dynamics may not be adequately captured by linear models, necessitating the use of more sophisticated ML approaches. The superior performance of the LSTM model can be attributed to its ability to capture complex temporal dependencies in sequential data, such as time-series soil moisture measurements. By leveraging its recurrent architecture, the LSTM model effectively learns from past observations and temporal patterns, enabling it to make accurate predictions even in the presence of non-linear relationships and noisy data.

When comparing the performance between the training and test datasets, it is observed that all models generally exhibit slightly better performance on the training data compared to the test data, as expected. However, the gap between training and test performance is relatively small, thus indicating that the models effectively generalize to unseen data and do not suffer from significant overfitting.

Furthermore, the LSTM model demonstrates robustness and scalability, exhibiting consistent performance across different soil depths. This suggests that the model's predictive capabilities generalize well to various soil profiles and environmental conditions, making it a versatile tool for soil moisture predictions in diverse agricultural and environmental applications.

In conclusion, the LSTM network emerges as a powerful and promising approach for soil moisture prediction, offering superior accuracy, robustness, and scalability compared to traditional regression and ensemble methods. By leveraging advanced ML techniques and IoT technologies, it is possible to pave the way for sustainable and data-driven approaches in

precision agriculture and environmental monitoring applications.

Future research should focus on further refining these models and exploring ensemble techniques to harness the collective strengths of different algorithms. Additionally, integrating additional environmental variables, such as precipitation, humidity, and solar radiation, could enrich the model's input features and improve its predictive accuracy. Moreover, deploying IoT-enabled sensor networks for real-time data collection and feedback loops could enable adaptive irrigation strategies and proactive management of water resources in dynamic agricultural landscapes.

3.3 Water requirements

This study adopts the Simplified Soil Water Balance Method to determine the irrigation requirements for plantations in Imjai Organic Garden. This experiment focuses on the water requirements of jasmine, date, and pomelo, as their water needs align with the soil moisture data collected at depths of 50 cm, 100 cm, and 150 cm, respectively. To calculate the water requirements for these crops, the experiment utilized the crop coefficient (K_c) values provided by the Irrigation Water Management Research Group, Irrigation Water Management Division, Royal Irrigation Department, Thailand, as shown in Table 3.^[40] The K_c values are essential for estimating crop evapotranspiration (ET_c) from reference evapotranspiration (ET_0) using the Penman-Monteith method. In this case study, the field capacity (FC) and wilting point (WP) from experiment site are set at different depths (i) at 50 cm: $WP = 10.87$, $FC = 21.67$, (ii) at 100 cm: $WP = 14.84$, $FC = 26.19$ and (iii) at 150 cm: $WP = 16.95$, $FC = 29.64$.

The temperature and soil moisture data were collected using IoT sensors. For each day, the maximum, minimum, and average temperatures were calculated, as shown in Fig. 9a. Daily rainfall data were obtained from the Smart Water Operation Center, Bureau of Water Management and Hydrology, Royal Irrigation Department, Thailand. The

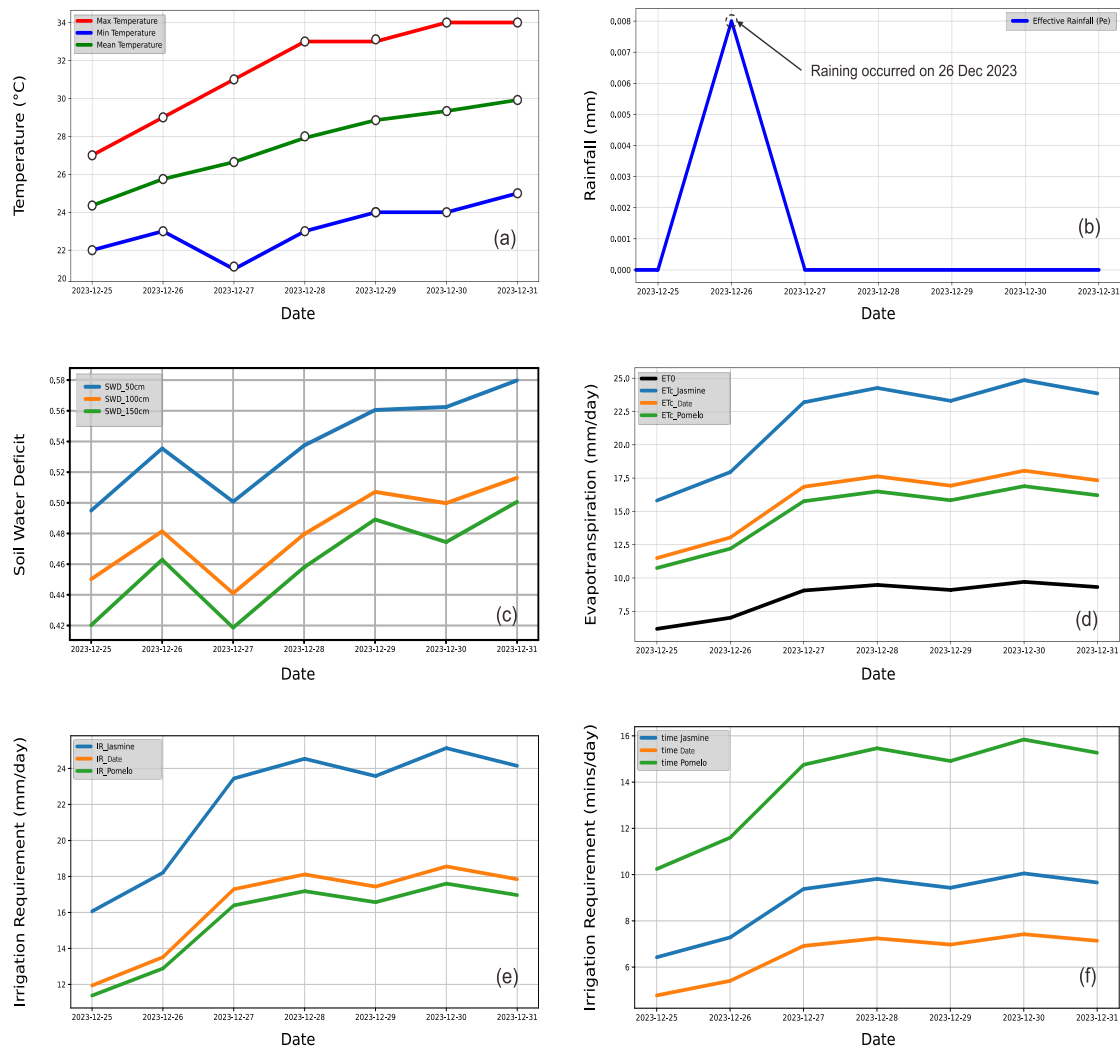


Fig. 9 Field measurement and predicted values for Irrigation Requirement and related variables: (a) max, min and mean temperature, (b) effective rainfall, (c) soil water deficit, (d) ET_0 and ET_c , (e) Irrigation Requirements, and (f) estimated time to water plants.

Table 3. Crop Coefficient (K_c) values for jasmine flower, date palms, and pomelo trees.

Month	Crop Coefficient (K_c) Values		
	Jasmine flower	Date palms	Pomelo fruit
Jan	2.35	2.21	1.62
Feb	1.35	2.02	1.45
Mar	1.49	2.22	1.12
Apr	1.08	1.94	1.02
May	1.84	1.74	1.13
Jun	1.46	1.78	1.97
Jul	0.90	1.96	2.44
Aug	1.74	2.07	2.36
Sep	2.18	2.18	1.97
Oct	2.32	2.18	1.96
Nov	2.19	1.88	1.9
Dec	2.56	1.86	1.74

Note: K_c values provided by the Irrigation Water Management Research Group, Irrigation Water Management Division, Royal Irrigation Department, Thailand.^[40]

effective rainfall was calculated for each day, as illustrated in Fig. 9b. Reference Evapotranspiration and Crop Evapotranspiration were then calculated based on these data, as shown in Fig. 9d. Soil moisture at different depths, along with watering times, was used to calculate the soil water deficit, as shown in Fig. 9c. Likewise, the irrigation requirements (IR) were calculated based on Crop Evapotranspiration and soil water deficit, as shown in Fig. 9e. These IR are calculated in millimeters per day. If each plant requires watering twice a day, the irrigation requirement (IR) can be adjusted by using the available data up until the scheduled watering times. The calculated IR should then be divided by two to reflect the total water needed across both watering sessions.

In Thailand, the standard water flow rate provided by the Metropolitan Waterworks Authority (MWA) is 13 liters per minute. Nonetheless, the water flow rate in agricultural farms may be higher or lower than this value. The water flow rate at the site is 10 liters per minute, or 600 liters per hour. After IR is calculated this value is based on 1 square meter. Therefore, the period of watering plants equals IR times the area of each

plant divided by the water flow rate. For example, the calculated IR for pomelo which uses a plant size 3×3 square meters is 15 millimeters. Therefore, the period of watering pomelo equals $= (15 \text{ millimeters} \times 9 \text{ square meters}) / 10 \text{ liters per minute} = 13.5 \text{ minutes}$. The estimated time to water plants is shown in Fig. 9f. At Imjai Farm, in the absence of rainfall, jasmine flowers, date palms, and pomelo trees require watering for 15, 15, and 25 minutes per day, respectively. In 2023, rainfall was recorded on 92 days, leaving 273 days when irrigation was necessary. Consequently, the total irrigation time for jasmine flowers, date palms, and pomelo trees amounted to 4,095, 4,095, and 6,825 minutes, respectively. However, based on experimental data, the actual irrigation times were reduced to 2,575 minutes for jasmine flowers, 2,943 minutes for date palms, and 5,542 minutes for pomelo trees. This resulted in water savings of 37%, 28%, and 19%, respectively. The results presented in this study indicate that the integration of IoT and ML was effective at managing the GW in the Imjai Organic Garden, Thailand. However, further research is necessary to confirm these findings using other case studies and other data across Southeast Asia. Moreover, the use of other ML algorithms for predicting irrigation requirements is also a matter of future studies. Other types of crops should also be examined in future investigations.

4. Concluding remarks

This study integrates IoT and machine learning (ML) to optimize water management via Groundwater Banking (GWB) in a farm in Chachoengsao, Thailand. By implementing real-time monitoring and predictive modeling, the system enhances irrigation efficiency, reduces maintenance needs, and ensures a sustainable water supply, significantly improving agricultural productivity. Based on this study, the following conclusions can be drawn:

- GBW integrated with IoT and ML improved water usage efficiency by 37%, 28%, and 19% for jasmine flowers, date palms, and pomelo trees, respectively, optimizing irrigation and boosting agricultural productivity through real-time data on soil moisture, temperature, and water levels.
- Virtual soil moisture sensors developed using ML models cut maintenance frequency, ensuring continuous monitoring and accurate soil moisture predictions, enhancing system reliability and cost-effectiveness.
- GBW integrated with IoT system shows a improvement in irrigation efficiency, demonstrating the potential of advanced technologies for sustainable water resource management and enhanced agricultural productivity in variable water availability regions.

Despite the proven benefits of GBW, limited resources and technical expertise for ongoing monitoring and maintenance remain significant challenges, impacting the long-term sustainability and effectiveness of such systems. Future studies should focus on refining ML models, exploring ensemble techniques, and incorporating additional environmental variables like precipitation and humidity. This

will further enhance predictive accuracy and ensure more effective, adaptive water management strategies in precision agriculture, especially in regions with variable water availability.

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Conflict of Interest

There is no conflict of interest.

Supporting Information

Appendix, available at

<https://drive.google.com/file/d/1MOnnjZKATyrTvZWMPgGQUCnM0gC9lMrJA/view?usp=sharing>.

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