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RESEARCH ARTICLE

Machine Learning for Peatland Ground Water Level (GWL) Prediction via IoT System

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ABSTRACT Peatland poses a severe environmental threat due to its potential for massive carbon emission during fires. Conventional Ground Water Level (GWL) monitoring in peatlands is labor-intensive and lacks real-time data, hindering effective management. To address this, this paper proposed an IoT system with neural network-based GWL prediction for real-time monitoring. By using atmospheric parameters, the neural network predicts GWL, allowing extra time for the responsible party to take the appropriate action to reduce the fire risk in peatland. The proposed neural network demonstrates promising results, with a Root Mean Square Error (RMSE) between 3.554 and 4.920, ensuring 99% accuracy within 14.760 mm range of the actual GWL. This finding underscores the novel approach of integrating IoT and neural networks for peatland GWL prediction, offering a significant advancement in real-time monitoring and fire risk mitigation strategies. The novelty lies in its capability to predict real-time GWL even in areas lacking the resources for conventional monitoring, using simple meteorological parameters.

INDEX TERMS Peatland, IoT system, machine learning, neural network, ASEAN, transboundary haze.

I. INTRODUCTION

Peatland are the wetlands whose soils are the accumulation of entirely or partially decayed organic matters. Due to the waterlogged condition in peatlands, the near-continuous soil saturation leads to anaerobic conditions, which subsequently causes slow decomposition [1]. As the production of organic matter surpasses its decomposition, peat accumulation will gradually increase. Therefore, a huge amount of carbon is locked up in peat [2]. Covering approximately 23.6 million hectares, the peatlands in ASEAN represent around 56 percent of global tropical peatlands. As such, the ASEAN peatlands store an estimated 68 billion tons of carbon, which is 14 percent of the global carbon stored in peatland.

Over the past few decades, human interventions, such as logging, deforestation, agricultural drainage, fire-fallow cultivation, and consequently increasing wildfires have turned the carbon-rich peatlands into potential gigantic carbon emitters. The estimated carbon emission is at about 2 billion tons, which represents 5 percent of global fossil fuel emissions. Since the severe fire incidents in 1997/1998, the threat of forest fire in ASEAN peatlands has gained huge interest. The study shows that the large-scale fire in Indonesia has released a massive amount of carbon into the atmosphere, which consequently caused a serious trans-boundary haze to its neighbouring countries, i.e., Malaysia, Singapore, and Thailand [3]. The severe haze pollution has affected millions of people's health, economic losses, disruption of transport and strained the diplomatic relations between the affected ASEAN countries. Besides the huge carbon releases, the situation also caused the widespread loss of unique and valuable peatland biodiversity and ecosystems.

Across the globe, the threat of forest fire is on the rise and responsible for burning over 370 million hectares of forest

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annually on an average basis [4]. To help the affected regions prepare an earlier mitigation plan and advanced warning system for fire management, the Southeast Asia Fire Danger Rating System (FDRS) Project was developed according to the Canadian Forest Fire Danger Rating System. This system can aid in predicting fire behaviour and is taken as a reference for policymakers in developing actions to protect life, property, and the environment. The FDRS is managed by the Malaysian Meteorological Department (METMalaysia) for Southeast Asia.

In Malaysia, the FDRS parameters are predicted according to the interpolated data collected from a pool of national weather stations, which does not necessarily represent the actual local climate in the forest. Furthermore, the FDRS parameters acquired focus mainly on the atmospheric conditions and do not include the ground data, such as GWL or water table, soil temperature and soil moisture. These ground data are very crucial for peatland forest fire planning, and management [5]. Currently, at least 50 percent of the peatland forest are drained with different intensity [6]. Therefore, peatland distribution and management have significantly influenced the insular Southeast Asian fire regions. In this aspect, the most integral approach is water table management. By maintaining a high GWL during the dry season, significant risks can be minimized. The maintaining of GWL can be achieved through drainage ditches blocking in peatland forests and installing and operating water control structures.

However, the lack of workforce to collect in-situ samples for analysis and monitoring purposes can be detrimental to peatland forest management, especially during the epidemic. Ideally, real-time, accurate, and readily accessible meteorological data collection is paramount for this study. To cater to this requirement, the Internet of Things (IoT) technology is the perfect candidate for the peatland management system. LoRA is a low-power wide-area network protocol developed based on spread spectrum modulation techniques for IoT. Our previous work has demonstrated the feasibility of LoRA for mangrove [7] and peatland [8] monitoring with proper tuning of transmission parameters.

With the incorporation of IoT systems, a more intelligent system can be implemented into the peatland forest fire management system. One of the most promising advanced methods in the current technological environment is the neural network. Neural network is a type of artificial intelligence that allows self-learning from collected data and then applies the learned knowledge without human intervention [9]. In our case, the inclusion of a neural network is a very logical and advantageous move because the data collected by the sensors through the IoT system can be learned and improve forest management. This paper has the following main contributions:

- LoRa-based IoT network is deployed in the Raja Musa Forest Reserve (RMFR), Kuala Selangor, Malaysia for peatland forest fire management.
- Accurate hourly data has been collected by the deployed IoT system.
- Performance of different machine and deep learning methods (Linear Regression, Long Short Term Memory (LSTM) and Deep Neural Network (DNN)) are modeled and compared for the water table prediction and timely fire threat warning system.

This project is part of an international initiative where sensory data from peatland sites of three ASEAN countries (Malaysia, Brunei, and Indonesia) are acquired and connected to a central cloud hosted by NICT Japan. This type of IoT-based peatland system could support the integrated management plan for North Selangor Peat Swamp Forest from 2014 to 2023 [10].

Groundwater prediction is pivotal for assessing the risk and management of peatland wildfires, which pose significant environmental and socioeconomic threats. While conventional approaches to groundwater prediction often rely on historical data for model training, our study introduces a novel method that does not require such data. Unlike previous methodologies, which rely on historical groundwater level data [8], our approach utilizes other relevant parameters to directly predict groundwater levels. This innovative methodology not only enhances the accessibility of groundwater prediction models but also broadens their applicability to regions lacking the resources for conventional groundwater monitoring. By eliminating the dependency on historical data, our study offers a groundbreaking solution to the challenges associated with limited groundwater monitoring capabilities in peatland areas. Additionally, our study contributes to the advancement of wildfire risk assessment by providing insights into the performance of various machine learning algorithms specifically tailored for predicting groundwater levels in peatland environments. This unique combination of methodological innovation and localized analysis distinguishes our study as a significant contribution to the field of wildfire risk management, offering promising prospects for improved prediction accuracy in regions vulnerable to peatland wildfires.

II. RELATED WORK

Due to the imminent fire threat on the peatland, especially during the drought seasons, fire detection is a major issue in ASEAN countries. Peatland forest fire not only damages the environment and destroy the diversity of the forest, but it also releases a tremendous amount of carbon into the atmosphere. Therefore, it is critical to achieve early detection or alert system to avoid the devastating consequences of peatland forest fires. Wireless sensor network has gained a lot of popularity due to its technology maturity and flexibility in various applications, such as localization [11], [12], smart transportation and tracking [13], healthcare [14], [15], and industrial automation [16], [17].

Hydrological forecasting, particularly the prediction of groundwater levels, plays a pivotal role in water resource management, especially in regions characterized by unique environmental conditions such as tropical peatlands. Recent studies have showcased the efficacy of machine learning algorithms in enhancing the accuracy and reliability of groundwater level predictions. For instance, Hikouei et al. [18] utilized machine learning algorithms to predict groundwater levels in Indonesian tropical peatlands, demonstrating the feasibility of employing advanced computational techniques in complex hydrological systems. Furthermore, Burgan [19] conducted a comparative analysis of various artificial neural network (ANN) algorithms and Multiple Linear Regression for daily stream-flow prediction in the Kocasu River, Turkey. Their findings underscored the superiority of ANN models in capturing the nonlinear relationships inherent in hydrological processes, thereby improving forecasting accuracy. Additionally, Lendzioch et al. [20] demonstrated the utility of UAV monitoring and machine learning in mapping groundwater levels and soil moisture in a montane peat bog. By leveraging remote sensing technology and advanced data analytics, they provided valuable insights into the spatiotemporal dynamics of groundwater resources, facilitating informed decision-making in water management practices.

To achieve timely and reliable detection, wireless sensor network has been implemented into the forest management system. In [21], the author has proposed a novel approach for fire detection in mines by using a network of sensors called WMSS. On the other hand, Chiwewe et al. [22] suggested a Zigbee-based WSN for fire detection in remote forest areas. In this project, temperature sensors are used to measure the atmospheric temperature to examine fire intensity in the forest. For improvement of accuracy, the author in [23] incorporated both multi-sensors and cameras in the WSN to avoid false alarms. More recently, Okafor and Delaney [24] proposed a system that enables the cost-efficient collection, curation, and processing of data in peatland areas through IoT-based autonomous sensing. Cui [25] proposed the use of smart sensors and convolution neural network (CNN) to monitor the forest and predict abnormality. Overall, it is well-documented that the IoT system is a viable technology for ecological sensing in remote areas such as peatland forests.

For peatland management in ASEAN peatland forests, IoT systems have been developed by Li et al. [8] and Essa et al. [26] for Malaysia and Indonesia, respectively. Li et al. [8] have developed ground sensors using IoT technology to improve the water table management at the peatland of Malaysia. Measuring instruments such as piezometers are stationed on-site for real-time sensing to clearly understand the water table while encouraging effective water table management. On the other hand, Essa et al. [26] used LoRa network to collect environmental parameters, such as soil and water temperature, soil moisture, water table and atmospheric humidity. The data collected will be displayed on a dashboard and accessible by respective agencies. Similar to Essa et al. [26], Li et al. [27], [28] and Liew et al. [29] also deployed an IoT system in peatland in Malaysia to monitor both ground data and atmospheric data.

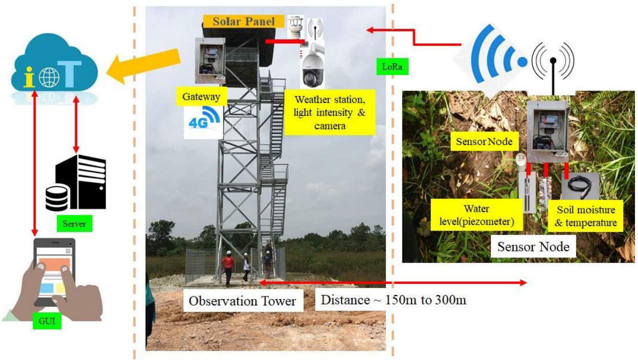


FIGURE 1. IoT-based peatland forest monitoring system.

These successful implementations of IoT systems for peatland management in ASEAN regions have demonstrated IoT technology's feasibility and compatibility in this context. Nevertheless, the full potential of IoT system for peatland management has not been achieved. None of the literature has detailed how the information collected by IoT systems can help refine peatland management. Over the last decades, the development of artificial intelligence, especially neural network has been staggering, with its application extended into different applications due to its unparallel learning and prediction capability. Early detection and warning system are essential for peatland management to mitigate and avoid the damage caused by forest fires. Therefore, artificial intelligence can play a massive role in peatland management.

This paper proposed an IoT system for peatland forest management in Malaysia. The IoT system deployed ground sensors and weather station to measure in-situ ground level and atmospheric parameters. Furthermore, the data collected will be fed into a neural network model to process the knowledge learnt to produce a prediction model for peatland management. This prediction model allows for early detection of water table using previous day water table information. Therefore, the risk of peatland fire can be reduced substantially.

III. METHODOLOGY

This section mainly introduces the deployment of IoT systems and the setting of machine learning for predicting the groundwater level of peatlands.

A. IoT-BASED PEATLAND MANAGEMENT SYSTEM

Figure. 1 shows the setup of the IoT system deployed at Raja Musa Forest Reserve (RMFR), Kuala Selangor, Malaysia for peatland forest management and monitoring system. This forest is selected as the study site for its forest fire incidents history, such as the fire during 98-El-Nino in 1998, and forest fires in 2000, 2005, and 2017 [5].

In this IoT system, two ground sensors are deployed to measure soil temperature, moisture, and water table. The two ground sensors are linked to a gateway via LoRa access technology. Apart from the data from ground sensors, the

FIGURE 2. LoRa gateway installed on top of the observation tower.

weather station is used to measure the atmospheric parameters. Similarly, the data collected by the weather station will be transmitted to the gateway. Figure 2. shows the LoRa gateway installed on top of the observation tower. Therefore, the LoRa gateway is an in-situ data aggregation point at the forest site. Then, the peatland data at the gateway is sent to the cloud using 4G cellular infrastructure. The cloud server is hosted by NICT Japan for dashboard implementation and remains accessible to the local community and forest management stakeholders.

The transmission range of LoRa depends on the propagation condition [30]. In this case, the LoRa signal is heavily distorted by the peatland foliage (approx. 2-10 meters in height and of various densities). Therefore, the gateway is installed on top of the observation tower with approximately 25 meters of height above the ground level, as illustrated in Figure 1. All the equipment at the observation tower is solar powered, while the ground sensors are battery-powered. To ensure the health of the ground sensors, the battery status and its communication parameters such as received signal strength indicator (RSSI) and signal to noise ratio (SNR) are sent to the gateway along with the collected data for ease of device monitoring.

Figure 3. shows the layout plan of the IoT-based peatland monitoring and management system deployed at RMFR. The observation tower has a latitude and longitude of (3.46595°, 101.441388°). The first ground sensor node (SN1) is located around 174 m to the west of the observation tower. The second ground sensor node (SN2) is located around 262 m to the southwest of the observation tower. Geographically, SN2 is 200 m to the south of SN1 to represent the readings at a lower gradient. To the north of SN1, there is a man-made water canal parallel to the access road. In comparison, SN2 is located deeper into the peatland.

The GWL or water table is measured using a piezometer of the ground sensor node. Prior to installing the piezometer, the borehole is prepared for the fixing of UPVC pipe. The UPVC pipe is terminated down to the mineral soil later with approximately 5.26 m depth as illustrated in Figure 4. The deep penetration into the ground ensures that the measured water level is the actual water table within the peat layer.

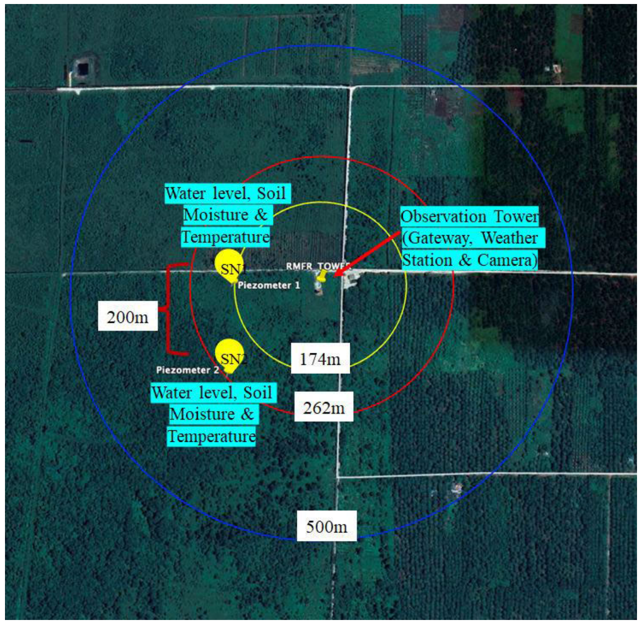


FIGURE 3. Layout plan of IoT-based peatland monitoring system.

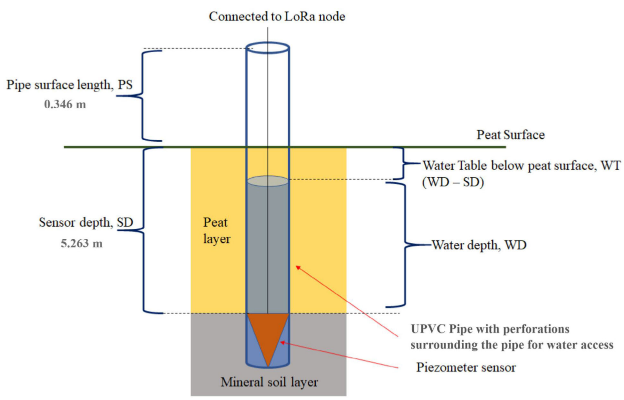


FIGURE 4. Piezometer for ground water level.

To protect the boreholes from wild animals, the perimeter is guarded with a 1-meter height fence. The weather station is installed at the observation tower to provide local atmospheric data, including the parameters required to derive FDRS (i.e., air temperature and humidity, wind speed, and precipitation). A closed-circuit television camera (CCTV) is installed at the observation tower to protect the area and the equipment.

In assembling the components of the system, a meticulous approach was undertaken to ensure optimal functionality and cost-effectiveness. The piezometer, a critical element in the setup, was carefully integrated into the system. Due to budget constraints, specific components were procured rather than complete systems, enabling tailoring the setup to the requirements. This approach allowed achieving the desired performance while adhering to budgetary limitations. The assembly process involved meticulous attention to detail and rigorous testing to ensure the reliability and accuracy of the system.

The sensors utilized in this study play a pivotal role in monitoring peatland groundwater levels. These sensors, readily available commercially, encompass a range of parameters crucial for comprehensive data collection, including air humidity, temperature, wind speed, precipitation, and UV radiation. The data gathered by these sensors are transmitted via LoRa antennas positioned on sensor nodes to LoRa gateway. Subsequently, utilizing 4G connectivity, the data are relayed to servers for storage and analysis, facilitating accessibility and usability for academic research endeavors. This integrated sensor network offers a robust framework for real-time monitoring and analysis, contributing to advancements in peatland management and environmental research.

B. MACHINE LEARNING FOR GWL PREDICTION

In certain regions where direct measurement of groundwater levels is impractical or unattainable due to various constraints, alternative approaches leveraging easily measurable parameters offer a promising solution for groundwater prediction. Parameters such as atmospheric temperature, humidity, wind speed, and precipitation serve as viable substitutes and can be readily obtained even in resource-constrained areas.

The selection of these parameters was a result of extensive consultations and discussions with multiple experts from the Malaysian Meteorological Department and Fire and Rescue Department. Their collective insights and expertise guided the decision-making process, ensuring that the chosen parameters were not only accessible but also highly relevant for accurate groundwater level prediction. This collaborative effort underscored the importance of interdisciplinary cooperation in developing practical solutions tailored to specific regional challenges. By adopting this approach, our study aims to empower regions lacking the means for traditional groundwater monitoring with a reliable and accessible method for predicting groundwater levels.

This section describes the work on modelling and predicting the GWL at peatland based on five atmospheric-based Fire Danger Rating System (FDRS) input parameters: air temperature, humidity, rain and wind speed. These parameters are chosen because they provide backward compatibility with existing sensory infrastructure since most weather stations are equipped with the relevant sensors. In addition, we compare the prediction results with an additional parameter of UV Radiation.

It is of paramount importance to highlight that the GWL cannot be predicted directly from the listed input parameters since its value at an instance of time, t is also a function at the previous instance of time t - 1. Thus, in this paper, we predicted its relative value Δwater level$_{\text{ij}}$ (i.e., the difference of water levels for two consecutive instances) in order to arrive at the intended objectives:

$$\Delta \text{water level}_{ij} = \text{water level}_i - \text{water level}_j \qquad (1)$$

Figure 5. describes the overall system framework. The hourly time interval was chosen in this study as it provides for a richer dataset yet without being too sensitive to noises. All the parameters were preprocessed and represented based on their mean values except for the rainfall information, which is based on the total accumulated precipitation listed in Table 1.

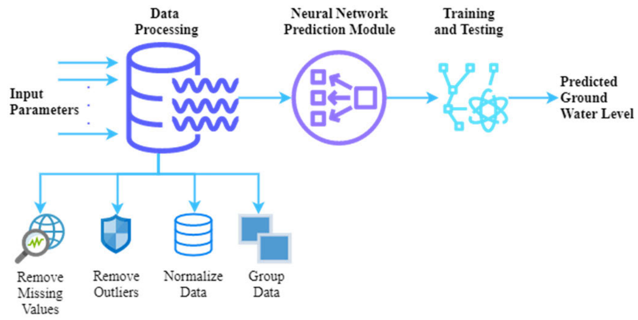


FIGURE 5. Neural network based prediction framework.

TABLE 1. Input and output data in an hour.

Input Parameter	Output Parameter
Mean air humidity (*%RH*) Mean air temperature ($\circ C$) Mean wind speed (*m/s*) Hourly accumulated precipitation (*mm*) Mean UV Radiation (W/m^2)	Mean relative water level (*mm*)

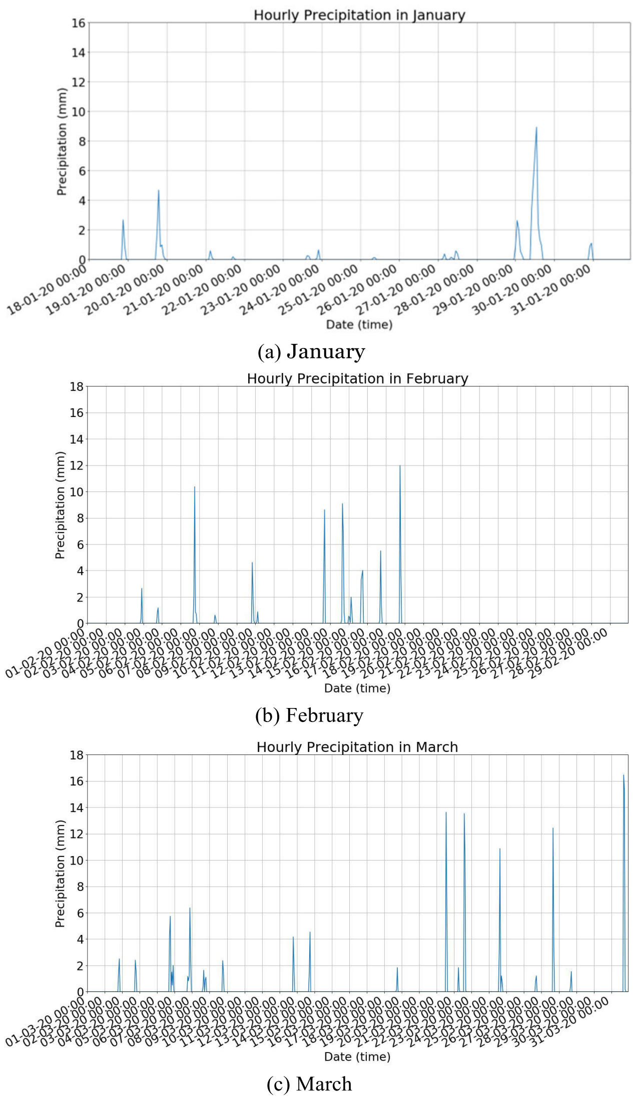
As a critical parameter for the prediction framework, the accumulated precipitation or rainfall collected by the system is illustrated in Figure 6. The data was collected from mid-January until the end of March, during the northeast monsoon. Northeast monsoon brings much heavy rain to peninsular Malaysia [31]. Therefore, the weather station recorded multiple instances of hourly precipitation exceeding 2 mm per hour. The mean hourly precipitation of peninsular Malaysia is around 0.276 mm per hour, according to Malaysia Meteorological Department [32].

Figure 6 depicts hourly precipitation data for January, February, and March, presented in three separate subplots. Each subplot illustrates the precipitation levels recorded over the respective months, with the vertical axis representing precipitation measured in millimeters and the horizontal axis denoting time. The time axis is divided into daily increments, with timestamps provided to indicate each day throughout the months under consideration. By visualizing the temporal distribution of precipitation, the figure facilitates an understanding of the variability and trends in rainfall patterns over the three-month period. This information is vital for assessing the impact of precipitation on groundwater levels and, consequently, for enhancing the accuracy of predictive models used in peatland fire management.

Table 2 describes the statistical summary of the data used in the study. Due to the extreme value characteristic showed by accumulated precipitation, a Gumbel distribution for the hourly precipitation was plotted in Figure 7. As noticed from

TABLE 2. **Statistical summary of the data.**

Parameter	Mean Humidity (%)	Mean temperature (℃)	Mean Wind Speed (m/s)	Accumulated Precipitation (mm)	Mean UV Radiation (W/m^2)	Mean relative water level at sensor node 1 (mm)	Mean relative water level at sensor node 2 (mm)
Mean	81.0675	24.6338	148693	0.2499	8.5377	2.1872e-02	0.0331
Std. dev.	14.8149	3.6025	0.7305	1.9269	11.3295	6.7542	7.0907
Minimum	39.5342	21.8106	0.0291	0.0000	0.0000	-0.18499	-15.7343
25%	68.5620	24.6338	0.6060	0.0000	3.6734e-41	-2.5226	-2.6782
50%	86.8717	26.4309	0.9753	0.0000	0.0547	-1.1400e-13	-0.6695
75%	94.1939	31.0916	1.5355	0.0000	17.1955	2.1022	1.6739
Maximum	98.4144	36.0589	6.1425	36.6833	37.3933	83.0776	87.0411



(a) January

(b) February

(c) March

FIGURE 6. **Hourly precipitation recorded.**

the graph, the distribution of the hourly accumulated precipitation is heavily focused around 0 to 3 mm. As a result, the mean and variance of the left-skewed Gumbel distribution

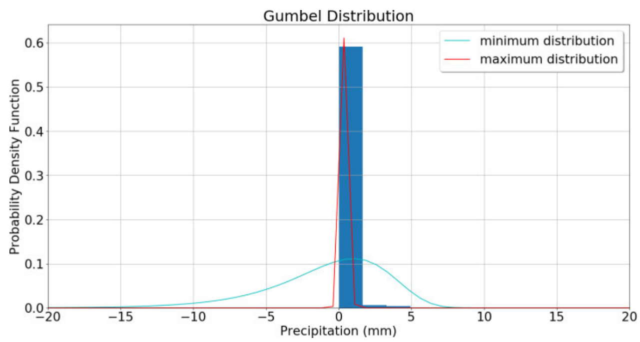


FIGURE 7. **Gumbel distribution of hourly precipitation.**

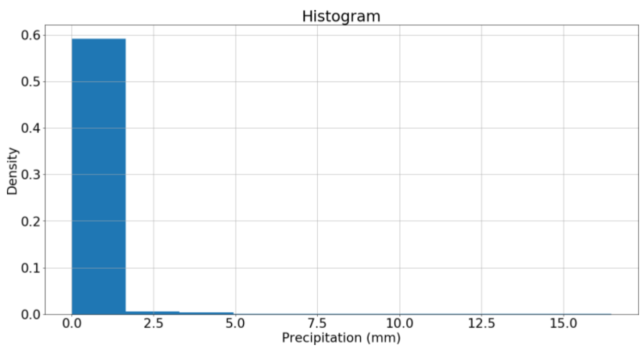


FIGURE 8. **Histogram of hourly precipitation.**

(minimum) are 1.032 and 3.299, respectively. The mean and variance of the right-skewed Gumbel distribution (maximum distribution) are 0.010 and 0.168, respectively.

Figure 8 shows the histogram of the hourly accumulated precipitation with its density. In the context of the histogram illustrating the hourly accumulated precipitation data, the density indicates the probability of observing a certain amount of precipitation within each interval. Therefore, it accurately reflects the distribution of precipitation levels across the dataset. The observation further fortified the status of accumulated precipitation as extreme value distribution, where approximately 59 percent of the data points recorded 0-2 mm of hourly precipitation. Therefore, a generalization

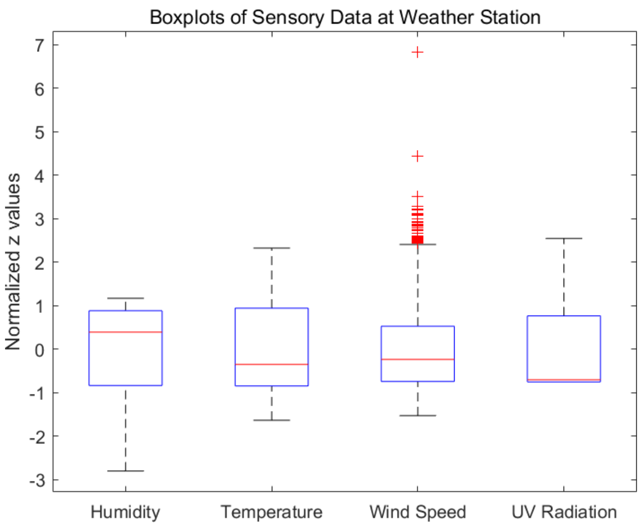


FIGURE 9. Boxplot of data used.

or normalization process is required prior to feeding the data to the neural network.

Table 2 describes the statistical summary of the data used in the study. Since the data ranges is not uniform and that some values are too small across all the parameters, data was then normalized based on the z-score values as such:

$$\Delta z - score = \frac{x - \mu}{\delta} \tag{2}$$

Z-score normalization, also known as standardization, is a statistical method commonly used to transform numerical data by scaling and centering it around a mean of 0 and a standard deviation of 1. When the normalized values are negative, it indicates that the original feature values are below the mean, whereas values greater than 1 or less than -1 suggest that the feature's values are relatively large or small compared to the mean, respectively. The absence of units in the normalized results is because they represent the extent of deviation of data points from the mean of the feature, rather than specific physical quantities. This normalization technique allows for fair comparisons between different features by removing the scale and location effects inherent in the original data. In summary, Z-score normalization provides a standardized framework for assessing the relative magnitude of feature values within a dataset, facilitating comparisons and interpretations across variables.

The data used are plotted in the form of box-plot in Figure 9. after z-score normalization. In addition, the scatter plots for input and output parameters were plotted, and their r Pearson Correlations were investigated and discussed in the later section. This leads to the machine learning model's design and development, which performs regression on the data.

C. LINEAR REGRESSION

The first machine learning model considered in this work is the machine learning model using Linear Regression. It is a simple supervised machine learning algorithm that predicts the output or dependent variable for a given set of input or independent variables through effectively modelling their linear relationship. It is used in this work for its ease of implementation and efficiency to train [33].

The dependent and independent variables used in this study are depicted in Table 1. Machine learning does not perform well with inputs with different scales, as observed from Table 2. Therefore, a transformation of feature scaling using a standard scaler is performed prior to the training process.

In the context of this study, the utilization of linear regression as a predictive model warrants elucidation. Despite its inherent limitations in capturing the non-linear dynamics of hydrological processes [34], linear regression serves a vital role in the methodological framework of this research. The decision to incorporate linear regression alongside other machine learning algorithms stems from its interpretability, simplicity, and comparative utility. Linear regression offers a transparent and comprehensible approach to modeling groundwater level fluctuations [35], enabling straightforward interpretation of coefficients and their respective impacts on the predicted outcome. This attribute is particularly advantageous in scenarios where stakeholders, such as policymakers and local communities, seek intuitive insights into the factors influencing groundwater dynamics. Additionally, linear regression facilitates a parsimonious representation of the underlying data-generating process [36], requiring fewer assumptions and parameters compared to its non-linear counterparts. This parsimony is conducive to efficient model training and inference, particularly in resource-constrained settings where computational resources may be limited.

While acknowledging the inherent limitations of linear regression in capturing the intricacies of groundwater dynamics, its inclusion in the modeling framework underscores a pragmatic approach to predictive modeling. By striking a balance between interpretability and predictive performance, linear regression complements the repertoire of machine learning methodologies employed in this study, thereby enriching the analytical toolkit available for groundwater level forecasting. It is important to note that LR's role in the research methodology is not intended to provide definitive predictions but rather to serve as a reference point for evaluating the efficacy of more complex modeling approaches. Through this nuanced approach, the research endeavors to contribute meaningfully to the discourse on predictive modeling in hydrology, fostering a more comprehensive understanding of the strengths and limitations of different methodologies in addressing real-world challenges.

D. LONG SHORT TERM MEMORY

The IoT system collects the data hourly, so it is a sequence of discrete-time data. Long Short Term Memory (LSTM) is well-suited for predicting time series data. It is a type of recurrent neural network (RNN) capable of recognizing patterns in the sequence of data.

In this study, the LSTM model has 5 neurons, 1 hidden layer and 1 output for predicted relative water level. MSE loss function and Adam stochastic gradient optimizer are used with a learning rate of 0.01. The look back, number of previous time steps used as input is 1. Hence, the dataset is created with X being the features at a given time (t), and Y is the relative water level at the subsequent time ($t + 1$).

The utilization of hourly data in this study is predicated upon the nuanced dynamics of groundwater behavior in peatland ecosystems, where rapid changes in environmental conditions can have profound implications for groundwater levels. Hourly data acquisition facilitates a granular examination of temporal variations in key parameters, offering unparalleled insights into the intricate interplay between hydrological processes and environmental factors. Moreover, the high-temporal-resolution dataset enables the detection of subtle fluctuations and transient phenomena that may be imperceptible at coarser temporal scales. By capturing the transient responses of groundwater systems to short-term meteorological events, hourly data provides a comprehensive understanding of groundwater dynamics, essential for accurate prediction and effective management of peatland ecosystems. Furthermore, the use of hourly data aligns with the evolving demands of hydrological research, emphasizing the need for high-temporal-resolution datasets to capture the complex interactions shaping hydrological processes. Consequently, the adoption of hourly data represents a methodological advancement in groundwater research, offering unprecedented opportunities to refine predictive models and enhance our understanding of peatland hydrology.

E. NEURAL NETWORK ARCHITECTURE

In this study, the number of hidden neutrons at each layer is kept fixed based on the number of input parameters. In other words, when we use all 4 FRDS input parameters (i.e., air temperature, humidity, rain and wind speed), the number of hidden neurons remain at 4. Whereas when we add another input parameter, UV Radiation, the number of hidden neurons remains 5.

This study uses a fully connected dense layer throughout the whole network. The dense layer is chosen mainly because the stacking of dense non-linear layers can create a higher order of polynomials. Thus, the dense layer can allow for modelling more complex mathematical model. The number of hidden layers is varied from 1 to 3 hidden layers and the performance is compared for all three setups. The network comprises only linear activation functions that are easy to train and effective for regression problems. The activation function used in the neural network is Rectified Linear Unit (ReLU). The adaptive moment estimation Adam algorithm is applied as the optimization technique to update the neural network weights throughout the whole network based on the mean square error as its performance parameter. Similar to the LSTM, a learning rate of 0.01 and MSE loss function is employed. Figure 10 illustrates the neural network topology for 5 inputs and 3 hidden layers used in this study.

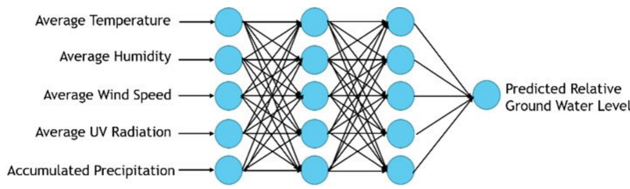


FIGURE 10. Example of a 5 inputs and 3 layers neural network topology.

TABLE 3. Distribution of data set.

Category	Total number of samples	Description
Training data set	1424	Further divided into 4 folds. Used to build regression model.
Validation data set	356	Used to validate the performance of the system

The neural network architecture utilized in this study plays a crucial role in modeling the complex relationships between input parameters and groundwater levels in peatland environments. The number of hidden neurons in each layer is tailored to accommodate the varying number of input parameters, ensuring adaptability and efficiency in the model's representation. By employing fully connected dense layers, we leverage the capacity of neural networks to capture intricate patterns and nonlinearities in the data, thereby enhancing the model's predictive capabilities. The utilization of Rectified Linear Unit (ReLU) activation functions and the Adam optimization algorithm further optimizes the network's performance, facilitating robust training and convergence. Additionally, the exploration of different configurations, ranging from one to three hidden layers, allows for a comprehensive evaluation of model performance. The depicted neural network topology exemplifies the intricate architecture employed in this study, showcasing its capacity to handle multiple inputs and hidden layers effectively. Overall, the tailored neural network architecture serves as a powerful tool for accurate groundwater level prediction in peatland environments, contributing to advancements in environmental monitoring and management.

F. EXPERIMENTAL SETUPS

In this study, a total of 1780 hourly samples collected across 72 days were used as shown in Table 3. In order to provide for more objective observation, the samples were randomly shuffled before they were divided into two sets, namely training and validation sets based on the 4:1 ratio. The training data set was used to build the machine learning model, LSTM model and neural network-based regression model. The training data set is further divided into 4 folds for the neural network. Here, the model accuracy is reported in its Root Mean Square Error (RMSE) to measure the difference between predicted and actual values. Finally, the model is tested on the remaining validation data set to arrive at an objective observation on its accuracy. Since the nature of neural network produces different performance due to random weights management, in this study, the simulations are repeated for ten runs for each setup, and the mean RMSE are reported.

G. LIMITATIONS AND CHALLENGES

In this study, several challenges and limitations were encountered, necessitating comprehensive recognition and resolution. Firstly, in peatland forest areas, the deployment of IoT systems faces difficulties in vehicular access due to the complex terrain and limited transportation routes. This hampers the installation and maintenance of equipment, posing logistical challenges. Secondly, sensor nodes are susceptible to damage by wildlife, such as monkeys, potentially leading to data collection instability and unreliability. Additionally, the current research exhibits localized characteristics and lacks universal validation. To further generalize the research findings, it is imperative to deploy more IoT systems in diverse regions for comprehensive analysis. However, this necessitates additional project funding to address the high costs associated with equipment procurement, deployment, and maintenance. Therefore, it is crucial to recognize these challenges and limitations and take appropriate measures to ensure the sustainability and success of the research endeavor.

IV. RESULTS AND DISCUSSION

Understanding the correlation between groundwater level, temperature, humidity, rainfall, wind speed, and solar radiation is crucial for accurate prediction of peatland wildfires. Groundwater level serves as a key indicator of peat moisture content, directly influencing fire susceptibility. Higher groundwater levels indicate a saturated peat substrate, reducing the risk of ignition and spread. Conversely, lower groundwater levels result in drier peat, increasing fire susceptibility. Temperature and humidity affect the rate of peat moisture loss, with higher temperatures and lower humidity levels accelerating evaporation and desiccation of peat. Rainfall replenishes soil moisture, mitigating fire risk by increasing groundwater levels and peat moisture content. Wind speed influences fire spread by facilitating oxygen supply and promoting rapid fire propagation. Solar radiation contributes to peat drying by evaporating surface moisture. Understanding the interplay between these parameters provides valuable insights into peatland fire dynamics, enabling more effective wildfire prediction and management strategies.

Prior to modelling, a statistical study is performed between the normalized input and output data as illustrated by all the scatter plots in Figure 11 (a)-(e). Pearson correlation coefficients of the data are tabulated in Table 4. Scatter plot shows the relationship between two variables effectively and allows quick identification of dominant variable(s) prior to the machine learning process.

Ideally, two variables that are highly correlated should be represented by an almost linear diagonal line in scatter plots and produce Pearson correlation coefficient r close to ± 1.

TABLE 4. Pearson correlation coefficients, *R*.

Parameters	Mean Relative Water Level at Sensor Node 1	Mean Relative Water Level at Sensor Node 2
Mean Humidity	0.13	0.20
Mean Temperature	-0.13	-0.20
Mean Wind Speed	0.28	0.22
Accumulated Precipitation	0.72	0.79
Mean UV Radiation	-0.22	-0.26

TABLE 5. Test score RMSE of different ML model.

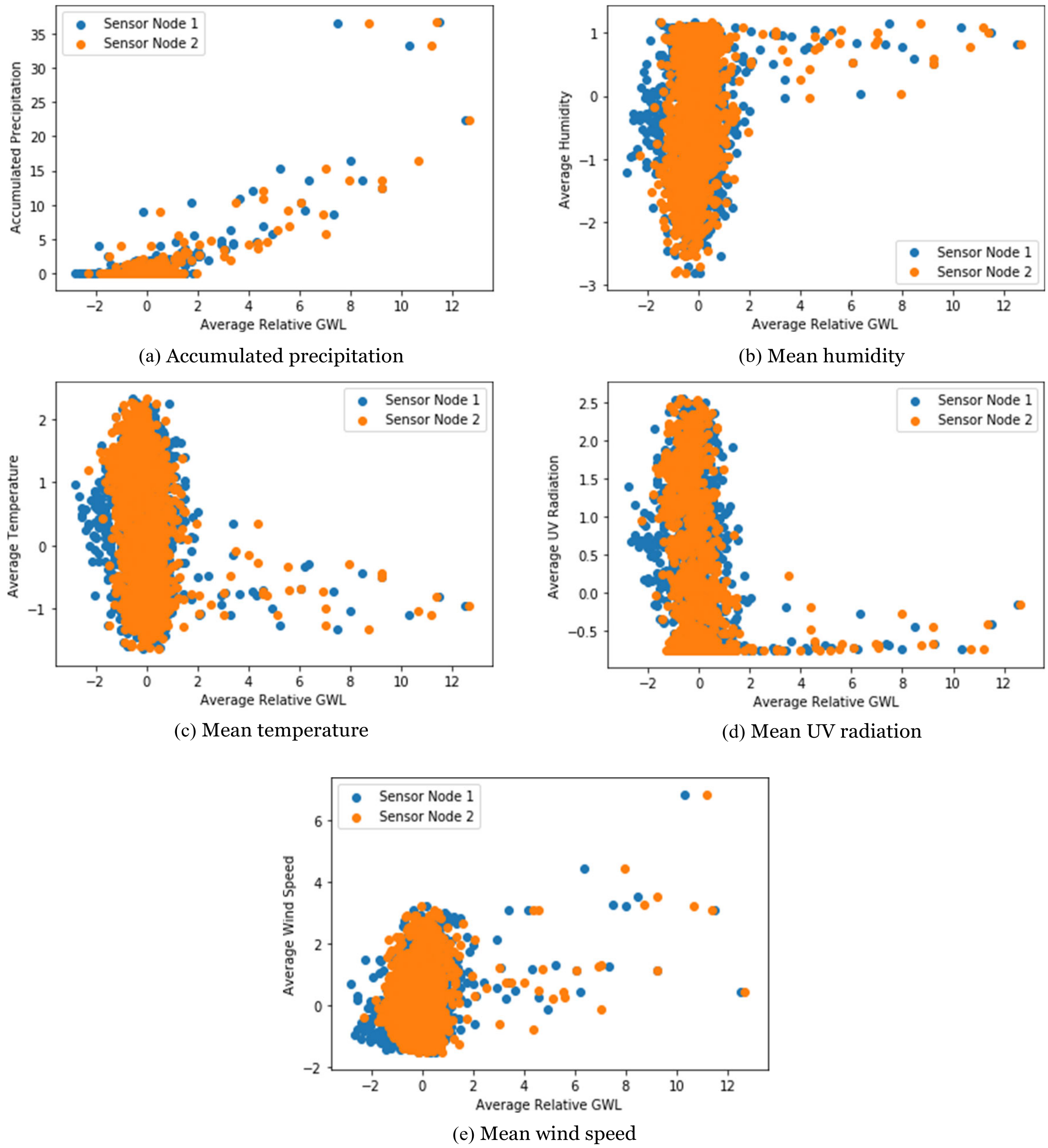
ML model	RMSE (mm)	
	Sensor Node 1	Sensor Node 2
Linear regression	5.351	5.364
LSTM	7.106	7.958
Neural network	3.866	3.554

The scatter plots for mean humidity, temperature, wind speed and UV radiation do not meet this criterion, which is reflected by their low Pearson correlation coefficient, r values. On the other hand, the scatter plot for accumulated precipitation is almost linear with regards to the relative GWL except for a small subset of data of extreme cases (i.e.,outliers) where accumulated precipitation is too high. This observation is also supported by higher Pearson correlation coefficient r values above 0.7. In this paper, we do not remove the outliers for the study since they are highly correlated (i.e., when the accumulated precipitation is high, similarly the relative GWL is also high). Moreover, a further Pearson correlation study between relative GWL of both sensor nodes shows that they are highly correlated (i.e., with a Pearson correlation coefficient r of 0.8). Their line plots almost overlap, as depicted in Figure 12.

However, accumulated precipitation is insufficient to model the relative water level to a level of acceptable accuracy, which remains the motivation of this research. Thus, this paper combines all the input parameters using a machine learning approach to predict the relative water level to improve its accuracy.

The RSMEs of each model in the prediction of relative GWL for sensor node 2 are tabulated in Table 5. RMSE for prediction on sensor node 2 is selected due to the higher correlation with the input parameters. It is observed that the neural network model has the best performance, followed by linear regression and LSTM. This advantage is because the neural network can account for the nonlinearities while linear regression cannot. On the other hand, the performance of LTSM suffers from the limit of dataset available, which can be seen from its training curve in Figure 13 (b).

Learning or training curves of the models are shown in Figure 13. Figure 13 (a) is the learning curve of the developed linear regression model. It is observed that the training curve and validation curve slowly converge as the training set



(a) Accumulated precipitation
(b) Mean humidity
(c) Mean temperature
(d) Mean UV radiation
(e) Mean wind speed

FIGURE 11. Scatter plots of normalised NN inputs vs relative GWL.

size increases. When the two curves converge, adding more training instances will not improve the model performance. Besides, the training MSE plateaus around the value of 35. The verdict is that the developed model suffers from high bias and low variance issues. So, a more complex model is needed to improve the performance, which is supported by the observation from the RMSE comparison where the neural network model can offer improved performance. For the neural network-based model, the training performance can be evaluated using training curves, as depicted in Figure 13 (b) and Figure 13 (c) for LSTM and neural network, respectively. As the epochs increase, the training loss decreases, and the neural network model has better performance than LSTM. In terms of the LSTM training curve, the training loss decreases with the epochs, but more data is required to explore the model's potential.

To further analyse the performance of the developed neural network, systematic experimentation is conducted to evaluate the effect of the different number of hidden layers. As a result, the neural network produces the following results as depicted in Table 6 and Table 7 for Sensor Node 1 and Sensor Node 2, respectively, which are tuned under the different number of hidden layers and input parameters. Fire Danger Rating System (FDRS) input parameters here are mainly air mean

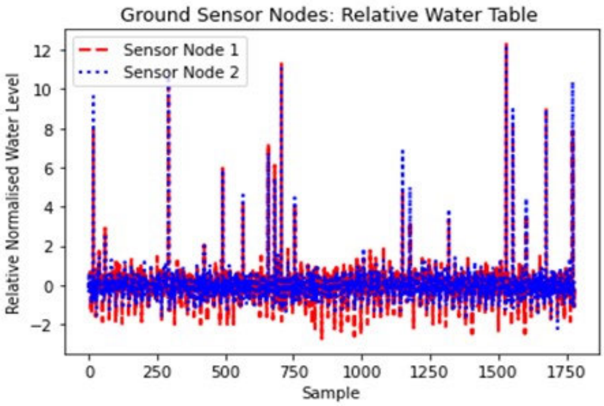


FIGURE 12. Relative ground water level for sensor node 1 and sensor node 2.

TABLE 6. Neural network prediction RMSE for sensor node 1.

NN topology	FDRS input parameters only		FDRS input parameters + UV radiation	
Number of hidden layers	Training RMSE (mm)	Validation RMSE (mm)	Training RMSE (mm)	Validation RMSE (mm)
1	4.518	4.374	4.512	3.866
2	4.516	4.362	3.568	4.920
3	4.490	4.818	4.306	4.170

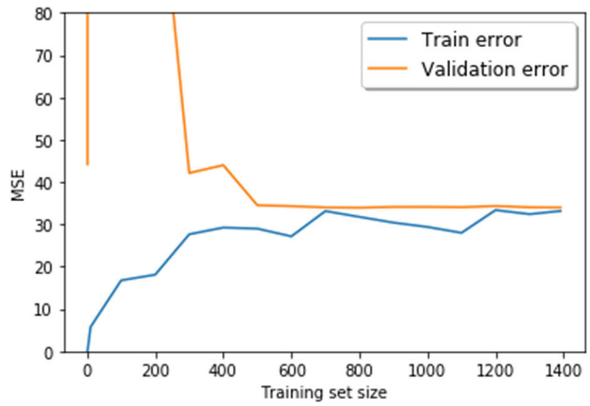
TABLE 7. Neural network prediction RMSE for sensor node 2.

NN topology	FDRS input parameters only		FDRS input parameters + UV radiation	
Number of hidden layers	Training RMSE (mm)	Validation RMSE (mm)	Training RMSE (mm)	Validation RMSE (mm)
1	4.954	3.946	3.688	3.554
2	4.354	3.994	3.802	3.572
3	4.478	3.682	3.956	3.936

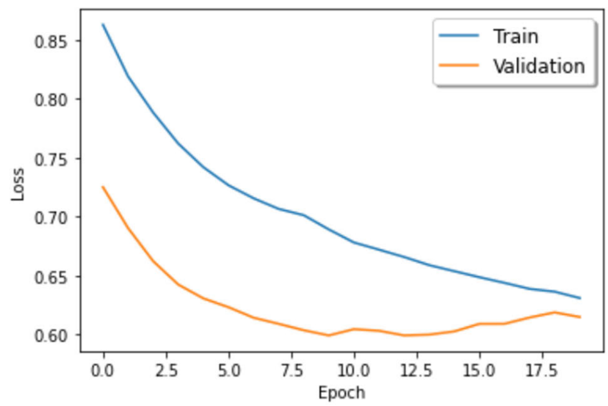
temperature, humidity, wind speed, and hourly accumulated precipitation.

Another conclusion we can draw from both tables is that the neural network model predicts better with an additional input UV radiation parameter. The prediction RMSE results are relatively accurate and promising, ranging between 3.554 and 3.866. However, for both Sensor Node 1 and 2, only one neural network hidden layer is sufficient for good performance. This could be attributed to the over-fitting Neural Network problem where the network over-fits the training set and decreases the ability to generalize to the new data. Therefore, increasing the number of hidden layers does not increase the accuracy in this case.

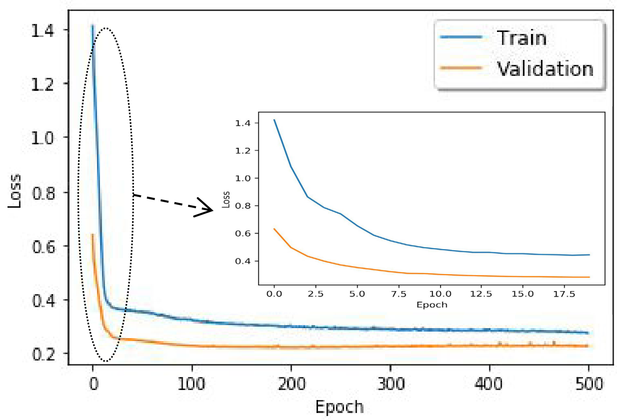
In general, the prediction results demonstrate that the model for Sensor Node 2 is more accurate with generally lower RMSE across all settings. This is coherent with the higher Pearson correlation coefficient r for relative GWL



(a) Linear regression



(b) LSTM



(c) Neural network

FIGURE 13. Learning or training curve of ML models.

of Sensor Node 2 with most input parameters compared to Sensor Node 1 (i.e., based on Table 4). In terms of location wise, Sensor Node 2 is planted in the middle of the peat swamp, whereas Sensor Node 1 is located nearer to the canal. Thus, the ground water near Sensor Node 1 is drawn out faster into the canal, affecting its level more than Sensor Node 2. Figure 14 shows the canal next to the Sensor node 1.

The importance of hourly water level simulation in peatland management and fire prevention cannot be overstated.

FIGURE 14. Water canal near to sensor node 1.

Furthermore, it is essential to emphasize that the dynamics of groundwater flow play a crucial role in shaping the geological conditions and fire occurrences in peatland areas [37], [38]. Peatlands play a crucial role in ecosystem dynamics, influencing vegetation growth, greenhouse gas emissions, biodiversity, and fire risk. Therefore, high temporal and spatial resolution simulation and monitoring of water levels in peatlands are essential. Hourly water level simulation not only helps us better understand the dynamic changes in hydrological processes in peatlands but also provides important insights for ecological conservation and fire risk assessment.

Furthermore, while we utilized a three-month data span for model construction and evaluation, it does not imply neglecting the significance of long-term data. On the contrary, we recognize the importance of long-term data for a comprehensive assessment of model performance. However, in this study, our primary focus was on validating the feasibility of IoT technology in peatland water level simulation and exploring its potential value in practical applications. Hence, we opted for a shorter time span for initial evaluation to validate the effectiveness and feasibility of our approach. Despite the shorter time span, our research results still provide valuable references and foundations for further studies.

In conclusion, hourly water level simulation provides a new approach for understanding and monitoring hydrological processes in peatlands, offering robust support for peatland management and conservation efforts. We believe that with the continuous development and refinement of IoT technology, hourly water level simulation will play an increasingly important role in peatland ecosystem management and fire prevention in the future.

V. CONCLUSION

This study developed an IoT-based Peatland management system to effectively manage fire threats in ASEAN peatlands. Real-time data collection by the IoT system allows instantaneous monitoring of peatland conditions. Analysis revealed a strong correlation between accumulated precipitation and ground sensor data, highlighting its suitability as input for neural network model training. The developed neural network effectively predicts groundwater levels, crucial for peatland fire management, as water management has proven to be an effective method for controlling fire threats. Importantly, our prediction results demonstrate high accuracy, with an RMSE ranging from 3.554 to 4.920 depending on the number of hidden layers.

The findings of this study provide valuable insights that can aid in the effective management and prediction of groundwater levels in peatland areas. By utilizing IoT-based monitoring systems and machine learning algorithms, accurate predictions of groundwater levels can be made, offering a proactive approach to mitigating the risk of peatland fires. These findings underscore the potential of integrating modern technology with hydrological knowledge to address environmental challenges and enhance disaster preparedness efforts.

For future works, the neural network will be trained with more collected data spanning over both dry and wet seasons to improve its prediction ability and accuracy. Furthermore, more analysis on the data collected by the weather station will be conducted to compare against the atmospheric data provided by the METMalaysia for better understanding on the peatland weather. Lastly, potential functionalities for integration with the IoT system for automated water table management will be investigated.

REFERENCES

[1] J. Rabiei, M. S. Khademi, S. Bagherpour, N. Ebadi, A. Karimi, and K. Ostad-Ali-Askari, "Investigation of fire risk zones using heat–humidity time series data and vegetation," *Appl. Water Sci.*, vol. 12, no. 9, Aug. 2022, Art. no. 216, doi: 10.1007/s13201-022-01742-z. [Online]. Available: https://d-nb.info/1273047303/34

[2] J. E. Householder and S. Page, "Tropical peat swamp forests," in *Encyclopedia of Inland Waters*, 2022, pp. 105–115, doi: 10.1016/b978-0-12-819166-8.00046-3. [Online]. Available: https://www.sciencedirect.com/referencework/9780128220412/encyclopedia-of-inland-waters#book-info

[3] L. Syaufina and S. I. Maulana, "Biomass burning emissions in Indonesia and policy measures—An overview," in *Biomass Burning in South and Southeast Asia*. Boca Raton, FL, USA: CRC Press, 2021, pp. 135–148, doi: 10.1201/9780429022036-11.

[4] C. Vitolo, F. Di Giuseppe, B. Krzeminski, and J. San-Miguel-Ayanz, "A 1980–2018 global fire danger re-analysis dataset for the Canadian fire weather indices," *Sci. Data*, vol. 6, no. 1, Feb. 2019, Art. no. 190032, doi: 10.1038/sdata.2019.32.

[5] A. A. Nuruddin, H. M. Leng, and F. Basaruddin, "Peat moisture and water level relationship in a tropical peat swamp forest," *J. Appl. Sci.*, vol. 6, no. 11, pp. 2517–2519, May 2006, doi: 10.3923/jas.2006.2517.2519.

[6] J. Miettinen, C. Shi, and S. C. Liew, "Land cover distribution in the peatlands of Peninsular Malaysia, Sumatra and Borneo in 2015 with changes since 1990," *Global Ecol. Conservation*, vol. 6, pp. 67–78, Apr. 2016, doi: 10.1016/j.gecco.2016.02.004.

[7] A. Jebril, A. Sali, A. Ismail, and M. Rasid, "Overcoming limitations of LoRa physical layer in image transmission," *Sensors*, vol. 18, no. 10, p. 3257, Sep. 2018, doi: 10.3390/s18103.

[8] L. Li, A. Sali, J. T. Liew, N. L. Saleh, S. M. S. Ahmad, A. M. Ali, A. A. Nuruddin, N. A. Aziz, I. S. Sitanggang, L. Syaufina, A. D. Nurhayati, H. Nishino, and N. Asai, "Estimation of ground water level (GWL) for tropical peatland forest using machine learning," *IEEE Access*, vol. 10, pp. 126180–126187, 2022, doi: 10.1109/ACCESS.2022.3225906.

[9] M. Chen, U. Challita, W. Saad, C. Yin, and M. Debbah, "Artificial neural networks-based machine learning for wireless networks: A tutorial," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 4, pp. 3039–3071, 4th Quart., 2019, doi: 10.1109/COMST.2019.2926625.

[10] J. Miettinen, A. Hooijer, R. Vernimmen, S. C. Liew, and S. E. Page, "From carbon sink to carbon source: Extensive peat oxidation in insular Southeast Asia since 1990," *Environ. Res. Lett.*, vol. 12, no. 2, Feb. 2017, Art. no. 024014, doi: 10.1088/1748-9326/aa5b6f.

[11] A. Paul and T. Sato, "Localization in wireless sensor networks: A survey on algorithms, measurement techniques, applications and challenges," *J. Sensor Actuator Netw.*, vol. 6, no. 4, p. 24, Oct. 2017, doi: 10.3390/jsan6040024.

[12] I. Strumberger, M. Minovic, M. Tuba, and N. Bacanin, "Performance of elephant herding optimization and tree growth algorithm adapted for node localization in wireless sensor networks," *Sensors*, vol. 19, no. 11, p. 2515, Jun. 2019, doi: 10.3390/s19112515.

[13] F. Zantalis, G. Koulouras, S. Karabetsos, and D. Kandris, "A review of machine learning and IoT in smart transportation," *Future Internet*, vol. 11, no. 4, p. 94, Apr. 2019, doi: 10.3390/fi11040094.

[14] N. Dey, A. S. Ashour, F. Shi, S. J. Fong, and R. S. Sherratt, "Developing residential wireless sensor networks for ECG healthcare monitoring," *IEEE Trans. Consum. Electron.*, vol. 63, no. 4, pp. 442–449, Nov. 2017, doi: 10.1109/TCE.2017.015063.

[15] D. K. Bangotra, Y. Singh, A. Selwal, N. Kumar, P. K. Singh, and W.-C. Hong, "An intelligent opportunistic routing algorithm for wireless sensor networks and its application towards e-healthcare," *Sensors*, vol. 20, no. 14, p. 3887, Jul. 2020, doi: 10.3390/s20143887.

[16] A. Cenedese, M. Luvisotto, and G. Michieletto, "Distributed clustering strategies in industrial wireless sensor networks," *IEEE Trans. Ind. Informat.*, vol. 13, no. 1, pp. 228–237, Feb. 2017, doi: 10.1109/TII.2016.2628409.

[17] H. Farag, E. Sisinni, M. Gidlund, and P. Österberg, "Priority-aware wireless fieldbus protocol for mixed-criticality industrial wireless sensor networks," *IEEE Sensors J.*, vol. 19, no. 7, pp. 2767–2780, Apr. 2019, doi: 10.1109/JSEN.2018.2888729.

[18] I. S. Hikouei, K. N. Eshleman, B. H. Saharjo, L. L. B. Graham, G. Applegate, and M. A. Cochrane, "Using machine learning algorithms to predict groundwater levels in Indonesian tropical peatlands," *Sci. Total Environ.*, vol. 857, Jan. 2023, Art. no. 159701, doi: 10.1016/j.scitotenv.2022.159701.

[19] H. I. Burgan, "Comparison of different ANN (FFBP, GRNN, RBF) algorithms and multiple linear regression for daily streamflow prediction in Kocasu River, Turkey," *Fresenius Environ. Bull.*, vol. 31, no. 5, pp. 4699–4708, Feb. 2022.

[20] T. Lendzioch, J. Langhammer, L. Vlček, and R. Minařík, "Mapping the groundwater level and soil moisture of a montane peat bog using UAV monitoring and machine learning," *Remote Sens.*, vol. 13, no. 5, p. 907, Feb. 2021, doi: 10.3390/rs13050907.

[21] B. Silva, R. M. Fisher, A. Kumar, and G. P. Hancke, "Experimental link quality characterization of wireless sensor networks for underground monitoring," *IEEE Trans. Ind. Informat.*, vol. 11, no. 5, pp. 1099–1110, Oct. 2015, doi: 10.1109/TII.2015.2471263.

[22] T. M. Chiwewe, C. F. Mbuya, and G. P. Hancke, "Using cognitive radio for interference-resistant industrial wireless sensor networks: An overview," *IEEE Trans. Ind. Informat.*, vol. 11, no. 6, pp. 1466–1481, Dec. 2015, doi: 10.1109/TII.2015.2491267.

[23] J. Zhang, W. Li, N. Han, and J. Kan, "Forest fire detection system based on a ZigBee wireless sensor network," *Frontiers Forestry China*, vol. 3, no. 3, pp. 369–374, Jul. 2008, doi: 10.1007/s11461-008-0054-3.

[24] N. U. Okafor and D. Delaney, "Considerations for system design in IoT-based autonomous ecological sensing," *Proc. Comput. Sci.*, vol. 155, pp. 258–267, Jan. 2019, doi: 10.1016/j.procs.2019.

[25] F. Cui, "Deployment and integration of smart sensors with IoT devices detecting fire disasters in huge forest environment," *Comput. Commun.*, vol. 150, pp. 818–827, Jan. 2020, doi: 10.1016/j.comcom.2019.11.051.

[26] S. Essa, R. Petra, M. R. Uddin, W. S. H. Suhaili, and N. I. Ilmi, "IoT-based environmental monitoring system for Brunei peat swamp forest," in *Proc. Int. Conf. Comput. Sci. Appl. Agricult. (ICOSICA)*, Sep. 2020, pp. 1–5, doi: 10.1109/ICOSICA49951.2020.9243279.

[27] L. Li, A. Sali, N. K. Noordin, A. Ismail, and F. Hashim, "Prediction of peatlands forest fires in Malaysia using machine learning," *Forests*, vol. 14, no. 7, p. 1472, Jul. 2023, doi: 10.3390/f14071472.

[28] L. Li, A. Sali, N. K. Noordin, A. Ismail, F. Hashim, M. F. A. Rasid, M. Hanafi, S. M. Razali, N. A. Aziz, I. Sukaesih Sitanggang, L. Syaufina, and A. D. Nurhayati, "Modeling of evaporation rate for peatland fire prevention using Internet of Things (IoT) system," *Fire*, vol. 6, no. 7, p. 272, Jul. 2023, doi: 10.3390/fire6070272.

[29] J. T. Liew, A. Sali, N. K. Noordin, F. Hashim, S. Mashohor, N. L. Saleh, Y. Ouzrout, and A. Sekhari, "Sustainable peatland management with IoT and data analytics," in *Proc. Work. Conf. Virtual Enterprises*. Cham, Switzerland: Springer, 2021, pp. 549–557, doi: 10.1007/978-3-030-85969-5_51.

[30] R. M. Sandoval, D. Rodenas-Herraiz, A.-J. Garcia-Sanchez, and J. Garcia-Haro, "Deriving and updating optimal transmission configurations for LoRa networks," *IEEE Access*, vol. 8, pp. 38586–38595, 2020, doi: 10.1109/ACCESS.2020.2973252.

[31] J. T. Lim, "Rainfall minimum in peninsular Malaysia during the northeast monsoon," *Monthly Weather Rev.*, vol. 104, no. 1, pp. 96–99, Jan. 1976, doi: 10.1175/1520-0493(1976)104<0096:RMIPMD>2.0.CO;2.

[32] F. Ahmad, T. Ushiyama, and T. Sayama, "Determination of Z-R relationship and inundation analysis for Kuantan river basin," Malays. Meterol. Dep. Res. Publication, Selangor Darul Ehsan, Malaysia, Tech. Rep. 2/2017, 2017, vol. 2, pp. 1–55.

[33] C. Konstantinos, I. Hatzilygeroudis, and I. Perikos, "Machine learning basics," in *Intelligent Computing for Interactive System Design: Statistics, Digital Signal Processing, and Machine Learning in Practice*. New York, NY, USA: Association for Computing Machinery, 2021, pp. 143–193, doi: 10.1145/3447404.3447414.

[34] Z. M. Yaseen, "A new benchmark on machine learning methodologies for hydrological processes modelling: A comprehensive review for limitations and future research directions," *Knowl.-Based Eng. Sci.*, vol. 4, no. 3, pp. 65–103, Dec. 2023, doi: 10.51526/kbes.2023.4.3.65-103.

[35] T. Rajaee, H. Ebrahimi, and V. Nourani, "A review of the artificial intelligence methods in groundwater level modeling," *J. Hydrol.*, vol. 572, pp. 336–351, May 2019, doi: 10.1016/j.jhydrol.2018.12.037.

[36] H. Zhang, G. Dong, J. Wang, T.-L. Zhang, X. Meng, D. Yang, Y. Liu, and B. Lu, "Understanding and extending the geographical detector model under a linear regression framework," *Int. J. Geographical Inf. Sci.*, vol. 37, no. 11, pp. 2437–2453, Oct. 2023, doi: 10.1080/13658816.2023.2266497.

[37] J. Li, Z. Pang, Y. Liu, S. Hu, W. Jiang, L. Tian, G. Yang, Y. Jiang, X. Jiao, and J. Tian, "Changes in groundwater dynamics and geochemical evolution induced by drainage reorganization: Evidence from ^{81}Kr and ^{36}Cl dating of geothermal water in the Weihe Basin of China," *Earth Planet. Sci. Lett.*, vol. 623, Dec. 2023, Art. no. 118425, doi: 10.1016/j.epsl.2023.118425.

[38] K. Zhang, Y. Li, Z. Yu, T. Yang, J. Xu, L. Chao, J. Ni, L. Wang, Y. Gao, Y. Hu, and Z. Lin, "Xin'anjiang nested experimental watershed (XAJ-NEW) for understanding multiscale water cycle: Scientific objectives and experimental design," *Engineering*, vol. 18, pp. 207–217, Nov. 2022, doi: 10.1016/j.eng.2021.08.026.

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