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RESEARCH ARTICLE

Estimation of Ground Water Level (GWL) for Tropical Peatland Forest Using Machine Learning

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ABSTRACT The tropical area has a large area of peatland, which is an important ecosystem that is regarded as home by millions of people, plants and animals. However, the dried-up and degraded peatland becomes extremely easy to burn, and in case of fire, it will further release transboundary haze. In order to protect the peatland, an improved tropical peatland fire weather index (FWI) system is proposed by combining the ground water level (GWL) with the drought code (DC). In this paper, LoRa based IoT system for peatland management and detection was deployed in Raja Musa Forest Reserve (RMFR) in Kuala Selangor, Malaysia. Then, feasibility of data collection by the IoT system was verified by comparing the correlation between the data obtained by the IoT system and the data from Malaysian Meteorological Department (METMalaysia). An improved model was proposed to apply the ground water level (GWL) for Fire Weather Index (FWI) formulation in Fire Danger Rating System (FDRS). Specifically, Drought Code (DC) is formulated using GWL, instead of temperature and rain in the existing model. From the GWL aggregated from the IoT system, the parameter is predicted using machine learning based on a neural network. The results show that the data monitored by the IoT system has a high correlation of 0.8 with the data released by METMalaysia, and the Mean Squared Error (MSE) between the predicted and real values of the ground water level of the two sensor nodes deployed through neural network machine learning are 0.43 and 12.7 respectively. This finding reveals the importance and feasibility of the ground water level used in the prediction of the tropical peatland fire weather index system, which can be used to the maximum extent to help predict and reduce the fire risk of tropical peatland.

INDEX TERMS Peatland, IoT system, FWI, machine learning, neural network.

I. INTRODUCTION

After the death of plants, they are decomposed by microorganisms and soil animals. In the humid or surface water environment, due to the lack of oxygen, the number of aerobic microorganisms decreases, which slows the decomposition of dead plants and forms the accumulation of organic matter. The accumulated organic matter is called peat. Under natural conditions, the production and storage of organic matter are far greater than decomposition, and the land where peat

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is accumulated is called peatland. Peatland is an important ecosystem with great utility, which is distributed in more than 180 countries [1]. In addition to controlling water supply [2], reducing drought [3] and flood disasters [4], they also provide unique aquatic habitats for endangered animals and plants [5], [6].

In Southeast Asia, peatlands are rich in biomass and water resources. They form part of tropical forests, where decaying organic matter accumulates for many years to form carbon-rich soils. The peatlands in Southeast Asia account for 11-14% of the total peat in the world [7].

However, peatlands around the world are being drained for land use conversion. In 1997, the carbon emissions caused by peatland fires in Indonesia were equivalent to 13% - 40% of the global carbon emissions from fossil fuel combustion every year [8]. It can be seen that fire is one of the main issues to cause carbon loss in peatland [9]. In addition, the fire in peatland is also the main reason for the haze crisis in Southeast Asia. To alleviate the haze crisis, the Indonesian government predicted spending up to 35 billion dollars in 2015 [10]. Due to the intensity and uncontrollability of field fires, peatlands burned by them emit a large amount of transboundary haze into the atmosphere. In order to control the global average temperature rise at 1.5 centigrade (announced prior to UNFCCC COP26) [11], peatland protection and restoration may be a natural solution with low cost, low technology content and great impact on climate action and biodiversity. Therefore, it is of great significance to study the carbon loss of peatlands caused by field fires.

On the other hand, due to the diverse locations and origins of the fire, the fire has distinct characteristics, and environmental and human interference factors can result in false alarms and missed fire alarms. Globally, the threat of peatland forest fire is rising with 370 million hectares of forest burned every year [12]. In order to alleviate this problem, the Southeast Asia Fire Danger Rating System (FDRS) project which is managed by the Malaysian Meteorological Department (METMalaysia) has been developed based on the Canadian Forest Fire Danger Rating System. However, this system does not include ground parameters, such as ground water level, soil temperature and soil humidity, which are important metrices for the management and monitoring of peatland forest fires [13], [14], [15]. This is due to the fact that the peatland forests with different ground water level currently account for 50% [16].

Furthermore, the lack of on-site real-time data is unfavorable to the management of the peatland forest. In order to collect real-time data, IoT technology is an excellent choice for peatland management. In addition, it is stable and feasible to utilize LoRa technology for data transmission and collection, because LoRa is a low-power WAN protocol developed based on the IoT spread spectrum modulation technology, and relevant studies have proven the feasibility of LoRa technology in forest transmission parameters [17], [18], [19]. With the adoption of IoT technology, this paper will also take a very favorable action to help the management of peatland forest, that is, introducing neural network. The neural network can self-study the collected data and learn to predict new data without artificial intervention for the prediction and monitoring of forest fires in peatland [20], [21].

Therefore, the feasibility of a fire weather index system for fire prediction in Malaysia combined with ground water level needs to be verified, which means the proposed improved Fire Danger Rating System (FDRS) especially for Raja Musa Forest Reserve (RMFR) in Kuala Selangor, Malaysia, by including DC with GWL into existing FDRS. The contributions of this paper are as follows:

- A model is proposed to integrate Ground Water Level (GWL) into Fire Weather Index FWI) system, which is the drought code (DC) that can be calculated by GWL.
- The correlation between the data measured by the peatland forest management and monitoring IoT system, which was established for innovation in peatland monitoring in Raja Musa forest reserve (RMFR), and the data published by the Malaysian Meteorological Department METMalaysia) verifies the validity and feasibility of the data measured by the IoT system.
- Based on a three-layer and five input (temperature, relative humidity, wind speed, rainfall, and previous ground water level) neural network, the ground water level is predicted by machine learning.

II. METHODOLOGY

This section mainly introduces the relevant parameters of the IoT system used in this paper, and how to use machine learning to predict the ground water level (GWL) to verify the feasibility of the fire weather index (FWI) system in Southeast Asia.

A. IoT SYSTEM

The data measured in this paper are from the IoT peatland forest management and monitoring system deployed in Raja Musa Forest Reserve (RMFR) in Kuala Selangor, Malaysia, as shown in Fig.1. (image from Google Maps)

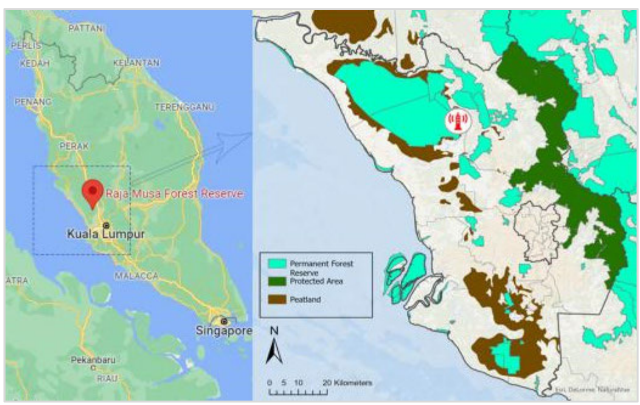

FIGURE 1. Location of RMFR (3°27′58″ N, 101°26′31″ E).

Fig.1 shows the specific orientation of the Raja Musa Forest Reserve on the left, and the enlarged area map on the right shows the specific distribution of the permanent forest reserve, the protected area and the peatland in the forest area, where the dark brown represents the peatland area. There are many peatlands in Raja Musa Forest Reserve, which can provide important site support for relevant research on peatlands. Furthermore, the peatland forest management and monitoring IoT system has been deployed in Raja Musa Forest Reserve, used for research and published a large number of achievements, such as reference [22], [23]. Its layout is shown in Fig. 2.

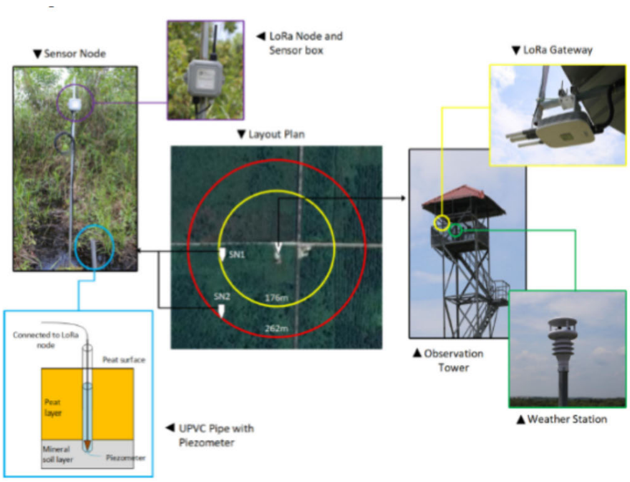

FIGURE 2. General layout of IoT system [22].

Fig.2 shows the structure of the peatland monitoring and management system using LoRaWAN technology. The system is mainly composed of an observation tower (located at 3°27'58" N, 101°26'31" E), meteorological station (used to collect ambient temperature and humidity, wind speed and rainfall), LoRa node and gateway (used to transmit and receive measurement data) and two ground sensor nodes (used to measure soil temperature, soil humidity and ground water level).

In the IoT system, two ground sensors are deployed to measure soil temperature, soil humidity and ground water level, as shown in Fig.3. Two ground sensors are connected to the gateway through LoRa access technology, and then the peatland data on the gateway is sent to the cloud using 4G cellular network. The first ground sensor node (SN1) is located about 176 m west of the observation tower. The second ground sensor node (SN2) is located about 262 m southwest of the observation tower. In contrast, SN2 is located deep in the peatland.

Particularly, the ground water level is measured using a piezometer at ground sensor nodes. The piezometer is installed in a UPVC pipe with small holes to prevent soil from hindering the operation of the pressure gauge and enable ground water to flow inside the pipe. As shown in Fig.4, the UPVC pipe reaches the mineral soil at a depth of about

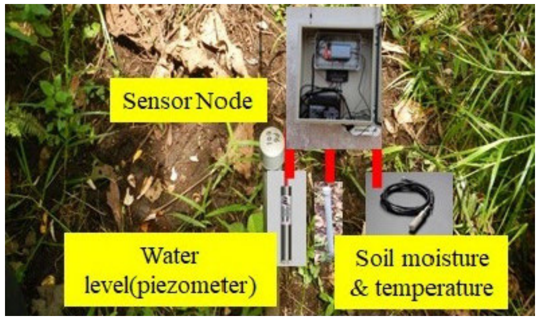

FIGURE 3. Sensor node.

5.26 m. Going deep into the ground can ensure that the measured water level is the actual water level in the peat layer. In order to protect the borehole from wild animals, the perimeter is protected by a 1 m high fence.

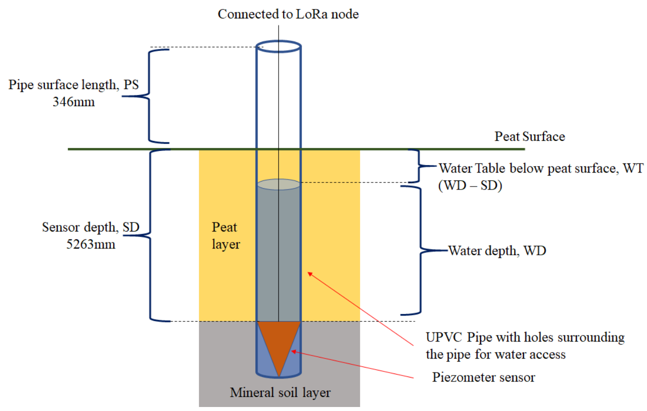

FIGURE 4. Sensor installation schematic.

B. GWL PREDICTION USING MACHINE LEARNING

Based on the data measured by the deployed IoT system and the Canadian Fire Weather Index (FWI) system proposed by Wang et al. [24] and Van Wagner [25], this study verifies the feasibility of introducing ground water level parameters to predict fires in tropical areas.

The Canadian Forest Fire Weather Index (FWI) system calculates the moisture content of ground combustibles through the change in weather conditions, and divides the potential fire risk level of forests according to the moisture content of combustibles at different levels from the surface to the underground. FWI consist of three fuel moisture codes representing different layers in the forest floor and three fire behaviour indices, as shown in Fig.5.

In this paper, the data of fire weather observations are all from the IoT system deployed in Section 2.A. The motivation of this study is to verify the feasibility of using ground water level for the FWI system in Southeast Asia. Therefore, in this paper, a part of the fire weather index system in Canada is modified, that is, DC is directly determined by ground water level, as shown in Fig.6.

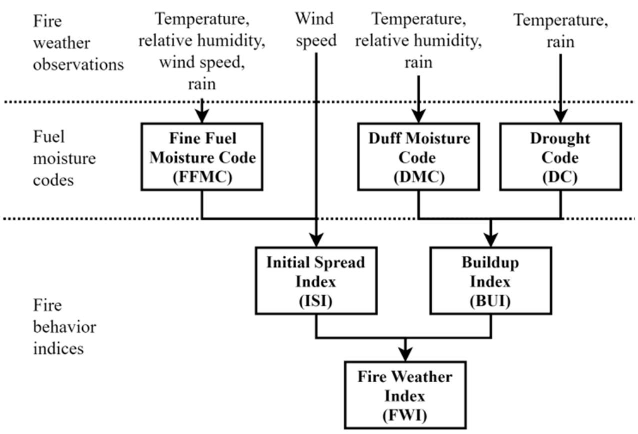

FIGURE 5. Basic structure of the canadian FWI system [25].

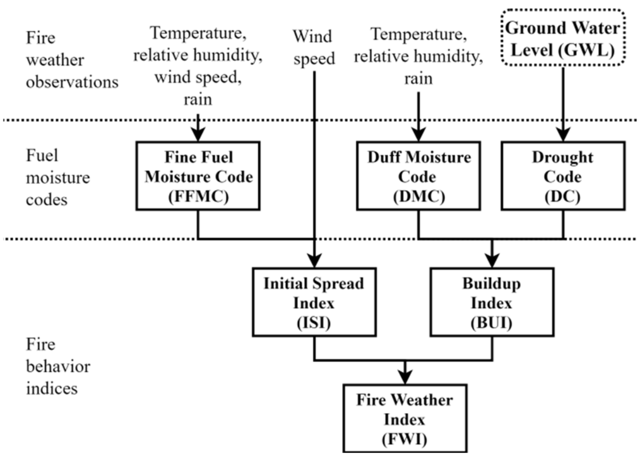

FIGURE 6. Proposed model of GWL used to predict the FWI system.

Fine Fuel Moisture Code (FFMC), which is a numerical rating of the moisture content of surface litter and other cured refined fuels on the forest floor is the first step to calculating FWI [26], which means the FFMC represents the water content of surface litter and other solidified refined fuels in stands with a depth of 1-2 cm, and the weight when drying is 0.5 kg/m^2. Besides, Duff Moisture Code (DMC) represents the moisture content of loose compacted and decomposed forest ground organic matter, with a depth of 5-10 cm and a dry weight of about 5 kg/m^2. In addition, the Drought Code (DC) represents the water content of the deep compact organic soil layer with a depth of 10-20 cm, and its weight is about 44 kg/m^2 when dry.

The second part of the FWI system reflects the relationship between current fire potential and the fire environment. Among them, the Initial Spread Index (ISI) is the numerical rating of relative fuel diffusion, which is not affected by fuel consumption. The Buildup Index (BUI) provides a numerical rating of the amount of fuel that can be used for combustion. In addition, the fire weather index (FWI) is the numerical grade of fire intensity, which is suitable as a general index of fire risk which refers to the ability of fire to cause, spread and destroy the whole forest area of the region.

In this paper, the DC in Canada's FWI system is modified to be directly determined by the ground water level according to the regional situation of Southeast Asia, which seems to reduce the decision index of DC and may reduce the accuracy of prediction. However, during the prediction of GWL using machine learning, hourly measurements of temperature, humidity, wind speed, rainfall and previous ground water level data from January to March 2020 will be taken into account. In the prediction of five input three-layer neural network structures, in which the number of hidden neutrons in each layer remains unchanged according to the number of input parameters, as shown in Fig.7.

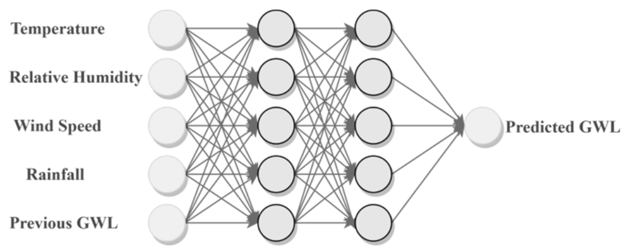

FIGURE 7. GWL prediction neural network.

Fig. 7 shows a three-layer five input recursive neural network (RNN) that can identify a large number of discrete-time data sequences using linear regression and is fully connected to dense layers. The dense layer is selected because it can allow a more complex mathematical model [27]. The linear regression model is chosen because it is an algorithm that can effectively establish a simple supervisory model for input and output. It has the advantages of easy implementation and easy training [28]. Specifically, this paper introduces the data (soil temperature, relative humidity, wind speed, rainfall and previous GWL) collected by the IoT system every hour into the input layer. Then, the input layer processes and classifies the data into the hidden layer. Each hidden layer will analyze and further process the output from the previous layer in the way of linear regression modeling, and then continue to transfer it to the next layer. Among them, the neural network in this paper predicts according to the proportion of 80% training data (i.e., 34089 samples) and 20% testing data (i.e., 8523 samples). The final output layer is the final prediction result of the neural network for all data processing.

III. RESULTS AND DISCUSSION

This section will verify the validity of the data collected from the deployed IoT system from January to March 2020 on an hourly basis against the data of METMalaysia in the same period (rainfall, temperature, wind speed and humidity have been measured by METMalaysia). The correlation between the data from the IoT system and the data from METMalaysia is shown in Table 1.

Table 1 shows that there is a high correlation of about 80% between the data measured by the deployed IoT

TABLE 1. Correlation between IoT system and METMalaysia.

Index	Correlation
Rainfall	0.790816124
Temperature	0.800850769
Wind Speed	0.805846921
Humidity	0.817400123

peatland detection system and the data measured by the METMalaysia base station (03°14′N, 101°15′E). Therefore, the data detected by the IoT system deployed in this research will support and contribute to the subsequent research.

In addition, according to the FWI system proposed by Wang et al. [24], they take temperature and rainfall as parameters for calculating DC, refer to Fig.5. In this paper, a new strategy for tropical areas is proposed, that is, the ground water level as the only parameter for calculation and its feasibility is verified.

In snowy areas, the higher snow cover can help lower the drought code. For tropical areas without snow, the deeper the ground water level, the more likely the drought code is to be lower. Therefore, according to the equation of calculating DC by snow height proposed by Waddington et al. [29], this paper replaces the snow height with the ground water height to obtain Equation 1.

$$DC = \frac{400 + GWL}{0.6} \tag{1}$$

The equations obtained by curve fitting in different ways between GWL data of IoT system and DC data given by METMalaysia are shown in Fig.8 and Fig.9.

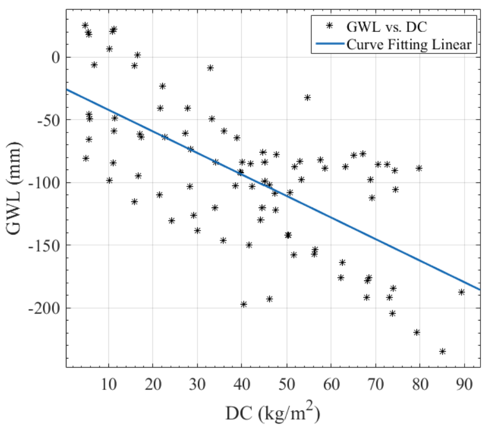

FIGURE 8. Linear curve fitting of GWL and DC.

Fig.8 shows the fitting curve obtained by linear curve fitting between the hourly ground water level data measured by the IoT peatland detection system deployed in RMFR from January to March 2020 and the data of DC in the same period published by METMalaysia, in which the fitting equation can be expressed as.

$$DC = -1.719 \times GWL - 24.95 \tag{2}$$

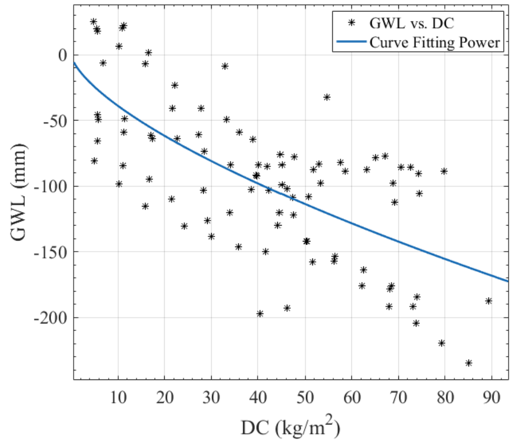

FIGURE 9. Power curve fitting of GWL and DC.

Fig.9 shows the fitting curve obtained by power curve fitting between the ground water level data measured by the IoT peatland detection system deployed in RMFR from January to March 2020 and the data of DC in the same period published by METMalaysia, in which the fitting equation can be expressed as.

$$DC = -8.39 \times GWL^{0.6664} \tag{3}$$

Then, the obtained DC equations are brought into the FWI system shown in Fig.6 for analysis and calculation. The feasibility of this idea is verified by comparing the correlation between the calculated parameters and FWI with the correlation between FWI and ISI, BUI, DMC, FFMC and DC given by METMalaysia, as shown in Table 2.

TABLE 2. Correlation with FWI in different equation.

	MET	Waddington J.M et al	Curve-fitting Linear	Curve-fitting Power
ISI	0.9575762	0.977729	0.955882	0.955212
DMC	0.8353773	0.730463	0.802142	0.790926
BUI	0.7838499	0.775366	0.801688	0.790630
FFMC	0.6938313	0.686382	0.660601	0.646227
DC	0.5053826	-0.303292	0.412702	0.348317

For a more intuitive comparison, Table 2 can be converted into a histogram, as shown in Fig.10.

By comparing the feasibility of the three equations in Table 2 and Fig.10, it is found that the data obtained by linear curve fitting has a higher and closer correlation with the data given by METMalaysia. Therefore, this paper believes that the equation between GWL and DC obtained by linear curve fitting can be considered to be adopted.

Since the feasibility of using GWL to calculate DC has been verified, it is predicted that GWL will have a fair value and contribution to the follow-up research related to this paper. Therefore, combined with the neural network structure in Fig.7 and the data measured by the IoT system, the GWL of

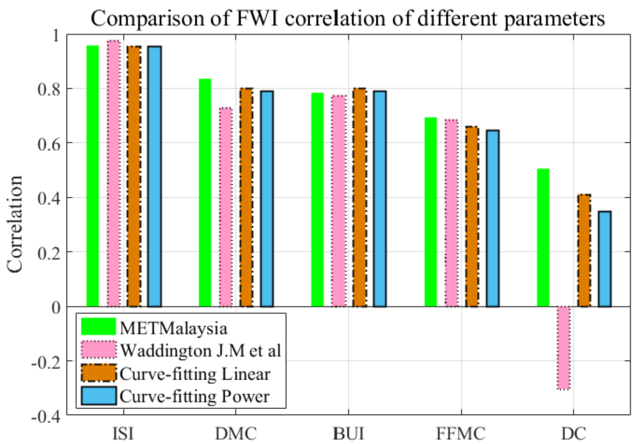

FIGURE 10. Comparison of FWI correlation of different parameters.

the two sensor nodes is predicted through machine learning, as shown in Fig.11.

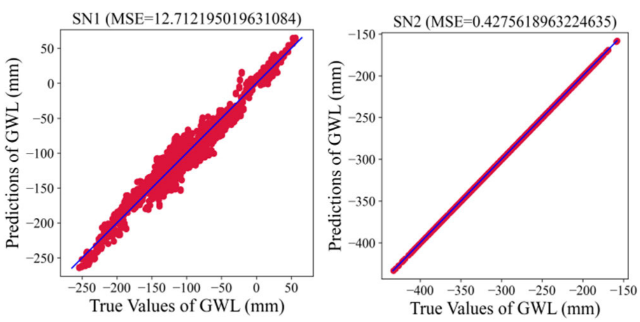

FIGURE 11. Machine learning prediction results of GWL.

Fig.11 shows the comparison between the true value and the predicted value of the ground water level where the Mean Squared Error (MSE) of the sensor node 2 is only about 0.43, which proves that the prediction value of ground water level predicted by the model proposed in this paper is reliable, and it has a profound contribution and helps to the research of peatland fire prediction. As for sensor node 1, the MSE is significantly higher than the prediction analysis of SN2, but it only reaches about 12.7. In contrast, the prediction result of the SN2 is more accurate because there is an artificial canal beside the SN1 that can directly connect with the river, while the SN2 is installed in deeper peatland (i.e the depth of SN1 is 25 cm, while the depth of SN2 is 50 cm), which makes the data detected by the SN2 more stable than that of the SN1. Therefore, it can be considered that the new strategy proposed in this paper, that is, for tropical peatland, using GWL instead of temperature and rainfall to calculate the FWI system, is completely feasible.

IV. CONCLUSION

This paper verifies that it is feasible to apply ground water level (GWL) as an input to the peatland fire weather index (FWI) system in tropical areas, spefically by formulating the Drought Code (DC) using GWL instead of temperature and rain in the existing model. DC formulation using ground data can be more accurate, considering the dynamics of peatland soil conditions in the tropical region. The paper has also shown a feasible prediction of GWL using Machine Learning, considering two sensor nodes deployed at Raja Musa Forest Reserve (RMFR), Kuala Selangor, Selangor, Malaysia.

The findings show that it is feasible to deploy an IoT system to measure and monitor peatland ground data for potential alert and preparedness system to management peatland forests in tropical region. The system can be implemented for transboundary haze management by mitigating peatland forest fires.

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