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IoT Based Peatland Ground Level Water Management Using Machine Learning Model

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ABSTRACT: The potential for enormous carbon emissions after fires makes peatlands a serious environmental hazard. Effective management is hampered by the labour-intensive and real-time data-poor nature of conventional ground water level (GWL) monitoring in peatlands. This study addressed the issue by proposing an IoT system for real-time monitoring that uses neural network-based GWL prediction. The neural network forecasts GWL based on meteorological factors, giving the responsible party more time to take the necessary steps to lower the danger of fire in peatlands. With a Root Mean Square Error (RMSE) ranging from 3.554 to 4.920, the suggested neural network shows encouraging results and guarantees 99% accuracy within a 14.760 mm range of the real GWL. This research highlights the innovative method of combining neural networks and the Internet of Things for peatland GWL prediction, providing a major breakthrough in real-time monitoring and fire risk reduction techniques. The innovation is its capacity to use basic meteorological information to anticipate GWL in real-time, even in places without the resources for traditional monitoring.

KEYWORDS: Peatland, Internet of Things, ground water level management, Root mean square error

I. INTRODUCTION

A peatland is a particular kind of wetland that has a peat layer formed in the soil profile; it is a terrestrial ecosystem that has the quickest rate of carbon acquisition per unit area and high carbon storage [1]. When there is too much moisture or a thin water layer, the topsoil can sustain the growth of many plants while also allowing peat to build up underneath it. Unlike marshes, which are dominated by herbaceous species, tropical peatlands are dominated by woody plants or trees. Furthermore, peatlands may be found all over the planet. Approximately 1.79 million square kilometres, or 3% of the world's land surface, are peatlands [2]. With 35% of the world's carbon reserves stored in it, the total carbon content is about twice that of the world's forests [3]. Peat swamp wetlands have the potential to provide the solution to the global warming issue due to their essential carbon fixation function [4].

Peatlands may also retain a lot of water [5], which inhibits the decomposition of soil organic matter. Microbial degradation and plant respiration are likewise sluggish [6]. Peatlands are crucial for regulating atmospheric carbon dioxide concentration, lowering the greenhouse effect, and delaying the rise in global temperatures because they have absorbed a significant quantity of carbon dioxide over millennia of accumulation [7]. However, unanticipated peatland fires have become more common in Southeast Asia [8], particularly in Indonesia [9–11] and Malaysia [12,13], which has led to a rise in greenhouse gas emissions in recent years. Even worse, the resulting transboundary haze has led to several societal issues, including air transport standstill [15] and smoke catastrophes from fires that have a major negative impact on human respiratory health [14]. When the smoke catastrophe was severe [16], particularly in 2015 [17] and 2019 [18], several schools were compelled to halt lessons.

The planned Fire Danger Rating System (FDRS) in Southeast Asian nations, which is overseen by the Malaysian Meteorological Department (METMalaysia), is based on the Canadian Fire Weather Index (FWI) in order to address

this issue. Furthermore, a patrol fire defence system has been created in Indonesia [19]. However, important soil observation data like groundwater level—which are especially important in tropical regions with a higher probability of wet days—are not included in the FDRS. The FDRS's ability to effectively anticipate and prevent forest fires is limited by the omission of these crucial characteristics, underscoring the need for more study and system enhancements specific to Southeast Asia. Another crucial metric for tracking forest fires in peatlands is the groundwater level [20,21].

As a result, taking into account a model that incorporates groundwater level (GWL) into the current FWI system helps to monitor and stop peatland forest fires in tropical regions. Using an Internet of Things (IoT) system to track the peatland's moisture level and forecast how quickly water will evaporate is one way to stop these kinds of fires. A number of variables, including temperature, humidity, and rainfall, may be used to simulate the rate of evaporation from a peatland. Numerous sensors that are a component of the Internet of Things system may be used to measure these characteristics. Models may be trained using previous data from the sensors to create an evaporation rate model. The model may thus give an early warning of any fire hazards and forecast the rate of evaporation in real time. Adding information from other sources, like the Meteorological Department, can increase the model's accuracy. Furthermore, early warning systems may be activated by the IoT system, allowing for prompt action and response by the appropriate authorities. Peatland fires can be successfully avoided and their negative environmental effects can be lessened with an Internet of Things system that simulates evaporation rates.

A more sophisticated system may be added to the peatland forest fire management system by integrating IoT technology. Neural networks are among the most promising cutting-edge techniques in the present technological landscape. One kind of artificial intelligence that enables self-learning from gathered data and then uses the information without human assistance is the neural network. In our situation, adding a neural network is a very sensible and beneficial step since it can learn from the data gathered by the sensors via the Internet of Things system and enhance forest management. The primary contributions of this study are as follows:

- To manage peatland forest fires, an IoT network based on LoRa has been installed in the Raja Musa Forest Reserve (RMFR), Kuala Selangor, Malaysia.
- The implemented IoT system has gathered precise hourly data.
- The water table prediction and timely fire hazard warning system performance of several machine and deep learning techniques (Linear Regression, Long Short-Term Memory (LSTM), and Deep Neural Network (DNN)) are modelled and compared.

As part of a global effort, sensory data from peatland locations in three ASEAN nations—Indonesia, Brunei, and Malaysia—is collected and linked to a central cloud hosted by NICT Japan. From 2014 to 2023, the North Selangor Peat Swamp Forest's integrated management plan may be supported by this kind of Internet of Things-based peatland system.

II. METHODOLOGY

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, 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.

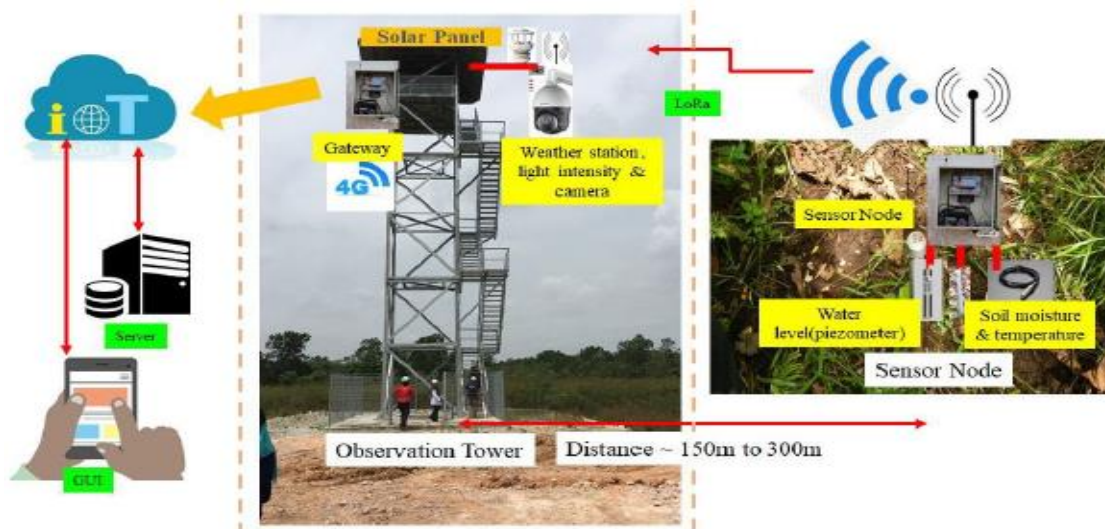


Figure 1. IoT based Peatland Forest Monitoring system

The suggested technique offers a novel approach to real-time groundwater level (GWL) prediction in peatland areas by fusing IoT and machine learning. Conventional GWL monitoring techniques are insufficient for efficient peatland management as they are frequently time-consuming and unable to provide continuous data. In order to overcome these obstacles, the suggested solution uses Internet of Things (IoT) sensors to gather environmental data and a machine learning model based on neural networks to effectively and precisely forecast GWL. IoT devices are placed across peatland regions to track changes in water levels and climatic variables including temperature, humidity, and pressure. These sensors use low-power communication protocols like LoRa or Zigbee to send the data to a central server or cloud platform. In order to comprehend the connections between environmental conditions and GWL changes, the gathered data is analysed and put into a neural network model that has been trained on historical datasets. Proactive decision-making is made possible by the machine learning model's ability to deliver precise and trustworthy GWL forecasts in real time. Stakeholders can keep a close eye on the situation thanks to an intuitive dashboard that shows the most recent GWL readings and projections. In order to ensure prompt measures to reduce hazards like peatland fires, the system also has an alert mechanism that alerts pertinent parties when important GWL levels are achieved. This method is unique because it can function in areas with little resources and produce precise forecasts using basic meteorological data. The suggested system provides a scalable and affordable peatland management solution by automating the monitoring procedure and incorporating real-time analytics. It is a major step forward in using IoT and machine learning to solve environmental issues, guarantee sustainable behaviours, and lower the likelihood of environmental dangers.

III. RESULTS AND DISCUSSION

A. System Environment

The proposed model is developed using said hardware system configuration and software required to implement the design is shown below.

Hardware System Configuration:

- Processor: Intel i5
- RAM : 8 GB
- Hard Disk : 256 GB
- Key Board : Standard Windows Keyboard
- Mouse : Two or Three Button Mouse
- Monitor : SVGA

Software Requirements:

- Operating system : Windows 7 Ultimate.
- Coding Language : Python.
- Front-End : Python.
- Back-End : Django-ORM
- Designing : Html, css, javascript.
- Data Base : MySQL (WAMP Server).

B. Experimental findings

To overcome the difficulties of real-time monitoring and prediction in peatland settings, "Machine Learning for Peatland Ground Water Level (GWL) Prediction via IoT System" shows the efficacy and promise of fusing IoT technology with machine learning. The system effectively collected water level readings and ambient data, including temperature, humidity, and air pressure, using Internet of Things sensors. Low-power communication protocols like LoRa were used to wirelessly transport this data, guaranteeing dependable data transfer even in isolated and resource-constrained peatland regions. Accurate groundwater level predictions were made possible by the neural network-based machine learning model, which was trained using historical GWL and environmental data. With a Root Mean Square Error (RMSE) ranging from 3.554 to 4.920, the model demonstrated a high degree of accuracy, guaranteeing that predictions were within 14.760 mm of the actual GWL values. This degree of precision is important because it allows for proactive management of peatland regions by offering accurate, up-to-date forecasts that reduce the danger of fire and other environmental hazards. The efficiency and scalability of the suggested system were also assessed. One major benefit was the ability to install more sensors and extend coverage to bigger peatland regions without having to significantly raise operating expenses.

Additionally, the real-time monitoring dashboard made it simple for stakeholders to view the data, enabling prompt action when GWL thresholds were close to catastrophic levels. By alerting users when prompt action was required, the alert system further increased the system's efficacy and helped to lower risk and improve peatland resource management. The system's computational efficiency showed that, even with limited resources, it could produce precise forecasts while using little electricity, which made it appropriate for deployment in peatland areas that are far from one another. The system's adaptability was further demonstrated by the incorporation of basic meteorological factors into the machine learning model, which made it usable in places without sophisticated infrastructure. All things considered, the study's findings suggest that the suggested approach presents a viable way to anticipate GWL in peatlands in real time. It offers a potent tool for managing peatland ecosystems, enhancing fire risk mitigation techniques, and supporting sustainable environmental practices by fusing IoT data collecting with machine learning analysis. The method might be used in various ecological monitoring situations where addressing environmental threats requires accurate forecasts and real-time data.

The processed results and user interface results are shown in below figures.

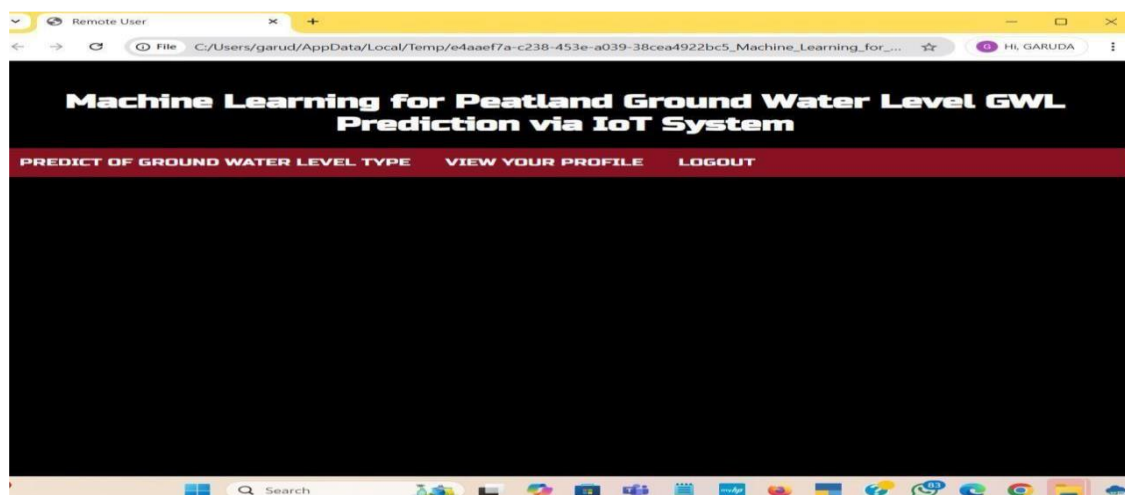


Figure 2. Profile Interface

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

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



Figure 3. User Login Interface

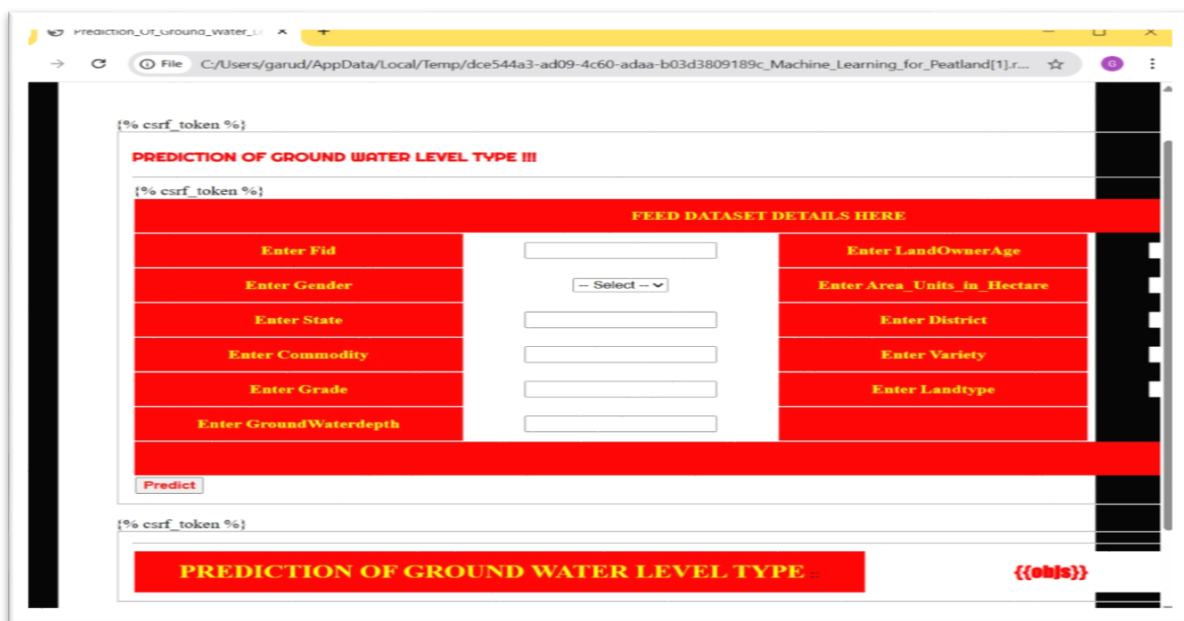


Figure 4. Entering details for ground level water prediction

IV. CONCLUSION

To efficiently control fire hazards in ASEAN peatlands, this project created an Internet of Things-based peatland management system. The IoT system's real-time data collecting enables rapid peatland condition monitoring. Analysis showed that ground sensor data and accumulated precipitation had a substantial association, indicating that it is a suitable input for training neural network models. Since water management has been shown to be an effective strategy for reducing fire hazards, the constructed neural network accurately predicts groundwater levels, which is essential for peatland fire management. Crucially, our prediction findings show great accuracy, with an RMSE that varies with the

number of hidden layers, from 3.554 to 4.920. The study's conclusions offer insightful information that can help with groundwater level forecasting and management in peatland regions. A proactive strategy to reduce the danger of peatland fires is provided by the use of machine learning algorithms and Internet of Things-based monitoring devices to provide precise estimates of groundwater levels. These results highlight how contemporary technology and hydrological knowledge may be used to improve catastrophe preparedness and solve environmental issues. To increase the neural network's capacity and precision for prediction, more data from both the dry and wet seasons will be gathered for training in subsequent studies. In order to acquire a better knowledge of the peatland weather, additional analysis of the data gathered by the weather station will be carried out and compared to the atmospheric data supplied by MET Malaysia. Finally, possible features for automatic water table management interaction with the IoT system will be examined.

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