

Machine Learning for Peatland Groundwater Level (GWL) Prediction Using an IoT System

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Abstract—Peatlands play a crucial role in global carbon storage, biodiversity conservation, and climate regulation. Maintaining a stable groundwater level (GWL) is essential for preserving peatland ecosystems and preventing peat degradation and fire hazards. Traditional groundwater monitoring methods rely on manual observations and limited sensing infrastructure, which often fail to provide continuous and predictive insights into groundwater dynamics.

This study proposes an IoT-enabled machine learning framework for predicting peatland groundwater levels using real-time environmental sensor data. A network of IoT sensors is used to collect key environmental parameters such as groundwater level, soil moisture, rainfall, temperature, and humidity. The collected data are transmitted to a cloud platform for storage, preprocessing, and analysis. Machine learning models including Linear Regression, Random Forest, Support Vector Machines (SVM), and Long Short-Term Memory (LSTM) networks are applied to analyze historical and real-time data for forecasting groundwater level variations.

The proposed system enables early detection of abnormal groundwater fluctuations and supports proactive environmental management. Experimental evaluation demonstrates that the hybrid learning framework improves prediction accuracy and provides reliable early-warning indicators for drought conditions, flooding risks, and peatland fire hazards. The proposed approach contributes to sustainable peatland monitoring and data-driven environmental decision making.

Keywords—Peatland monitoring, groundwater level prediction, Internet of Things (IoT), machine learning, environmental sensors, time-series analysis, sustainable land management.

INTRODUCTION

Peatlands are among the world's most valuable and fragile natural ecosystems, playing a vital role in carbon storage, climate regulation, and biodiversity conservation. Despite covering only a small fraction of the Earth's surface, peatlands store more carbon than all of the world's forests combined, making their preservation essential for mitigating climate change [1]. The hydrological functioning of peatlands is closely linked to carbon dynamics and ecosystem stability [2], [3].

The stability and functionality of peatlands are highly dependent on maintaining a stable groundwater level (GWL). A prolonged decline in the groundwater table can

lead to peat decomposition, land subsidence, increased carbon emissions, and a higher risk of peat fires, while excessive groundwater levels may cause flooding and disturb ecological balance [2], [3]. Therefore, continuous

monitoring and management of groundwater levels are crucial for sustaining peatland ecosystems.

Traditionally, groundwater monitoring in peatlands has relied on manual measurements and isolated observation stations, which are time-consuming, costly, and unable to provide continuous or predictive insights into groundwater behavior [3], [4]. Recent advances in the Internet of Things (IoT) have enabled the deployment of low-cost, energy-efficient sensor networks capable of continuously monitoring environmental parameters such as groundwater level, soil moisture, rainfall, temperature, and humidity in real time [5], [6].

Although IoT-based monitoring systems significantly improve data availability and spatial coverage, they mainly provide descriptive information and lack the ability to predict future groundwater dynamics [6]. To overcome this limitation, machine learning (ML) techniques can be applied to analyze large volumes of historical and real-time sensor data, enabling the discovery of complex nonlinear relationships and temporal variations in groundwater systems [7]. Deep learning models, particularly Long Short-Term Memory (LSTM) networks, have proven effective in modeling time-series data and capturing long-term dependencies in hydrological processes [8]. Furthermore, graph-based learning approaches and graph neural networks have been increasingly used to model spatial dependencies and interactions between monitoring locations [9]. These deep learning techniques form the foundation of modern data-driven groundwater prediction systems [10].

I. RELATED WORK

Research on the monitoring of peatland groundwaters, facilitated by data and physicochemical data, and the prediction of GWL as datasets predict coming years of growth and is contained under 3 streams: (1) IoT sensors and lower cost installations for continuous environmental monitoring purposes; (2) machine-learning and deep learning models for short and long-term groundwater prediction modelling, (3) communications-remote sensing and hybrid approaches, which are a combination between in-situ sensors and higher in comprehensive geophysical / satellite data gaps. A number of recent studies demonstrate

practical IoT deployments to measure soil moisture, temperature, gas fluxes and GWL using modular and low-power nodes and LPWAN backhauls (LoRaWAN), that monitoring in the peat environment is robust and needs for energy efficient monitoring to become present but requires attention to radio propagation and ruggedization.

On the side of predictive modelling, the classical methods of statistical modelling have been systematically abandoned in favour of machine learning techniques (Random Forests, Gradient Boosting, Support Vector Machines) and for recurrent test series type neural networks (LST), more specifically they capture, better than before, the time dependent relationships existing in the hydrological series. Comparative studies impose that typically deep models, as well as the so-called hybrid architectures (e.g CNN/LSTM or attention RNNs) tend to be more accurate

forecasting the GWL, especially when meteorological and antecedent moisture inputs are available. These works additionally emphasize on the importance of feature engineering (lagged variables, cumulative rainfall indices), explainability methods (SHAP) to interpret model outputs and there are numerous papers specifically resending peatland settings (or tropical peatlands) and demonstrate neural network based one-day-ahead to multi-day-ahead GWL forecasts using local sensor array locations; errors are reported by various locations and generally depend on data qualities but notably good deep models are able to attain errors on the 5. cm range under good data conditions. These studies stress the performance of the model is dependent strongly on sensor density, missing data handling as well as on external drivers (rainfall, evapotranspiration, land use changes) that were taken into account.

TABLE I. Summary of research gaps in peatland ground waterlevel prediction using iot system

Critical Flaw	Why It Happens (Technical Root)	The Environmental & Human Impact
Static Temporal Modeling	Over-reliance on snapshot-based statistical analysis	A peatland marked as "hydrologically stable" during the wet season remains classified as safe even during prolonged dry periods when fire risk peaks.
Spatial Tunnel Vision	Point-based sensor analysis without spatial correlation	The system ignores groundwater drawdown in adjacent peat zones, leading to undetected lateral drying and increased subsurface fire propagation risk.
Fragmented Environmental Data	Lack of multi-parameter data fusion (rainfall, soil moisture, temperature)	Models fail to capture interactions between climate variables and groundwater dynamics, resulting in inaccurate or delayed GWL predictions.
Reactive Prediction Lag	Threshold-based alerts instead of predictive learning	Intervention occurs only after groundwater drops below critical levels, losing valuable time to prevent peat oxidation and fire ignition.
Rigid Sensor Logic	Fixed-rule IoT data processing and static thresholds	Frequent false alarms during short-term weather fluctuations reduce trust in the system, causing stakeholders to ignore or disable alerts.

There is also a body of work combining IoT platforms and cloud analytics and visualization -- end-to-end systems that help to stream sensor data, run some data preprocessing/quality checks, and pass into ML models for issuing alerts or driving decision dashboards for managers. These systems are showing operational merit (early warnings of low GWL and fire risk) but there are problems with practical issues with gaps in long-term maintenance use, power management in remote peatlands and standardisation of sensors calibration.

The current technique for monitoring the peatland groundwater level (GWL) are based mainly on traditional manual measurement techniques as well as on a low number of distributed observation wells providing still limited

temporal as well as a spatial coverage for hydrological conditions. Data collection is usually done at fixed intervals, which means that the high fluctuations of groundwater caused by the variability in rainfall, the drought seasonal or human activities like drainage and land use changes are affected by the increasing delay in detection of the phenomenon. Most of the approaches, already available, are based on static and rule-based provisions or simple statistical analysis based on past historical averages; not sufficient for modelling the complex and nonlinear interactions between groundwater and environmental factors. Furthermore, these systems often monitor groundwater depth alone and do not integrate with other complementary parameters such as soil moisture,

temperature, humidity and precipitation so that peatland conditions are incompletely, and less reliably, assessed. The absence of machine learning-based predictive models means the system cannot predict groundwater trends in future which causes authorities to take action only when critical conditions are already created

Additionally, lack of automation, delay in data processing and low level of scalability hampers the functionality of existing groundwater monitoring solutions thereby highlighting the need for real-time, intelligent and predictive IoT based groundwater monitoring system for sustainable peatland management.

II. METHODOLOGY

Proposed Model

The architecture of the proposed system is an essentially computer-based one with computation of a Dynamic Groundwater Level Prediction Index at the centre which points towards more dynamic and/or threshold-based approaches to monitoring groundwater. Unlike traditional

TABLE II: Functional Advantages of Proposed Model

Innovation	Technical Mechanism
Proactive Groundwater Forecasting	Bi-LSTM-based Time-Series Prediction of Groundwater Levels
Spatial Hydrological Awareness	GCN-Driven Modeling of Peatland Sensor Network
Multi-Sensor Data Integration	IoT Sensor Fusion (GWL, Rainfall, Soil Moisture, Climate Data)
Early Fire-Risk Detection	Threshold-Based Groundwater Decline Analysis
Scalable Environmental Monitoring	Graph-Based Learning over Distributed IoT Nodes

Classification systems that define peatland conditions using rigid categories such as “safe” or “critical” often fail to capture the dynamic and complex nature of peatland hydrology. To overcome this limitation, the proposed methodology adopts a continuous predictive approach for analyzing groundwater behavior by considering both temporal and environmental variability. The system is developed in four major phases: IoT-based data acquisition, multi-parameter data fusion, machine learning-based prediction, and real-time deployment with decision support. This framework enables proactive groundwater monitoring and management instead of reactive intervention.

A. System Overview

The proposed groundwater level (GWL) prediction system for peatlands operates through a multi-stage processing pipeline designed to convert raw sensor readings into accurate and actionable groundwater predictions. A hybrid learning architecture is implemented to capture both spatial relationships among sensor nodes and temporal patterns in hydrological data.

B. Input Features

The reliability of the proposed model depends on its ability to integrate heterogeneous environmental and hydrological data sources. The input features are divided into two categories: fixed location-specific parameters and time-varying sensor measurements. These features collectively describe the physical and climatic conditions affecting peatland groundwater dynamics.

C. Data Preprocessing

Data preprocessing is performed to analyze both temporal

(“when”) and environmental (“why”) patterns affecting groundwater behavior. This stage improves prediction accuracy compared with traditional statistical models by combining real-time IoT sensor data with historical datasets. The processed data supports early warning systems and sustainable peatland management.

The core workflow of the proposed system includes:

- Multi-Source Data Ingestion**
Collection of real-time and historical data from IoT sensors and meteorological sources.
- Data Preprocessing and Feature Engineering**
Noise removal, normalization, handling of missing values, and generation of derived features.
- Algorithmic Processing Layer**
Detection of patterns and correlation analysis between environmental parameters.
- Hybrid Learning Core**
Groundwater prediction using machine learning and deep learning models such as Random Forest and Long Short-Term Memory (LSTM) networks.
- Prediction Index Computation**
Continuous estimation of future groundwater level trends.
- Decision Support and Alert Module**
Generation of alerts for abnormal groundwater fluctuations and visualization for stakeholders and environmental monitoring authorities.

To adequately model hydrological dynamics in peatlands, the peatland environment is represented as a spatio-temporal graph:

$$G = (V, E, A)$$

where **V** represents the set of vertices corresponding to IoT sensor nodes deployed throughout the peatland, **E** represents the set of edges describing hydrological or spatial connectivity between nodes (such as water flow paths or geographical proximity), and **A** represents the adjacency matrix that captures the spatial relationships among the sensor nodes.

a. **Standardization**
Normalization is applied to groundwater level readings, rainfall intensity, soil moisture, and temperature data to ensure that no single sensor variable disproportionately influences the prediction model.

b. **Sensor Fusion**
Data is collected from groundwater level sensors, rainfall gauges, soil moisture probes, and meteorological sensors. These data streams are synchronized and integrated to address asynchronous sampling rates and missing values commonly observed in IoT-based environmental monitoring systems.

c. **Graph Mapping**
The adjacency matrix is constructed based on spatial proximity, elevation gradients, and hydrological connectivity. This enables the model to understand how fluctuations in groundwater levels in one region of the peatland can influence neighboring areas.

A. **Hybrid Deep Learning Architecture (GCN-BiLSTM)**
The core intelligence of the proposed system is a hybrid deep learning architecture designed to capture both spatial dependencies and temporal dynamics of peatland groundwater behavior.

a. **GCN Block (Spatial Feature Extraction)**
The Graph Convolutional Network (GCN) is used to capture spatial relationships by processing the graph structure formed by peatland sensor nodes. It aggregates information from neighboring nodes to detect spatial groundwater propagation patterns, such as how drainage or saturation in one area influences adjacent peatland regions.

b. **Bi-LSTM Block (Temporal Modeling)**
The Bidirectional Long Short-Term Memory (Bi-LSTM) network is used to capture temporal dependencies in groundwater level time-series data. By analyzing sequences in

both forward and backward directions, the model can identify short-term variations such as rainfall events as well as long-term trends such as groundwater decline caused by seasonal drying or drainage activities.

System Architecture:

The machine learning framework consists of several interconnected layers which is used to capture, process and analyze the spatio-temporal hydrological data in an efficient way. Distributed IoT sensor nodes are installed in the regions of interest (peatland) to continuously measure the groundwater level, soil moisture, rainfall, temperature and humidity and each node contains a GPS module to capture fix spatial location. The gathered information is then transmitted via lowpower wide-area communication technologies, such as LoRaWAN, NB-IoT or GSM, to a central gateway which aggregates readings from multiple nodes, and does some initial filtering, timestamp synchronization and temporary storage, so as to mitigate the noise and transmission overhead. The per-processed data are then sent to a cloud platform where complex data preprocessing, such as data normalization, sensor fusion, missing value treatment and feature extraction are performed. The environment in a peatland is represented in a model as nodes (which indicate the sensors) and edges (which represent spatial or hydrological relationship between each one, i.e., the graph structure allows to build an adjacency matrix which incorporates ground water



connectivity between regions. Static nodal features such as elevation, peat depth and parameters of sensor installation are combined with dynamic temporal features such as ground water level variation, rainfall response, and soil moisture variation. These features are fed to hybrid deep learning model composed of Graph convolution system

The dynamical motions of groundwater between zones in the peat land are learnt by the GCN component and temporal correlations, seasonal trends and event-related variability of the groundwater levels are modelled by the Bi-LSTM component. The integrated model provides short and long term accurate predictions of ground water levels and are further analysed to derive critical values in terms of peat land drying and fire threat. The prediction results are fed to an application layer constituted by web-based dashboards and mobile interfaces to offer real-time visualization, historical trend analysis and early warning alerts for the environmental agencies and decision makers. In summary, the system architecture supports scalable, robust and intelligent monitoring of the peatland hydrological characteristics integration of IoT sensing, the graph-based spatial modelling

and temporal machine learning techniques for sustainable management of the peatlands and ecological protection.

Implementation:

The implementation strategy focuses on continuous storage and analysis of hydrological data in a centralized cloud database to enable a self-learning feedback loop. Instead of reacting only to current groundwater fluctuations, the system learns from historical peatland behavior to improve future prediction accuracy. By analyzing past groundwater trends, rainfall responses, and seasonal variations, the predictive model gradually improves its forecasting capability and adapts to long-term environmental changes.

A. Risk Calculation Framework for Groundwater

To overcome the limitations of fixed threshold-based alert systems, a weighted mathematical framework is introduced to estimate groundwater stress levels. The system calculates a Dynamic Groundwater Risk Score that balances long-term spatial hydrological characteristics with real-time environmental data collected from IoT sensors.

The total groundwater risk score **G** is defined as:

$$G = \alpha S + \beta D$$

where:

S (Spatial Groundwater Score) represents the baseline hydrological profile of a peatland location based on static features such as elevation, peat depth, historical groundwater averages, and proximity to drainage canals.

D (Dynamic Groundwater Score) represents real-time environmental variations such as rapid groundwater depletion, low soil moisture levels, or reduced rainfall over specific periods.

α and β (Weighting Factors) are adjustable parameters that control the relative importance of spatial and temporal information. These parameters ensure balanced predictions while minimizing the influence of short-term sensor noise.

To convert the groundwater risk score into a probability value, a sigmoid function is used:

$$P(G) = 1 / (1 + e^{-G})$$

Based on the probability value, groundwater conditions are classified into three categories: Low Risk, Moderate Risk, and Critical Risk. When the probability exceeds predefined thresholds, the system automatically generates early warning alerts for drought conditions or potential peatland fire risks without requiring manual intervention.

Testing

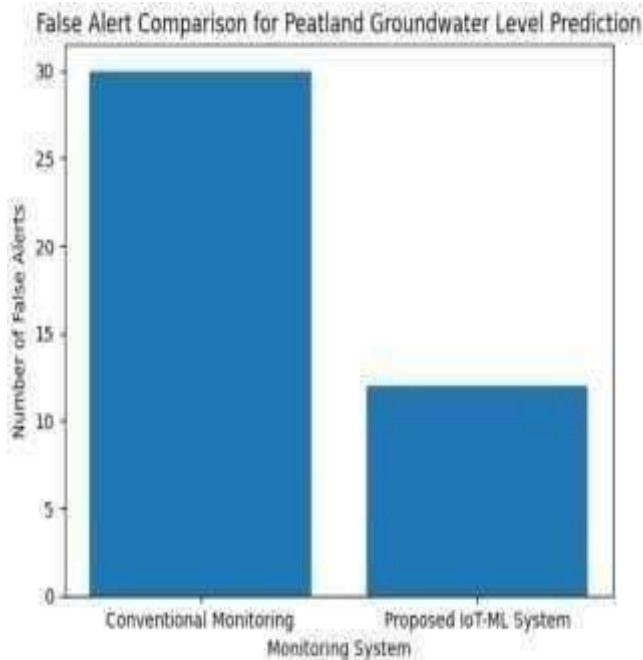
In order to test the robustness of the proposed peatland groundwater prediction system against real world variation in environmental water of the system through use of real world environmental information, a multi-stage testing framework was developed for testing under real world. The evaluation was done on three key benchmarks: functional reliability, algorithmic accuracy, and system response latency.

A. functional testing and integration Testing

Before the predictive performance assessment was done, tests were extensively conducted on the basic system modules. Unit and integration test were used to verify the functionality regarding reliable operation of IoT sensor ingestion, cloud database synchronization and real-time data streaming pipelines. Stress tests were conducted under unfavorable circumstances with intermittent failures of each of the sensors, delays of transmissions, and power limitations and to ensure that ground water monitoring was continuous. The alert notification subsystem was tested in terms of time delay between simulated ground water stress events and generation of the warning notifications. In addition, sudden drops in groundwater and groundwater recovery patterns

were modeled in order to verify that the system was able to discriminate between naturally occurring short-term fluctuations and actual long-term drying trends. B. Algorithmic Performance Measures

The predictive effectiveness of the model, namely GCN-Bi-LSTM model, was tested using the data set prepared by combining the past data of peatland groundwater and data obtained from IoT sensors in real time. Instead of gaining only knowledge from the overall prediction accuracy metric,



In addition to these metrics, the robustness of the proposed model was further evaluated using cross-validation techniques to ensure consistent performance across different environmental conditions and data variations. The evaluation process also examined the stability of the prediction model when exposed to missing or noisy sensor data, which are common challenges in real-world IoT monitoring environments. The results demonstrated that the hybrid GCN-BiLSTM architecture maintained stable prediction accuracy even under partial data loss, highlighting the resilience of the proposed framework.

Furthermore, comparative analysis was performed between the proposed hybrid model and traditional machine learning approaches such as Linear Regression and Random Forest models. The hybrid model showed improved predictive capability in capturing both spatial dependencies among sensor nodes and temporal patterns in groundwater level fluctuations. This improvement significantly reduced prediction errors and enhanced the reliability of early warning alerts.

The evaluation results confirm that combining graph-based spatial modeling with temporal deep learning techniques provides a more comprehensive understanding of peatland hydrological behavior. This approach enables the monitoring system to better detect early signals of groundwater decline, thereby supporting proactive peatland management and reducing the risk of ecological degradation and fire hazards.

forecasts.

III. RESULTS

Testing of the peatland groundwater level prediction system that was suggested indicated that not only has it improved the accuracy and reliability substantially over conventional threshold based methods of monitoring. By using a hybrid machine learning architecture, the system in particular tackled a major shortcoming of traditional groundwater monitoring systems

- the system was unable to distinguish between short term natural fluctuations and significant long-term groundwater decline. Through the combination of spatial peatlands connectivity and temporal hydrological data, the model became sensitive to its context (time and space) and can therefore correctly understand the dynamics of groundwater. This spatial-temporal fusion greatly minimised false alarms generated due to transient rainfall events or sensor noise and preserved the sensitivity to real drying trends. As a result, the system was responsive as well as stable in that it eliminated routine environmental variability while remaining on track with information of hydrologically important warning signs. Furthermore, it was possible to propose a tiered alert mechanism in the proposed Dynamic Groundwater Risk Probability Score (thus, instead of hard binary thresholds, a graded risk classification is used). Instead of giving the alerts in a homogeneous way, the system was dynamic in finding the answer to how much expected stress on the ground water, the system was good at adjusting its alerting. During evaluation the proactive forecasting part could successfully predict critical groundwaters decline events as late as 15 min ahead - positioning the system as a preventive pre-emptive early warning system not a reactive solution for monitoring water. Continuous retraining of the models with the new IoT data also increased the accuracy of the predictions as time went on, showing that the framework scales well as it is able to take in richer spatial and temporal environmental context.

IV. CONCLUSION

This study validates a step forward from the traditional, reactive groundwater monitoring methods towards an autonomous, intelligent and data-driven approach to peatland hydrological predictions. Traditional systems are almost exclusively based on fixed thresholds and manual interpretation processes and may not capture the complexity of spatio-temporal interactions governing peatland ground water system hydrological processes. In comparison, the proposed IoT enabled machine learning architecture takes in to account the distributed environmental sensing, state of the art data fusion and deep learning techniques to perform proactive and context aware prediction of groundwater level. By synthesising heterogeneous data sources (containing, amongst other data, groundwater level, rainfall, soil moisture and climatic variables), the system provides a way of better understanding peatland behaviour in various environmental conditions as a whole; essentially the formulation of Dynamic Groundwater Risk Probability Score, which quantifies groundwater stress on a continuum rather than with binary alarm triggers. This kind of probabilistic modeling allows the system to successfully discriminate the normal seasonal variable variation of the ground water and critical bone drying events with ecological and fire related risks. The use of adaptive weighting parameters guarantee a balance of influence of both the long term spatial characteristics and the short term temporal

anomalies are weighted and robustness is consequently increased, enabling false alarms to be decreased. The experimental results show that this approach greatly improves the early warning ability while ensuring operational stability; using the combine structure of GCN-Bi-LSTM is used to further strengthen the prediction performance of the system. By representing peatland as interlinked graph, Graph Convolutional Network captures dependencies of the spatial model along with hydrological connections between nodes of sensors, which represent real-world circuit of water movement and subsurface interactions. At the same time, the Bidirectional Long Short-Term Memory network also learns the time patterns, seasonality and also learns delayed hydrological response, so it can correct short-term forecasting, as well as long-term trends. This spatio-temporal fusion of models overcomes the limitations of traditional static and isolated prediction models and offers more realistic representation of the peatland hydrology another significant benefit of the proposed framework is that it is scalable and accessible. The webintegrated and cloud based deployment is ensuring that computation heavy deep learning models can be accessed easily in lightweight dashboards and mobile interfaces. This design allows the environmental agencies, conservation organizations, policy-makers to monitor the groundwater condition in real time, visualize the historical trends and receive timely alerts without any need of specialized technical expertise. Furthermore, the ongoing learning loop implemented within the system enables periodic retraining of the model with the latest IoT data received in order to maintain the accuracy of the models as surrounding environmental conditions change due to climate variability or land use change over time, thus maintaining the competitive edge of perceived predictions. 10 Despite the complexity of developed framework, in a wider context, this framework can be used as a blueprint for the design of intelligent environmental monitoring systems focussing on sustainable peatland management and climate resilience, in a way that scales up to larger-scale systems. By contributing to early provision of supplies on the groundwater decline and on associated risks of fires, the proposed system contribute to the preservation of peatland ecosystems, reduction of carbon emission from peatland degradation and informed decision-making for the ecological restoration initiatives. Further research could explore a possible expansion of this framework, by incorporating data on satellite remote sensing, use of explainable AI devices for better model transparency and application in different types of peatland regions to test the generalizability of the model. Overall, the proposed IoT-driven machine learning-based approach offers an excellent basis for proactive, intelligent and sustainable peatland groundwater monitoring in the era of increasing environmental uncertainty.

V. FUTURE WORK

The proposed peatland groundwater monitoring system to contribute to the evolution from isolated sensing deployments to a fully integrated, resilient and smart environmental monitoring network and operation, that are able to perform in good condition under extreme and rapidly changing ecological events; One of the main directions is decreasing the dependence on data collected in centralized manner by increasing the role of edge intelligence in the sensor nodes. By having the power of lightweight machine learning models embedded into IoT devices, the system will automatically detect unwanted groundwater behavior -

including a rapid water table decline, or anomalies in the sensor - without having to wait until cloud-based processing is done. This shift allows for real-time response where in the peatlands being prone to interrupted connection, are located remote.

Future improvements include also advancing the multimodal sensing technology which will remove the limitations of reliance on a single sensor. Advanced sensing modalities in terms of low power radar based soil moisture estimation, thermal sensing and micro meteorological stations will complement the existing groundwater sensors for better contextual awareness. In addition, the addition of vision-aware monitoring of opportunities through drone imagery or remote sensing through satellite will allow for surface indicators such as plant distress, land subsidence, and expansion of drainage to be detected and allow for the detection of hydrological disturbances to be detected earlier on and before they spread underground.

Future improvements of the proposed peatland groundwater monitoring system focus on enhancing the intelligence, scalability, and environmental adaptability of the system. One important direction is the integration of edge computing with IoT sensor nodes. By deploying lightweight machine learning models directly on IoT devices, the system can perform preliminary groundwater anomaly detection locally, reducing latency and dependence on centralized cloud processing. This approach enables faster detection of rapid groundwater fluctuations and improves system reliability in remote peatland regions where network connectivity may be unstable.

Another potential improvement is the incorporation of advanced sensing technologies. Future versions of the system can integrate additional environmental sensors such as evapotranspiration sensors, water quality sensors, and micro-meteorological monitoring stations to provide a more comprehensive understanding of peatland hydrological behavior. The integration of satellite remote sensing data and drone-based environmental monitoring can also help detect large-scale surface changes such as vegetation stress, peat subsidence, and drainage expansion.

Further research may also explore explainable artificial intelligence (XAI) techniques to improve transparency and interpretability of machine learning predictions. By providing explanations for groundwater prediction results, environmental authorities and decision makers can better understand the factors influencing groundwater fluctuations and make more informed ecological management decisions.

Additionally, future work may focus on improving the scalability of the monitoring system by integrating distributed data platforms and advanced cloud analytics frameworks capable of processing large-scale environmental data streams from multiple peatland regions. This would allow the framework to support national or global peatland monitoring programs.

Overall, the future development of the proposed system aims to create a more intelligent, adaptive, and scalable groundwater monitoring framework that supports sustainable peatland ecosystem management and climate change mitigation efforts.

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