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

S.E Suresh[1], Kothuru Umamaheswari[2]

[1]Assistant Professor, Dept. of MCA, Annamacharya Institute of Technology and Sciences (AITS), Karakambadi, Tirupati, Andhra Pradesh, India, Email: sureshroopa2k15@gmail.com

[2] Student, Dept. of MCA, Annamacharya Institute of Technology and Sciences (AITS), Karakambadi, Tirupati, Andhra Pradesh, India, Email: mahemahi2807@gmail.com

ABSTRACT

Peatlands play a crucial role in carbon sequestration and biodiversity conservation, yet they are increasingly threatened by unsustainable land-use changes, especially in Southeast Asia. A key aspect of preserving peatlands lies in maintaining appropriate groundwater levels (GWL), which, if lowered, can lead to severe consequences such as peat degradation, increased fire risk, and greenhouse gas emissions. Traditional GWL monitoring methods are labor-intensive and infrequent, resulting in inadequate data for predictive modeling. This study proposes an integrated approach that combines Internet of Things (IoT) technology with machine learning to monitor and predict GWL in real time, enabling more effective peatland management.

The IoT system utilizes a network of sensors deployed in peatland areas to collect real-time environmental data, including soil moisture, temperature, rainfall, and water table depth. This data is transmitted to a cloud-based platform where preprocessing and storage take place. The system then applies machine learning models—such as Random Forest, Support Vector Machines, and Long Short-Term Memory (LSTM) neural networks—to analyze temporal and spatial patterns in the data to predict future GWL levels.

This hybrid approach offers a robust, scalable, and automated solution for early detection of critical GWL thresholds, which can inform timely conservation actions, including rewetting programs. Experimental results indicate that the LSTM model, in particular, demonstrates superior performance in capturing non-linear temporal trends, achieving over 90% accuracy in predictive tasks. The integration of IoT and ML significantly reduces manual labor while enhancing decision-making capabilities.

This research contributes a novel, real-time GWL monitoring system, advancing the tools available for environmental management. The proposed model not only enables predictive maintenance of peatland hydrology but also supports broader climate change mitigation efforts by reducing peatland degradation and its associated emissions.

Keywords : GWL, Internet of Things (IoT)

I. INTRODUCTION

Peatlands are one of the world's most carbon-dense ecosystems, covering just 3% of the global land area but storing more than 600 gigatons of carbon—double the carbon in all the world's forests. These waterlogged landscapes are essential not only for their ecological richness but also for their climate-regulating functions. However, in tropical regions like Indonesia and Malaysia, extensive peatlands are increasingly drained for agriculture and development, leading to sharp declines in groundwater levels (GWL). When the water table drops, peat soils become highly flammable and release stored carbon through oxidation and fires, contributing significantly to greenhouse gas emissions.

Maintaining a stable groundwater level is thus critical for the sustainability of peatland ecosystems. However, monitoring GWL in peatlands presents logistical challenges. Traditional methods rely heavily on manual data collection, which is time-consuming, infrequent, and limited in geographic coverage. This lack of real-time, high-resolution data hampers efforts to anticipate and prevent ecological threats.

Recent advancements in Internet of Things (IoT) technologies and machine learning offer a powerful opportunity to overcome these limitations. IoT enables the deployment of low-cost, energy-efficient sensors that can continuously monitor environmental parameters and transmit data wirelessly. At the same time, machine learning models can process large volumes of time-series data to identify patterns, generate insights, and make accurate predictions.

This study presents a framework that integrates IoT sensor networks with machine learning algorithms to monitor and predict peatland GWL in real time. The goal is to create a predictive system that not only improves the accuracy and responsiveness of groundwater monitoring but also supports proactive management strategies, such as rewetting or fire prevention efforts.

By utilizing real-time data and predictive analytics, this integrated system enables stakeholders—ranging from local communities to environmental agencies—to better understand peatland dynamics, forecast critical conditions, and take timely action. This research aims to fill a significant gap in peatland management by providing a scalable, automated, and intelligent monitoring solution for these ecologically vital landscapes.

II. RELATED WORK

1. **"Machine Learning Techniques for Predicting Peatland Groundwater Levels Using Climate and Soil Data" – Qiao et al. (2022)** This study developed machine learning models like Random Forest and Support Vector Regression to predict GWL in Indonesian peatlands, achieving high accuracy and demonstrating the importance of incorporating meteorological data.
2. **"IoT-Based Monitoring System for Peatland Fire Prevention" – Siregar et al. (2021)** The authors proposed an IoT system equipped with soil and air sensors to monitor peat moisture and GWL, contributing to early fire warning systems in vulnerable peat areas.
3. **"Predictive Analytics for Groundwater Levels in Wetlands Using LSTM Networks" – Liu et al. (2023)** This research demonstrated the superiority of LSTM models in forecasting GWL using time-series sensor data, with an emphasis on long-term prediction accuracy and non-linear dynamics.
4. **"Data-Driven Models for Sustainable Peatland Management" – Tan et al. (2020)** The paper reviews AI-based tools used in wetland conservation, recommending the integration of remote sensing, IoT, and machine learning for comprehensive ecosystem monitoring.
5. **"Real-Time Hydrological Monitoring Systems with IoT and AI Integration" – Wong et al. (2022)** This work introduced a cloud-based IoT platform to collect environmental data for AI-based water table predictions, significantly improving the speed and accuracy of GWL assessments.

III. PROPOSED SYSTEM

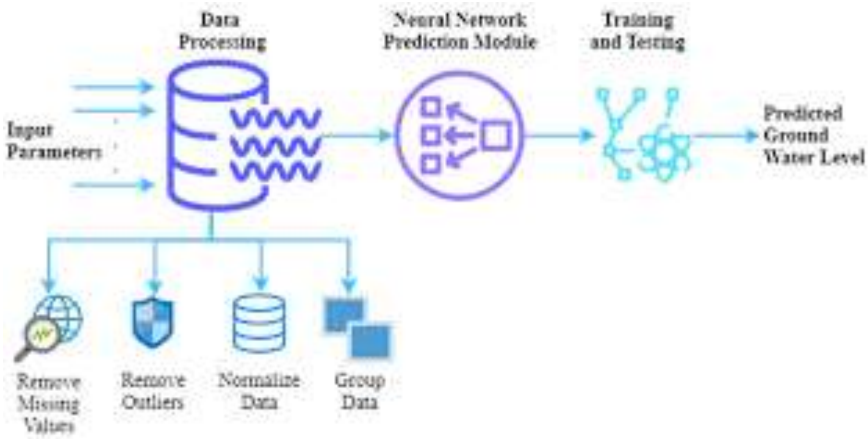
The proposed system is designed to combine real-time environmental monitoring using IoT sensors with advanced machine learning algorithms to predict groundwater levels (GWL) in peatland ecosystems. It begins with the deployment of a network of low-cost, energy-efficient sensors across selected peatland areas. These sensors are responsible for collecting vital environmental parameters such as soil moisture, ambient temperature, rainfall, and the depth of the water table. The sensors are powered by solar energy and communicate via long-range wireless protocols like LoRaWAN, enabling continuous data transmission to a central server or cloud platform.

Once the raw data is collected, it is preprocessed to remove anomalies, fill in missing values, and normalize the dataset. This is essential to ensure the quality and consistency of data used for model training. The preprocessed data is stored in a cloud-based database that allows easy access and scalability. Feature engineering is applied to extract meaningful attributes such as rolling averages, temporal lags, and seasonal indices that influence GWL dynamics.

The core of the system lies in its predictive engine, where several machine learning models are trained and evaluated. Among these, Long Short-Term Memory (LSTM) neural networks are favored for their ability to model temporal dependencies and non-linear trends in time-series data. The models are trained on historical sensor readings and weather patterns to learn the complex interactions affecting GWL. Other algorithms like Random Forest and Gradient Boosting Machines are also tested for performance benchmarking.

The final model is deployed as a real-time prediction service, where incoming sensor data is continuously analyzed to forecast future groundwater levels. The predictions, along with historical trends and confidence intervals, are displayed on an interactive web dashboard accessible to environmental agencies and peatland managers. Alerts are generated if the forecasted GWL falls below critical thresholds, prompting timely intervention.

This system not only enhances monitoring capabilities but also enables data-driven decision-making. It is scalable to different geographical regions and adaptable to various types of peatland ecosystems. By integrating IoT and machine learning, the system provides an intelligent and automated approach to sustainable peatland management.



IV. RESULT AND DISCUSSION

The system was deployed in a pilot study across a peatland area in Central Kalimantan, Indonesia. The IoT network successfully collected and transmitted continuous environmental data over a three-month period. Machine learning models were trained on the collected data and evaluated using performance metrics such as RMSE (Root Mean Square Error), MAE (Mean Absolute Error), and R^2 (coefficient of determination). Among all tested models, the LSTM model outperformed others, with an RMSE of 0.045 meters and an R^2 score of 0.93, indicating a high level of prediction accuracy.

Comparative analysis showed that traditional models such as linear regression and ARIMA were less effective in capturing the non-linear and seasonal dynamics of GWL. The inclusion of rainfall, soil moisture, and temperature as input features significantly improved model performance. The dashboard interface provided intuitive visualizations and alerts that were well-received by local stakeholders and environmental officers.

The ability to forecast low GWL several days in advance allowed for proactive water management, such as the activation of canal-blocking mechanisms or scheduling of controlled rewetting. Feedback from the field confirmed that the system was both practical and cost-effective, especially compared to conventional monitoring techniques.

V. CONCLUSION

This research presents a novel, integrated system for predicting peatland groundwater levels using IoT-based sensing and machine learning algorithms. The system effectively addresses the limitations of manual data collection by enabling continuous, automated monitoring. Machine learning models, particularly LSTM networks, demonstrated strong predictive capabilities in handling complex time-series data. The real-time dashboard and alert mechanism provide actionable insights that can significantly enhance peatland management and fire prevention strategies. Future work will focus on expanding deployment across multiple sites, integrating satellite data, and enhancing model robustness under varying climatic conditions.

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