



**FIRE WEATHER INDEX PREDICTION MODEL BASED ON IOT SYSTEM
FOR PEATLAND FOREST IN TROPICAL REGION**

By

LU LI

**Thesis Submitted to the School of Graduate Studies, Universiti Putra
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The Internet of Things (IoT) has revolutionized the way to collect and analyze data, allowing for more efficient and accurate predictions in various fields. IoT systems are becoming increasingly popular in monitoring and managing natural resources due to their ability to collect real-time data from remote locations. Peatland forests, in particular, require continuous monitoring to prevent degradation and mitigate the risk of peatland fires, making IoT systems valuable for conservation and fire prevention efforts. This thesis examines the current challenges in fire weather prediction and ground water level estimation for peatland forests. One major issue is the lack of integration of ground water level measurements into the existing Fire Weather Index (FWI) system, which hampers accurate assessment of fire risk in these unique ecosystems. Additionally, the absence of machine learning techniques hinders effective prediction of ground water levels and FWI values. By proposing innovative solutions, this study aims to enhance fire risk assessment models and improve decision-making processes for peatland forest management.

In this thesis, a LoRa-based IoT system was deployed in Raja Musa Forest Reserve (RMFR) in Kuala Selangor, Malaysia, to monitor peatland forests and prevent fire. Furthermore, the IoT system's feasibility was verified by comparing the correlation between its data and data from the Malaysian Meteorological Department (METMalaysia). This thesis proposes an improved tropical peatland Fire Weather Index (FWI) system by integrating Ground Water Level (GWL) measured by an IoT system into the existing FWI system. Four objectives are pursued: 1) Integrate GWL into the Drought Code (DC) calculation of the existing FWI system; 2) Integrate GWL into the Duff Moisture Code (DMC) calculation of the existing FWI system; 3) Predict GWL using Machine Learning (ML) combined with measurement of the IoT system; 4) Predict the FWI using ML combined with measurement of the IoT system.

The performance of the proposed model is evaluated using IoT measurement data and actual values published by METMalaysia. The results show that the IoT system data has a high correlation of 0.8 with METMalaysia's data. The proposed model using GWL for DC formulation improves the FWI system's accuracy. The proposed DMC model that uses GWL and relative humidity achieves a correlation of 0.9071 and a Mean Square Error (MSE) of 2.5633 with actual values. The MSE between predicted and real GWL values from the two sensor nodes deployed through neural network machine learning are 11.069 and 13.256, respectively. Finally, the proposed neural network-based models using four and nine fire factors as input parameters achieve a MSE of 1.537 and 1.116, respectively, and the correlation of the nine-input model is 0.890, while the four-input model is 0.852. This thesis contributes to the growing research on applying IoT and machine learning techniques for environmental monitoring and disaster prevention. These findings have significant practical value in predicting and reducing the risk of tropical peatland fires, which cause devastating damage to the peatland forest ecosystem.

Keywords: LoRa, IoT System, Machine Learning, Peatland Fire Monitoring

SDG: GOAL 9: Industry, Innovation And Infrastructure

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia
sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

MODEL RAMALAN INDEKS CUACA KEBAKARAN BERDASARKAN SISTEM IOT UNTUK HUTAN TANAH GAMBUT DI WILAYAH TROPIKA

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Internet Pelbagai Benda (IoT) telah merevolusikan cara mengumpul dan menganalisis data, membolehkan ramalan yang lebih efisien dan tepat dalam pelbagai bidang. Sistem IoT semakin popular dalam pemantauan dan pengurusan sumber semula jadi kerana keupayaannya mengumpul data secara masa nyata dari lokasi terpencil. Hutan tanah gambut khususnya memerlukan pemantauan berterusan untuk mencegah degradasi dan mengurangkan risiko kebakaran tanah gambut, menjadikan sistem IoT berharga dalam usaha pemuliharaan dan pencegahan kebakaran. Tesis ini mengkaji cabaran semasa dalam ramalan cuaca kebakaran dan penentuan paras air tanah untuk hutan gambut. Salah satu isu utama adalah ketiadaan pengintegrasian pengukuran paras air tanah ke dalam sistem indeks cuaca kebakaran yang sedia ada, yang menghalang penilaian risiko kebakaran yang tepat dalam ekosistem unik ini. Tambahan pula, ketiadaan teknik pembelajaran mesin menghalang ramalan yang berkesan bagi paras air tanah dan nilai indeks cuaca kebakaran. Dengan mencadangkan penyelesaian inovatif, kajian ini bertujuan untuk meningkatkan model penilaian risiko kebakaran dan meningkatkan proses membuat keputusan untuk pengurusan hutan gambut.

Dalam tesis ini, sistem IoT berasaskan LoRa telah diterapkan di Hutan Simpan Raja Musa (RMFR) di Kuala Selangor, Malaysia, untuk memantau hutan gambut dan mencegah kebakaran. Selain itu, kebolehlaksanaan sistem IoT telah disahkan dengan membandingkan korelasi antara data sistem tersebut dan data daripada Jabatan Meteorologi Malaysia. Tesis ini mencadangkan peningkatan sistem Indeks Cuaca Kebakaran untuk tanah gambut tropika dengan mengintegrasikan Aras Air Tanah yang diukur oleh sistem IoT ke dalam sistem Indeks Cuaca Kebakaran sedia ada. Empat objektif dicapai: 1) Mengintegrasikan Aras Air Tanah ke dalam pengiraan Kod Kemarau dalam sistem Indeks Cuaca Kebakaran sedia ada; 2) Mengintegrasikan Aras Air Tanah ke dalam pengiraan Kod Lembapan Duff dalam sistem Indeks Cuaca

Kebakaran sedia ada; 3) Meramalkan Aras Air Tanah menggunakan Teknik Pembelajaran Mesin berdasarkan pengukuran sistem IoT; 4) Meramalkan Indeks Cuaca Kebakaran menggunakan Teknik Pembelajaran Mesin digabungkan dengan pengukuran sistem IoT.

Prestasi model yang dicadangkan dinilai menggunakan data pengukuran IoT dan nilai sebenar yang diterbitkan oleh Jabatan Meteorologi Malaysia. Keputusan menunjukkan bahawa data sistem IoT mempunyai korelasi yang tinggi iaitu 0.8 dengan data Jabatan Meteorologi Malaysia. Model yang dicadangkan menggunakan Aras Air Tanah untuk formulasi Kod Kemarau meningkatkan ketepatan sistem Indeks Cuaca Kebakaran. Model Kod Lembapan Duff yang dicadangkan yang menggunakan Aras Air Tanah dan kelembapan relatif mencapai korelasi sebanyak 0.9071 dan Ralat Mean Square sebanyak 2.5633 dengan nilai sebenar. Ralat Mean Square antara nilai Aras Air Tanah yang diramalkan dan sebenar dari dua nod sensor yang diterapkan melalui pembelajaran mesin rangkaian neural adalah 11.069 dan 13.256, masing-masing. Akhirnya, model berdasarkan rangkaian neural yang dicadangkan menggunakan empat dan sembilan faktor kebakaran sebagai parameter input mencapai Ralat Mean Square sebanyak 1.537 dan 1.116, masing-masing, dan korelasi model sembilan input adalah 0.890, manakala model empat input adalah 0.852. Tesis ini memberikan sumbangan kepada penyelidikan yang semakin berkembang mengenai penggunaan IoT dan teknik pembelajaran mesin untuk pemantauan alam sekitar dan pencegahan bencana. Penemuan ini mempunyai nilai praktikal yang signifikan dalam meramalkan dan mengurangkan risiko kebakaran tanah gambut tropika, yang menyebabkan kerosakan dahsyat kepada ekosistem hutan tanah gambut.

Kata kunci: LoRa, Sistem IoT, Pembelajaran Mesin, Pemantauan Kebakaran

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LIST OF ABBREVIATIONS

2G	The 2 nd generation of mobile phone mobile communication technology standards
3G	The 3 rd generation of mobile phone mobile communication technology standards
4G	The 4 th generation of mobile phone mobile communication technology standards
5G	The 5 th generation of mobile phone mobile communication technology standards
AQI	Air Quality Index
ASEAN	Association of Southeast Asian Nations
BNPB	Badan Nasional Penanggulangan Bencana
BUI	Buildup Index
COP26	Conference of the Parties 26
DC	Drought Code
DMC	Duff Moisture Code
DR	Data Rate
FBP	Fire Behavior Prediction
FDRS	Fire Danger Rating System
FFMC	Fine Fuel Moisture Code
FSS	Fixed Satellite Service
FWI	Fire Weather Index
GIS	Geographic Information System
GPS	Global Positioning System
GWL	Ground Water Level
IoT	Internet of Things
ISI	Initial Spread Index

IUCN	International Union for Conservation of Nature
LET	Long Term Evolution
LoRa	Long Range Radio
LPWAN	Low-Power Wide-Area Network
MAE	Mean Absolute Error
MC	Moisture Content
METMalaysia	Malaysian Meteorological Department
ML	Machine Learning
mmWave	Millimeter Wave
MSE	Mean Squared Error
NB-IoT	Narrowband-Internet of Things
NICT	National Institute of Information and Communications Technology
R^2	Pearson product-moment correlation coefficient
RMFR	Raja Musa Forest Reserve
RMSE	Root Mean Square Error
UNFCCC	United Nations Framework Convention on Climate Change
UPVC	Unplasticized Polyvinyl Chloride
WiFi	Wireless Fidelity
WiPNET	Wireless and Photonic Networks Research Centre of Excellence
WLAN	Wireless Local Area Network
WSN	Wireless Sensor Network
WWAN	Wireless Wide Area Network

CHAPTER 1

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 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], and storing many carbon [5], they also provide unique aquatic habitats for endangered animals and plants [6].

Forest burning is a burning phenomenon in nature. However, a fire that has lost human control can spread freely in the forest and cause particular harm and loss to the forest ecosystem and human beings. It becomes a forest fire [7]. There are hundreds of thousands of forest fires in the world annually, and the affected area accounts for about 0.1% of the total forest area [8], causing severe damage and loss to forest resources, forest ecosystems, human life, and property. Especially since the 1980s, the global climate has been continuously warming, and forest fire is rising. Every year, forest fires cause substantial economic losses to countries all over the world [9]. With the rapid development of high-tech represented by computers, the application of forest fire prediction and forecast has become a powerful tool for forest fire management in more and more forested countries around the world.

Climate change, field fire burning, peatland drainage, and permafrost melting may all lead to changes in carbon storage in peatland, making organic carbon in peatland plants and soil convert into carbon dioxide and methane and release them into the atmosphere, thus affecting the carbon balance of peatland [10]. In addition, the burning of peatland will also bring a lot of haze hazards, which is a tremendous challenge to air pollution.

Moreover, fire in the peatland could cause harm not only to the wildlife, flora and fauna, but also to human. Due to the severity and uncontrollability of the wildland fire, the peatland burned by it emits a large number of greenhouse gases and haze smoke into the atmosphere. As the global temperature continues to rise, the frequency of peatland fires in the short term (millennium scale) will increase, and the fire intensity will increase. Therefore, it is of great practical significance to study the prediction of peatland fires in the field to improve the level of disaster prevention and reduction in peatland and provide the necessary basis for the forestry department to make prevention decisions.

In the realm of wildfire prediction and management, the Canadian Forest Fire Weather Index (FWI) System employs key parameters such as the Drought Code (DC), Duff Moisture Code (DMC), and Fire Weather Index (FWI) to assess and quantify the potential for forest fires [11]. The Drought Code represents the moisture levels in the deep organic layers of the soil, reflecting long-term drought conditions. Concurrently, the Duff Moisture Code gauges the moisture content in the shallow organic layers of the forest floor, providing insights into immediate fire danger by assessing the flammability of decomposing organic material.

The escalating threat of uncontrollable forest fires in peatlands, underscores the need for advanced predictive tools in forest fire management. While previous research by Canadian and Indonesian scholars manually calculated the Fire Weather Index (FWI) [12], this study aims to enhance the field by employing an Internet of Things (IoT) system coupled with machine learning. This innovative approach seeks to provide real-time and automated FWI calculations, advancing disaster prevention and reduction strategies in peatland ecosystems. Building upon the foundation laid by previous researchers, this study contributes to the evolution of FWI methodologies, aligning with the global trend towards more efficient and technologically driven solutions.

1.1 Background

Peat is a critical mineral resource formed and accumulated in peat bogs. It is a complex polymer hydrophilic system with multi-component, multi-level and semi-colloidal characteristics transformed from the remains of marsh plants. Peat has high organic matter and humic acid content, rich fiber content, loose and porous, good aeration and water permeability, large specific surface area, strong adsorption and chelation capacity, strong ion exchange capacity and salt balance control capacity [13]. The free radical of peat humic acid belongs to the semi-quinone structure [14]. It can be oxidized to quinone and reduced to phenol. It plays an essential role in the redox of organisms and has high biological activity and physiological stimulation. Therefore, it is widely used in industry, agriculture, medicine, environmental protection and other fields. It is an organic mineral resource with significant value but has yet to be rationally utilized. The advantages of peatland can be summarized as follows:

- a. **Hydrological Regulation:** Peatland is a huge water storage reservoir with a strong water holding capacity, and it is also an essential freshwater resource reservoir. Peat plants can store a large amount of water, and the peat itself can also maintain a water storage capacity of 3~9 times or more than its weight [15]. Because of this water storage capacity of peatland soil, peatland is called a natural reservoir, which can regulate river runoff, reduce flood peak and homogenize flood.

- b. **Natural Habitats:** The semi-water semi-land transition characteristics and high habitat heterogeneity of peatland [16] make it an essential habitat for a variety of rare and endangered wild animals and plants, as well as a living place for microorganisms and soil animals.
- c. **Climate Regulation:** Peat marsh is the place where peat forms and accumulates. The carbon dioxide fixed by marsh plants accumulates in the form of peat. It temporarily exits the geological cycle, becoming a unique gathering place of atmospheric carbon dioxide, which is of great significance in controlling the increase of atmospheric carbon dioxide concentration. From a global perspective, if the marshes are entirely drained, the carbon emission is equivalent to 35%~50% of the emissions from deforestation and fossil fuel burning [17]. As the peatland has a sufficient water supply and intense plant transpiration, the marsh evaporation is 1~2 times the water surface evaporation [18]. Transpiration and evaporation of peatlands can maintain the local air humidity.
- d. **Purification:** Peat purifier functions through sedimentation, adsorption, absorption, ion exchange, redox and catabolism. A lot of research and practice show that peatland has an essential role in intercepting and filtering nitrogen and phosphorus [19,20], and its interception amount can reach 70%~90%. At the same time, due to its small proportion and rich organic matter, peat is an oil-absorbing material with a strong adsorption capacity [21].
- e. **Information Response:** The indicators such as plant silicates species combination and peat cellulose isotope composition in peat can be used to reflect environmental climate change. In some cases, it can provide data that cannot be provided by fossils, such as sporopollenin [22].

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 [23].

However, peatlands around the world are being drained. 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 [24]. It can be seen that fire is one of the main issues to cause carbon loss in peatlands [25, 26]. In addition, peatlands burned to emit a large amount of transboundary haze into the atmosphere because of the intensity and uncontrollability of field fires. In order to control the global average temperature rise at 1.5 centigrade (announced prior to UNFCCC COP26) [27], peatland protection and restoration may be a natural solution with low cost, low technology content and significant 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, the smog disaster in Southeast Asia is mainly caused by peatland fires. The Southeast Asian haze disaster is when farmers in many parts of Sumatra, Indonesia, often clean up their farmland by slashing and burning cultivation in a large area. The smog drifts with the monsoon and affects the environmental pollution disasters in Singapore, Malaysia and other neighbouring Southeast Asian countries. Slash and burn farming uses fire in the tropical rainforest and other forest mountains to clear empty land for farming. It is a long traditional agricultural culture in Indonesia. The burning ashes are also natural fertilizers, and mountain people can farm and harvest. After a few years, the fertility of the land declined, and the mountain people burned new land to open up wasteland, so the cycle continued. In short, after the crops are harvested, the stems and leaves of the plants are dried in the field and burned into ash, or the weeds are burned to open up a wasteland. The plant ash can be used as a natural fertilizer. In order to plant rubber and palm, Southeast Asian countries burn a fire to open up wasteland, saving time, labour and cost.

As the region with the largest area of carbon mud land in the world, the water in the carbon mud land has gradually decreased in recent years with Indonesia's colonization of wasteland. The exposed surface is in contact with the air, but the carbon mud burns, which intensifies the continuation of the fire. The hazards of smog include but are not limited to the sudden increase of respiratory disease infection rate, and even lead to the stagnation of maritime transport and aviation when schools are suspended seriously.

In 2015, the haze disaster in Southeast Asia was an air pollution crisis that affected many countries in Southeast Asia, including Brunei, Indonesia, Malaysia, Singapore, southern Thailand, southern Vietnam and the Philippines, and even Cambodia, the Mariana Islands and Guam [28]. Haze disaster is a long-term problem. Every dry season, Southeast Asia will encounter haze disasters of different strengths and weaknesses, which will spread rapidly during the dry season.

Due to the haze disaster, the Indonesian National Disaster Management Agency (Badan Nasional Penanggulangan Bencana, BNPB) issued a state of an emergency order in six provinces of Riau, Jambi, South Sumatra, West Kalimantan, Central Kalimantan and South Kalimantan on September 4, 2015 [29]. In Beiganbalu, the capital of Riau Province, thousands of residents were forced to evacuate and flee to nearby Medan and Padang [30]. The air pollution index level recorded by Indonesia in Central Kalimantan Province (calculated according to PM10 concentration) rose to 2300 points at the end of September of the year and even to 3000 points at the end of October, setting a new record

high [31]. In Indonesia alone, the number of victims has exceeded 28 million, of which more than 140000 reported suffering from upper respiratory diseases [32].

The mountain fire that caused smog was caused by the consortia and farmers engaged in illegal slash-and-burn farming activities and levelling the land in this cheap way. In Sumatra and Kalimantan, Indonesia, the vast peat swamp forest will be easy to catch fire in the dry season, and the peat composed of layers of plant residues and organic matter will also produce a large number of carbon emissions due to the density. In 2015, because the El Niño phenomenon made the local climate arider, the spread of mountain fires became faster, and the haze caused by mountain fires became particularly serious [33].

In 2015, a dense haze shrouded Indonesia, Brunei, Malaysia, Singapore and other countries. An ecological disaster occurred in Indonesia, and more than 2.6 million hectares of land were burned. At that time, toxic smog raged in most parts of Southeast Asia for several weeks, causing the air quality index of Sumatra and Kalimantan to soar to nearly 2000, far exceeding the standard harmful to human health (300), and causing 500000 people to suffer from acute respiratory infections, including 19 deaths, extensive school closures, and traffic congestion in many regions [32]. The daily greenhouse gas emissions caused by Indonesia's fires even exceed the single-day emissions of the United States [34]. On August 17, 2016, Malaysia's Air Quality Index (AQI) exceeded the region's "unhealthy" level for the first time in the dry season, with the highest AQI value reaching 110 [35].

Slash-and-burn farming has been a cheap way to clear land, cultivate and produce pulp, paper and palm oil for decades. The peatland forest fires in Indonesia usually occur once a year, but because of the extremely hot and dry drought, the forest fires burn more fiercely and for a longer time. In addition, it is difficult to extinguish peat fires, including that peat fires are primarily located in remote areas, it is difficult for vehicles to pass through the soft peat lands, and it is necessary to inject a lot of water into the ground to extinguish underground fires.

In addition, peat fires emit twice as much smoke as high-temperature forest fires. According to the data of the World Conservation Union, when the worst forest fire broke out in Indonesia in the past 20 years in 2015, the daily carbon emissions during the peak period of peat fire reached 16 million tons, higher than the total carbon emissions of the United States in the same period [36].

In the face of a large area of the peat fire, no matter how much water is thrown, it is not enough, so the effect of throwing water to extinguish the fire is minimal. Another problem is that underground fire is difficult to detect because it will not generate enough heat on the ground, so it cannot be detected by the satellite radar that captures hot spots. At the same time, the haze will also affect

aviation, shipping, tourism and other industries, causing direct and indirect economic losses to regional countries.

It can be seen from this that peatland fires have caused severe and indelible impacts on Southeast Asia in terms of life and economy. On the other hand, peat is a non-renewable resource, which must be used reasonably, and economically and strive to improve its utilization rate. The environmental impact assessment shall be conducted before peat resource development; Systematic land reclamation planning should be carried out in the design of peat resource exploitation; Different utilization and protection measures are determined according to different peat types, peat land development and damage degree. Modern peatlands with good hydrological conditions, well-developed vegetation and important environmental functions and benefits should be actively and steadily protected. They can be developed in an orderly manner for those dead peatlands that have lost their due environmental functions and benefits due to degradation and destruction caused by human or natural factors. At the same time, the utilization of peat should focus on agriculture, industry and other high-value-added utilization. Different types and levels of peat have different physical and chemical properties, so different utilization methods should be adopted to improve mining efficiency. When mining peat, a layer of peat can be left to facilitate the natural recovery of peatland.

In addition, peatlands are very easy to cause fire due to wildfire or human activities carelessly, which is difficult to extinguish, resulting in unnecessary waste of peat resources. Therefore, scientific management of water resources in peatlands and maintenance of appropriate hydrological conditions are of great significance for the protection and rational utilization of peatlands.

Therefore, it is of great significance and high economic value to study the way of fire prediction for peatland protection. It has important practical significance for improving the level of peatland disaster prevention and reduction and providing the necessary basis for forestry departments to make preventive decisions.

1.2 Problem Statements

As an important way of peatland protection, peatland fire prediction has an indelible advantage for peatland restoration and reduction of unnecessary losses. However, in the actual situation, there are still many practical problems, such as human, material and financial resources, that need to be solved. In this project, for the peatland Fire Weather Index (FWI) system in tropical areas, the following three issues are mainly studied:

- a. **Extensive data of peatland.** The peatland area is large, which is difficult to measure and monitor. It is time-consuming, laborious and expensive. Furthermore, the lack of real-time data on the spot is unfavourable to the management of peatland forests. Collecting real-time data for this Internet of Things technology is an excellent choice for peatland management. In addition, it is stable and feasible to transmit and collect data with Long Range Radio (LoRa) technology because LoRa is a Low-Power Wide-Area Network (LPWAN) protocol developed based on the spread spectrum modulation technology of the Internet of Things (IoT) technology, and relevant research has proved the feasibility of Long Range Radio (LoRa) technology in forest transmission parameters [37]. With the adoption of the Internet of Things (IoT) technology, this paper will also take a very favourable action to help the management of peatland forests, that is, to introduce neural networks. The neural network can self-learning the collected data and learn to predict new data for the prediction and monitoring of forest fires in peatlands without manual intervention [38]. Currently, the Malaysian Meteorological Department (METMalaysia) relies extensively on manual data collection methods across various meteorological stations. The labor-intensive process involves gathering data manually and subsequently performing calculations. This approach not only consumes considerable human resources but also introduces the potential for errors and delays in acquiring crucial information. The utilization of Internet of Things (IoT) systems emerges as a transformative solution, offering real-time data acquisition, reducing dependence on manual efforts, and enhancing the efficiency and accuracy of meteorological data processing. The shift towards IoT-based systems becomes imperative for overcoming the limitations inherent in the current manual practices employed by METMalaysia.
- b. **Uncontrollable fire.** Fire is flexible, random, and uncontrollable index is uncertain, so it is difficult to get the first information in time. Due to the different locations and causes of fire, fire presents different characteristics, and environmental and human interference factors may lead to false alarm and missing alarm of fire. Globally, the threat of forest fire in peatland is increasing with 370 million hectares of forest burned every year [39]. 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 according to the Canadian forest fire danger rating system. However, this system does not include ground parameters, such as Ground Water Level (GWL), soil temperature and soil humidity, which are important indexes for the management and monitoring of peatland forest fires [40]. This is due to the fact that the peatland forests with different Ground Water Level (GWL) currently account for 50% [41].

- c. **Fire Weather Index (FWI) system suitable for tropical areas.** At present, there is no perfect system model for the groundwater level in tropical areas to apply to fire prediction. In recent years, machine learning has developed rapidly in the academic and commercial fields by virtue of its strong recognition rate in many traditional recognition tasks. At the same time, machine learning has a strong ability to handle complex recognition tasks. Machine learning uses neural networks to perform data on a large number of data, has a strong fitting ability, and uses neural networks to train for subsequent classification and detection layer by layer, and segmentation provides good feature support. In view of the excellent ability of machine learning in training massive data, this paper will adopt the method of machine learning through training a large number of meteorological data, including groundwater level, to establish a scientific forest fire prediction model suitable for tropical peatland, so as to provide scientific theoretical support for the prevention of forest fire and the improvement of the prevention and mitigation system.

1.3 Aim and Objectives

As one of the essential human resources, forest resources not only provide a lot of resources for human production and life, but also maintain the ecological balance of the earth. But at present, forest fires frequently occur, causing a large number of people and property losses, which has become one of the most important natural disasters threatening forest resources. Therefore, the study of forest fire risk prediction methods is of great practical significance for avoiding the occurrence of forest fires and protecting forest resources.

This project aims to provide a scientific theoretical basis for peatland forests, to prevent and mitigate disasters, and to avoid unnecessary sacrifice and a series of adverse chain reactions caused by the fire in peatlands in tropical areas to the maximum extent. In addition, the project also needs to achieve the following four main objectives:

Objective 1: To integrate Ground Water Level (GWL) measurements from the Internet of Things (IoT) system into the calculation of the Drought Code (DC) within the existing Fire Weather Index (FWI) system.

Objective 2: To incorporate Ground Water Level (GWL) data obtained through the Internet of Things (IoT) system into the computation of the Duff Moisture Code (DMC) within the established Fire Weather Index (FWI) system.

Objective 3: To develop a predictive model for Ground Water Level (GWL) using advanced Machine Learning (ML) techniques in conjunction with IoT system measurements.

Objective 4: To employ Machine Learning (ML) techniques with IoT system data to forecast the Fire Weather Index (FWI), incorporating various environmental parameters such as GWL, soil temperature, soil humidity, solar radiation, rainfall, wind speed, and air pressure.

These objectives collectively address the interdependencies within the proposed framework, where GWL influences DC and DMC calculations. Additionally, GWL, along with other meteorological parameters, contributes to the predictive models for both GWL and FWI. This holistic approach accommodates uncertainties in DC and DMC, ensuring a more accurate FWI prediction by utilizing a broader set of parameters.

1.4 Thesis Contributions

This project mainly analyzes the monitoring and prediction of forest fires in peatlands. Starting from three aspects of data monitoring, machine learning and model prediction, it uses machine learning-related algorithms for modelling and analysis. Finally, it forms a more comprehensive forest fire prediction method, which is scientific. This thesis mainly has the following contributions.

- 1) The Ground Water Level (GWL) is used to calculate the Drought Code (DC). Considering the regular rainy season in tropical areas, there is a certain degree of groundwater level in peatland forests in tropical areas. Theoretically, the groundwater level is related to the Drought Code (DC). Moreover, there needs to be relevant research in the existing fire prediction system to successfully integrate the groundwater level directly to calculate the fire weather index. Therefore, this project has verified the feasibility of using groundwater level to calculate the Drought Code (DC), which is of specific technological innovation value.
- 2) An efficient model integrating the Ground Water Level (GWL) into the existing Fire Weather Index (FWI) system is proposed. The Duff Moisture Code (DMC) can be calculated by replacing the temperature, rainfall and humidity with the Ground Water Level (GWL) and humidity under conditions of low complexity. This model has a lower complexity because it does not depend on previous periods' values, so it does not need to consider the last calculation values to carry out this iteration, as the Canadian Fire Weather Index (FWI) system does. It only needs to give the current groundwater level and humidity two parameters to calculate a more accurate Duff Moisture Code (DMC). This discovery can make an indelible economic contribution to the fire prevention of peatland forests in tropical areas.
- 3) After the feasibility of Ground Water Level (GWL) used to calculate Drought Code (DC) and Duff Moisture Code (DMC) is verified, the prediction of Ground Water Level (GWL) becomes particularly important. As a unique and essential parameter in this project, the

prediction of Ground Water Level (GWL) can play a milestone in the follow-up study of this project. Once the Ground Water Level (GWL) can be predicted stably and accurately, the forest fire prediction in peatland has played a different role in accuracy.

- 4) The Fire Weather Index (FWI) is a direct indicator reflecting the possibility of forest fire, so it has good scientific contribution and research value to predict a peatland's forest fire weather index. Machine learning predicts the Fire Weather Index (FWI) through massive data measured by the Internet of Things (IoT) system. Error analysis is conducted between the predicted value and the actual value to verify the authenticity and accuracy of forest fire prediction, which can help alleviate the social and economic losses caused by peatland forest fires.

In addition, this thesis mainly has the following innovations.

- a. The Ground Water Level (GWL) and Fire Weather Index (FWI) can be effectively simulated and predicted through the monitoring data analysis and machine learning prediction of the Internet of Things (IoT) system. It has dramatically improved the handling efficiency of relevant government departments in response to fires and reduced the losses caused by forest fires and forest fire mitigation costs.
- b. The Internet of Things (IoT) system is introduced to conduct all-weather real-time data monitoring of peatland forests, and the data monitored by relevant sensors are transmitted in the cloud through wireless transmission technology, which is convenient for subsequent analysis and research, and provides valuable data support for real-time intelligent monitoring and modelling analysis of peatland forests. At the same time, it also provides an excellent economical substitute for the loss of human, material and financial resources caused by the problematic traffic of vehicles and pedestrians in the forest.
- c. In view of the characteristics of the rainy season in tropical areas, the project has innovated and successfully used the Ground Water Level (GWL) directly to calculate the Drought Code (DC) and used the Ground Water Level (GWL) combined with air humidity directly to calculate the Duff Moisture Code (DMC) for the first time, providing a more accurate and stable idea for the prediction of peatland forest fires in tropical areas.
- d. This project is a new attempt at interdisciplinary forestry science and computer communication research. It conforms to the concept of scientific and technological development and innovation and the interdisciplinary development trend. Based on the needs of forestry science and the technical means of computer communication discipline, it provides a more diversified theoretical basis and perspective and is easier to produce creative achievements. With the development of

modern science and technology, more sophisticated and cutting-edge research needs to break through the limitations of a single discipline. Interdisciplinary integration is an inevitable trend of future scientific development and a significant driving force to accelerate scientific and technological innovation.

- e. The data analysis algorithm developed uses the open-source software Jupyter notebook. This is an economical and effective forecasting method, which provides an excellent way to reduce financial expenditure for the prevention and control of forest fires in peatlands.

1.5 Thesis Scope

With the continuous development of society, the continuous development of human beings on peatland forests has caused the loss of ecological environment resources of peatland forests, making the forest resources of peatland increasingly scarce. The losses caused by forest fires in peatlands are still highly huge, and the challenges faced by forest fire prevention in peatlands can not be underestimated. Therefore, scientific and practical means can be used for human prevention and control to avoid forest fires in peatlands to the maximum extent. The fire must meet three important conditions from the source: fire weather, fire source and combustibles. A peatland forest fire cannot occur when one condition is not met. Because fire sources and combustibles can be controlled manually, and meteorological information can also be predicted in advance through professional meteorological monitoring systems, it can be believed that forest fires in peatlands can be prevented through human regulation. Therefore, it is of great significance to study the prediction model of forest fire risk in peatlands for scientific prevention of forest fires in tropical regions and the construction of disaster prevention systems. The research scope of this paper can be summarized as shown in Figure 1.1.

Specifically, in this project, the research scope of peatland forest fire prediction mainly involves data monitoring of the Internet of Things (IoT) system, machine learning and prediction model algorithms. The Internet of Things (IoT) monitoring will include the development and construction of the Internet of Things (IoT) system, data transmission, data storage, and data processing. Moreover, machine learning involves data cleaning, training, testing and error analysis. The last part is the design of the prediction model algorithm, which also includes the integration of Ground Water Level (GWL) into the Fire Weather Index (FWI) system and the validation of its effectiveness.

Peatland forest fire prediction

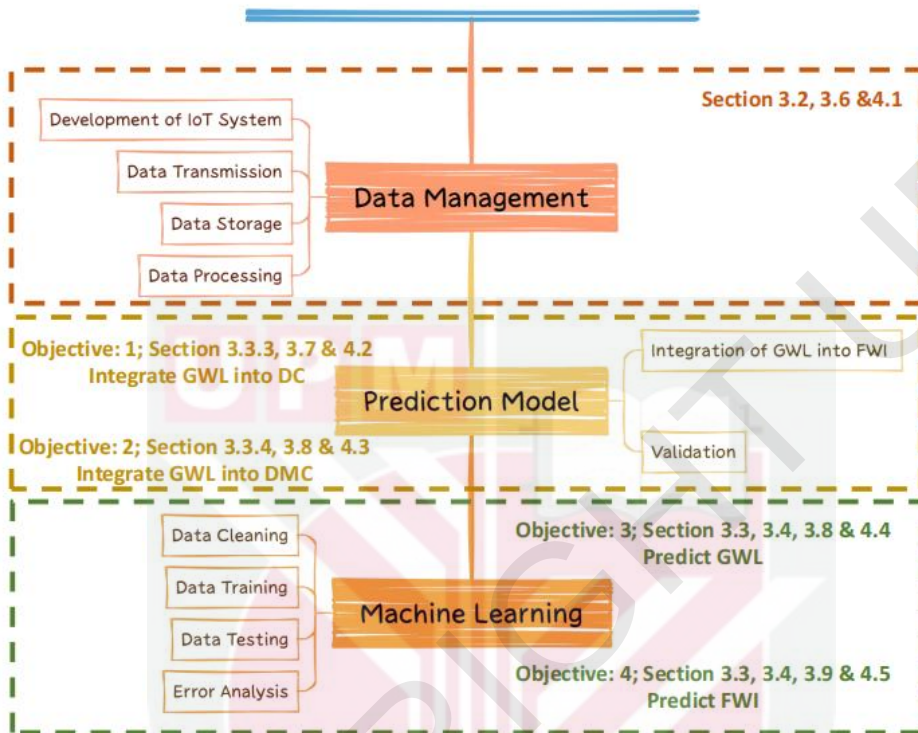


Figure 1.1: Thesis Scope

1.6 Report Outline

Peatland, due to its strong natural ecological advantages and natural carbon accumulation, is the key to maintain the ecological balance of sustainable development and the main protection site to reduce carbon emissions. However, the occurrence of uncontrollable forest fires, especially in tropical areas where high temperatures often occur in dry seasons, has caused serious persecution to peatlands that cannot be ignored, which not only poses a threat to the ecological environment, but also has a negative impact on human life and economic development. Therefore, the purpose of this paper is to study the prediction and forecast of forest fires suitable for peatland in tropical areas, and to provide epoch-making significance and contributions to reduce unnecessary natural and economic disasters. This paper is mainly divided into five chapters, and the specific contents of each chapter are as follows.

Chapter 1. Introduction. Firstly, the project background introduces that peatland plays an essential role in the economy, ecology and society and extends the imperative importance of peatland forest protection in tropical areas. Then, some important technical problems and challenges of peatland forest protection at the present stage were explained and confirmed through the problem statement, and three critical issues of this paper for peatland in tropical areas were proposed to solve the problem of extensive peatland data, randomness and uncontrollability of peatland fires, and peatland fire prediction model suitable for tropical areas. Then, it discusses the purpose of the implementation of this paper and describes the four specific goals to be achieved. The research innovation and scope and project plan outline involved in this project are also mentioned in the following part.

Chapter 2. Literature Review. In this part, the research status of the peatland is discussed in detail. This paper combs and discusses the relevant research status of peatland from three aspects: carbon loss of peatland fire, data monitoring of peatland, and prediction of peatland fire. At the same time, it analyzes the technical challenges faced by the prediction of peatland fire in tropical areas and the future development direction and proposes appropriate ways for this paper, which further proves the importance of this paper. It provides an influential reference value for researchers in related fields.

Chapter 3. Methodology. This is a specific description of the implementation process, methods and parameters of this paper. Starting from the introduction of the peatland forest experimental site involved in this project, the structure and equipment parameters of the Internet of Things (IoT) system established for peatland data monitoring are described in detail. In addition, the integration of Ground Water Level (GWL) into the Fire Weather Index (FWI) system model and the machine learning algorithm model involved in this paper are also introduced. It also points out the measurement and simulation parameters involved in this project, which provides theoretical support for the subsequent research.

Chapter 4. Results and Discussion. In view of the objectives to be achieved by this project, this chapter successively explains the forest monitoring system of the Internet of Things built in peatland forests; The feasibility of using groundwater level to calculate drying code is verified; The machine learning of neural network is used to train and predict the groundwater level and fire weather index of different sensor nodes. The results prove the feasibility of monitoring the peatland forest Internet of Things (IoT) system and the feasibility of integrating the Ground Water Level (GWL) into the Fire Weather Index (FWI) system in tropical areas. The error analysis between the actual measured value and the model predicted value verifies the accuracy and rationality of the prediction of groundwater level and fire weather index, which provides a solid scientific theoretical value and epoch-making technical contribution for subsequent research.

Chapter 5. Conclusion And Future Research. This chapter mainly summarizes the feasibility of applying groundwater levels to peatland forest fire prediction in tropical areas and shows the final results of this paper. At the same time, it also looks forward to the development direction that has not been involved in this paper but is related to peatland fire prediction, aiming to play a guiding role in the follow-up research.



CHAPTER 2

LITERATURE REVIEW

This chapter provides an overview of the impact of wildfires on carbon loss in peatland forests, with a focus on the Southeast Asian region. It also discusses the advantages and challenges of implementing an Internet of Things (IoT) system for monitoring peatland forest environments, and proposes the use of machine learning techniques for analyzing large datasets generated by such a system. Additionally, the chapter details the development and progress of the Fire Weather Index (FWI) system for predicting forest fire risks, emphasizing the importance of considering factors such as topography, altitude, and human and lightning activities when applying the system. By combining these topics, this chapter aims to provide a comprehensive understanding of the key factors involved in monitoring and preventing forest fires in peatland forests, and to highlight potential future research directions for improving the accuracy and effectiveness of wildfire management in this important ecosystem.

2.1 Introduction

Peatland is an organic accumulation composed of partially decayed plant materials, which have accumulated for hundreds of years under the condition of ponding [42]. Peatland is distributed on all continents and is called peat swamp forest, swamp or marsh [43]. Although some tropical lowlands in Asia are found, especially in Indonesia and Malaysia, where there are many swamps and forests [44], most of the peatland exists in the northern permafrost zone [45]. Tropical peatlands are home to many endangered species, including Sumatran tigers, gorillas and orangutans [46]. In the north, sub-Arctic and Arctic peatland provide habitat for species with unique adaptability, such as reindeer and musk ox [47]. Peatland also supports the development of the local economy and the living practice of residents.

On the other hand, peatland, a marsh wetland with a peat layer developed in the soil profile, is a terrestrial ecosystem with the most extensive carbon storage and fastest carbon accumulation per unit area. The surface soil is often too wet or has a thin layer of accumulated water, and many swamp plants grow above it, which leads to peat accumulation below. Peatland is distributed all over the world. The global peatland area is about 1.79 million square kilometres, accounting for 3% of the global land area [48]. The total carbon content is about twice the total carbon content of the global forest, and it stores 35% of the global carbon storage [49]. Due to its vital carbon sequestration function, peat swamp wetlands may become a "savior" to solve the problem of global climate change.

Plants in peat wetlands absorb carbon dioxide from the atmosphere through photosynthesis and convert it into plant-production substances. When swamp plants die, the plant residues return to the soil. In the anaerobic environment of stagnant water, organic matter slowly decomposes and accumulates yearly to form peat soil, thereby fixing carbon. Peatland can absorb carbon dioxide in the atmosphere stably. Its carbon accumulation is significant in controlling atmospheric carbon dioxide concentration, reducing the greenhouse effect and slowing global temperature rise.

In addition, peatland has super water storage capacity, which can greatly slow the decay rate of organic matter in the soil, and the respiration of plants and microbial decomposition is slow. After centuries of accumulation, peatland has absorbed a lot of carbon dioxide. According to the data from the International Union for Conservation of Nature (IUCN), peatlands around the world can store 3 billion tons of carbon every year, and the total carbon storage has reached 550 billion tons, which is more than the total carbon of all other vegetation types in the world [50].

Although peatland has a strong carbon storage function, once the wetland is damaged, the carbon stably blocked in the soil will be released into the atmosphere. The wetland will change from a carbon sink to a carbon emission source, which will intensify the process of global warming. Generally, the accumulation rate of peatland is less than 1mm every year, and it takes tens of millions of years to form a peatland with a particular scale. However, it only takes ten days to drain peatland. Assuming all the water in the global marsh wetlands is drained, carbon escaping stored in peatlands will equal 35%~50% of the total emissions from deforestation and fossil fuel combustion. This means that greenhouse gases will increase by about 40% compared to the current level, greatly exacerbating global warming.

Before the 20th century, some peatlands were used as fuel and food sources by human beings and were damaged, but most peatlands were completely preserved because they were not affected by human beings. Since the 20th century, humankind has increased the development of natural peatlands, resulting in a sharp decline in global peatlands. According to incomplete statistics, more than 90% of peatland in Western Europe has been lost. Today, this land faces fire threats, rising temperatures, and development. Because peatland soil is soft and elastic, and the content of organic matter and humic acid is high, it was often used as farmland after drainage. Thousands of years of carbon deposition may be completely released overnight.

Therefore, it is essential to understand the fire characteristics of peatland forests to lay the foundation for the follow-up scientific protection of peatland forests to adopt benign technical means. This chapter mainly describes the carbon loss caused by peatland fire and introduces the research progress of the Internet of Things monitoring technology and fire weather index system.

2.2 Carbon Loss From Peatland Fires

Climate change, field fire burning, peatland drainage and permafrost thawing may all lead to changes in the carbon storage of peatland so that organic carbon in peatland plants and soil can be converted into carbon dioxide and methane and released into the atmosphere, thus affecting the carbon balance of peatland [51]. Because of the intensity and uncontrollability of the wildfires, the peatland burned by the wildfires emits a large amount of greenhouse gases into the atmosphere. Figure 2.1 shows the three primary forms of peatland fire: deep burning in peatland, residual flame burning and serious flame causing damage and burning of surrounding buildings.



Figure 2.1 : Primary Forms of Peatland Fire [52].

In 1997, the carbon emissions from peatland fires in Indonesia amounted to 13% - 40% of the global carbon emissions from fossil fuel combustion yearly [52]. Figure 2.2 shows the impact of predicted global warming on carbon emissions from peatland fires with climate change.

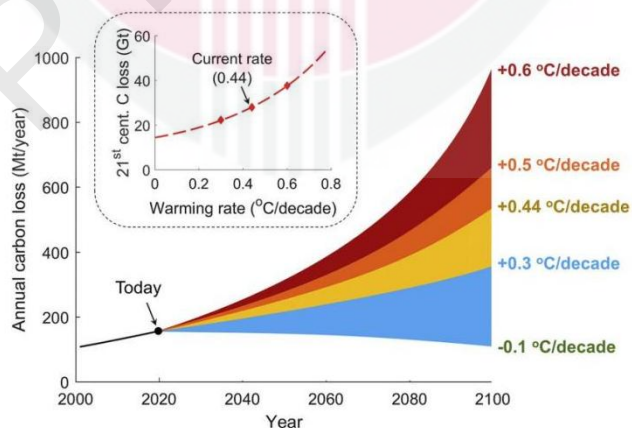


Figure 2.2: Global Warming on Carbon Emissions [52]

It can be seen that fire is one of the main ways to cause carbon loss in peatlands [53,54]. In recent years, more attention has been paid to the carbon cycle of peatlands under climate change conditions [55] and drainage [56]. Then, in the context of frequent global wildfires, whether peatlands can continue to play a carbon sink role [57] is also worthy of researchers' attention. The fire in peatland has great harmfulness. With the rising global temperature, the frequency of peatland fires in the short term (millennium scale) increases, and the fire intensity increases. Therefore, studying the carbon loss in peatlands caused by field fires is significant.

2.2.1 Types of Peatland Fires

According to whether there is flame in the process of field fire, the field fire in peatland can be divided into flaming combustion and smouldering combustion. The open burning fire in peatland is a surface fire, with a blazing speed of about 10 km/h and a short overall duration [58]. The smouldering fire in peatland occurs in the soil under the peatland, which can continue to burn at low temperatures, high water content and low oxygen concentration [59]; Its combustion rate is generally 0.5 meters per week, but the combustion time is relatively long and can generally last for several weeks, months, or longer [60]. Therefore, open burning fire in peatlands mainly causes loss of surface peat and biomass, while smouldering fire in peatlands mainly causes loss of underground peat in peatland.

Compared with the open burning fire in peatland, the combustion temperature, diffusion rate and thermal power of smouldering fire are lower. The typical peak temperature of a smouldering fire in peatland is 450~700 °C, and the degree of incomplete combustion of carbon (the ratio of carbon monoxide content and carbon dioxide content generated during combustion) is different the two. The ratio of carbon monoxide content and carbon dioxide content generated by smouldering outdoor fire in peatland is about 0.4, while the ratio of carbon monoxide content and carbon dioxide content generated by smouldering outdoor fire in peatland is about 0.1 [61], which indicates that carbon emission forms and rates caused by smouldering outdoor fire and smouldering outdoor fire in peatland are different. Therefore, both impacts on carbon loss in peatland should be considered simultaneously.

Although the combustion state of smouldering and open-burning fires in peatland is different, the occurrence of smouldering and open-burning fires is often coupled, and the two are closely related. The smouldering fire in the field of peatland can lead to the occurrence of open burning fire. Although the heat source (i.e. fire embers or lightning) is too weak to ignite the flame directly, the smouldering peat can still transfer the burning range from underground to the surface [62]. As the soil of the peatland is often wet or flooded, it is not prone to fire [63]. However, the rising temperature and human drainage of peatland reduce the soil moisture content of the peat surface layer. The frequency of

open burning and smouldering fires in the peatland field is increasing. In addition, smouldering fire is unpredictable and uncontrollable compared to the open burning fire in Peatland. We do not fully understand how peatland smouldering fire burns, spreads and stops. Therefore, it is difficult to formulate any strategy to prevent or mitigate peatland smouldering fires.

2.2.2 Carbon Loss of Vegetation and Soil

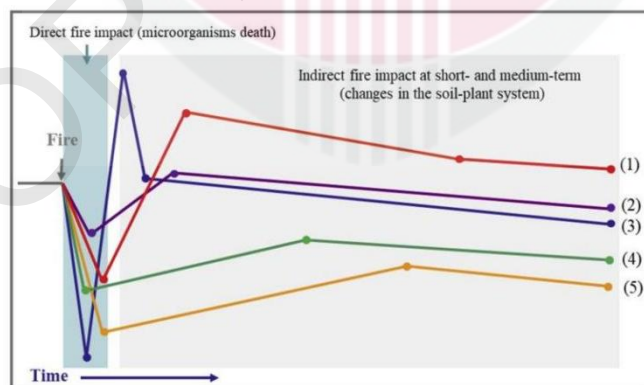
The most direct impact of field fires on peatland soil is that they consume a large amount of biomass and surface peat soil in the combustion process and emit greenhouse gases such as carbon dioxide and methane into the atmosphere, resulting in the loss of soil carbon [64]. The total amount of greenhouse gases released by peatland fires every year in the world is equivalent to 15% of the total amount of greenhouse gases emitted by human activities [65]. Research shows that about 6×10^{12} kg carbon is stored in the surface vegetation of peatland in the western part of the Canadian mainland [66]; The total carbon concentration stored in the surface vegetation of peatland in northern England is about 820 g/m^2 carbon [67]. Without considering the impact of other factors, the fire will directly cause carbon emissions in peatland vegetation.

On the other hand, due to the diversity of plants in peatlands and the particularity of field fires, it is difficult to accurately assess the carbon loss of surface vegetation in peatlands. However, as a part of the terrestrial ecosystem, the loss of surface biomass in peatlands caused by fires cannot be ignored. The loss of organic carbon in peat surface soil caused by fire is also a central part of carbon loss in peatlands [68]. During the fire, the organic matter in the peat surface soil is rapidly heated, and the high temperature can extend to a depth of 10-20 cm below the soil surface at most [69]. The research shows that the organic carbon loss of peatland in northern Canada caused by field fires is $1.7\sim 2.3 \text{ kg/m}^2$ carbon [70]; Other studies show that the loss of organic carbon in peatland in northern Canada caused by wildfires is $5\%\sim 12\%$, which is equivalent to $5.9\sim 14.1 \text{ kg/m}^2$ of carbon [71].

The results of the planned burning study conducted in peatland in northern England show that the carbon accumulation rate of peatland burned once is 46 g/m^2 carbon per year, and the peat accumulation rate is 118 g/m^2 per year; The carbon accumulation rate of peatland burned six times is 36 g/m^2 carbon per year, and the peat accumulation rate is 93 g/m^2 per year [72]; That is, with the increase of burning times, although the carbon and peat accumulation rate of peat surface layer decrease, it is still slowly accumulating. In addition to the carbon loss of peatland caused by an open fire, smouldering fire also caused the loss of organic matter in deep soil, especially the loss of old carbon stored in the deep peatland for a long time [73]. This inactive carbon is not included in the global carbon cycle but is caused by smouldering fires to release greenhouse gases into the atmosphere, thus affecting the global carbon

balance [74]. Therefore, the carbon loss caused by high-intensity or large-scale fires in peatlands will be more significant. The carbon loss caused by the 2016 Fort McMurray Horse River wildfire in Canada was equivalent to soil carbon accumulation from 240 to 860 years [75]. The fire evidence of Indonesia's millennium peatland shows that the average turnover time of soil carbon is 800 years [76]. It can be seen that the field fire directly led to the loss of a large amount of carbon in the peatland. In addition to directly burning the surface plants and organic matter of surface soil in peatland, the field fire also changed the soil structure and microbial community, thus indirectly affecting the output of soil carbon in peatland [77].

Although the temperature of field fires with different intensities is different, the fire directly changes the soil structure of the peatland. Research has shown that during low-intensity wildfire combustion (especially when the soil temperature is maintained below 300 °C), hydrophobic materials in the soil evaporate and deposit on the surface of aggregates, forming a hydrophobic film, improving the soil's water resistance and the stability of aggregates [78]. Research on soil structure and water retention of burned and unburned peat cores in Alberta, Canada, shows that burning makes the peat surface more compact, thus slowing down the decline of groundwater level and reducing the decomposition rate of peatland soil [79]. Other studies have shown that hydrophobic substances are deposited on the soil surface of peatland to protect soil organic matter from microbial invasion, thus reducing the loss of carbon in the soil [80]. Some studies also show that due to the high-temperature effect of field fire combustion, soil organic matter adsorbs minerals, causing a blockage in soil aggregates, making soil enzymes and microorganisms unable to contact organic matter, thus reducing the soil respiration rate and forming an ideal barrier to protect soil organic matter [81]. In addition to changing the soil structure of peatland, field fires also affect soil carbon decomposition by directly burning microorganisms in the soil.



(1 and 5) Changes is microbial community composition. Heating resistant (1) and sensitive (5) microorganisms
 (2) Total microorganisms number
 (3) Microbial activity
 (4) Microbial biomass

Figure 2.3 : Different Microbial Parameters After Fire [82]

Figure 2.3 shows the changes in different microbial parameters over time after a fire. Whether an open fire or a smouldering fire in the field, many soil microorganisms die during combustion, leading to a profound change in the microbial community [82]. Significantly when other microorganisms die, it increases the community advantage of bacteria and ascomycetes [83], changes the original microbial balance of peatland soil, and then affects the decomposition rate of soil carbon by affecting microbial enzyme activity [84]. In general, field fires have changed the soil structure and microbial community of peatland, increased the stability of soil organic matter, and reduced the rate of soil carbon emissions. However, the specific mechanism is still unclear.

2.2.3 Plant Recovery After Peatland Fire

The impact of wildfires on the carbon pool of peatland mainly depends on the ability of plant restoration in the peatland ecosystem and the accumulation of pyrolytic carbon in the soil. After the fire, although the peatland made up for the loss of soil carbon through pyrolytic carbon entering the soil in the short term, in the long term, the restoration and change of plants will have a more far-reaching impact on the soil carbon storage of peatland. Generally speaking, although the carbon loss of peatland caused by fires of different intensities is different, most of the carbon loss after the fire will be recovered with the regeneration of plants [85]. Research shows that surface plants can rapidly regenerate after peatland undergoes low-intensity fire or planned fire [86]. Figure 2.4 shows the growth of surface ferns in Kalimantan peatland two years after it was burned in 2015.



Figure 2.4 : Recovery of Kalimantan Peatland After Fire [86]

On the other hand, in the UK, planned recurrent burning is commonly used to manage grouse moors, promoting the regeneration of dwarf shrubs by burning down patches/patches of plants [87]. After a low-intensity fire in the UK moorland, young trees such as *Calluna vulgaris* will sprout and sprout densely [88]. The planned burning of peatland in the north, with the increase of burning

times, the species diversity of plant community and the abundance of peatland species are also increasing [89].

Compared with low-intensity burning, high-intensity burning will severely impact the composition of the peatland plant community. After the drought of peatland in northwest Europe, severe wildfires hindered the regeneration of *Phytolacca* but promoted the dominant growth of pioneer bryophytes [90]. Severe wildfires have altered the community composition of *Phytolacca*, prolonging its regeneration cycle [90]. In addition, high-intensity burning reduced the number of sphagnum spp. in peatland, making it difficult for sphagnum spp. to regrow and recover [91], thus slowing down the accumulation of peat layer.

In addition to the influence of fire intensity, the length of burning rotation is also an essential factor in determining the composition of the plant community in the burning sample plots. The shorter burning cycle means more frequent burning, which makes peatland often in the initial stage after burning, which may lead to a thinner moss layer and weaker growth of sphagnum, reducing the carbon input of peatland soil, and potentially affecting the carbon balance of peatland [87]. Therefore, plant restoration after fire, as the long-term impact of field fire on peatland and as the carbon input of peatland soil in the future, will be an aspect that cannot be ignored.

2.2.4 Subsection Summary

In order to continue to play the role of peatland in the global carbon balance and reduce the carbon loss of peatland caused by field fires, the role of peatland in the carbon cycle after burning should be studied in the future. The smouldering of peatland causes the deep burning of peatland soil, which may affect the carbon accumulated in the soil that has not participated in the active carbon cycle for hundreds to thousands of years. Therefore, research on the prevention and monitoring of peatland field fires should be carried out to enhance the carbon sink function of peatland.

2.3 IoT Monitoring in Peatlands

With the development of industry and economy, environmental problems have become more and more serious. Peatland fires have brought severe impacts on human health and the ecological environment. The peatland resources are facing a difficult situation. The overexploitation of peatland forest resources has led to serious ecological damage, and the overexploitation of groundwater has led to prominent environmental, geological problems. Therefore, peatland forest prevention and control must be attached to great importance to promote sustainable economic and social development.

As a new type of environmental monitoring method, the Internet of Things technology is based on the network and closely connects various environmental factors to form a new network pattern, ensuring the real-time accuracy of remote data transmission and improving the timeliness of environmental monitoring [92]. Relevant personnel can provide timely and effective feedback on data and develop solutions based on existing problems. With the rapid development of IT technology, the application of the Internet of Things in environmental monitoring will continue to deepen.

In addition, smart forestry is a new forestry development model that fully utilizes new generation information technologies such as cloud computing, the Internet of Things, mobile internet, big data, etc., and forms a three-dimensional perception, collaborative and efficient management, prominent ecological value, and integrated services both internally and externally through perceptual, IoT, and intelligent means. The construction of intelligent forestry is a new direction for the development of modern forestry, playing an essential role in improving the ecological environment, enhancing forestry productivity, and promoting forestry modernization. It is an inevitable requirement for building a beautiful earth. Forestry work has the characteristics of a harsh working environment, large area, long cycle, and heavy tasks [93].

The Internet of Things (IoT) technology has advantages in real-time perception, rapid response, and precise control, achieving real-time, automatic, and long-term perception of forestry information. It is an important part of the three-dimensional perception of smart forestry and one of the critical technologies in constructing smart forestry. At present, the forestry Internet of Things has achieved preliminary application. This section reviews the architecture and standardization, perception technology, transmission technology, intelligent information processing technology, integration and application status of the Internet of Things. It analyzes the key issues that need to be addressed in the monitoring of Internet of Things technology, outlines the application progress made in using forestry Internet of Things technology for smart forest industry construction, explores the existing shortcomings and future development strategies, To provide a reference for the development of the Internet of Things in forestry and the construction of intelligent forestry.

2.3.1 Architecture of IoT Technology

The Internet of Things technology utilizes information-sensing devices to connect objects to the network according to agreed protocols and exchange and communicate information through information dissemination media to achieve intelligent recognition, positioning, tracking, supervision, and other functions [94]. Figure 2.5 shows the overall architecture of the Internet of Things cloud platform for achieving secure information sharing and ensuring information security.

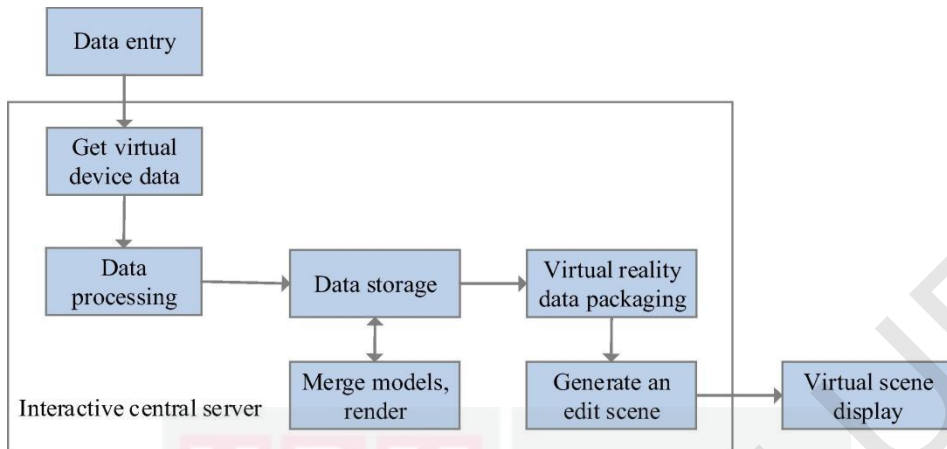


Figure 2.5 : IoT Information Cloud Architecture [94]

The Internet of Things consists of perception, network, and application layers in environmental monitoring. The perception layer is responsible for perceiving and obtaining various ecological monitoring data; The network layer is responsible for obtaining data from the perception layer for wireless remote transmission; The application layer is responsible for data processing through cloud computing technology. The conceptual model of the Internet of Things is shown in Figure 2.6.

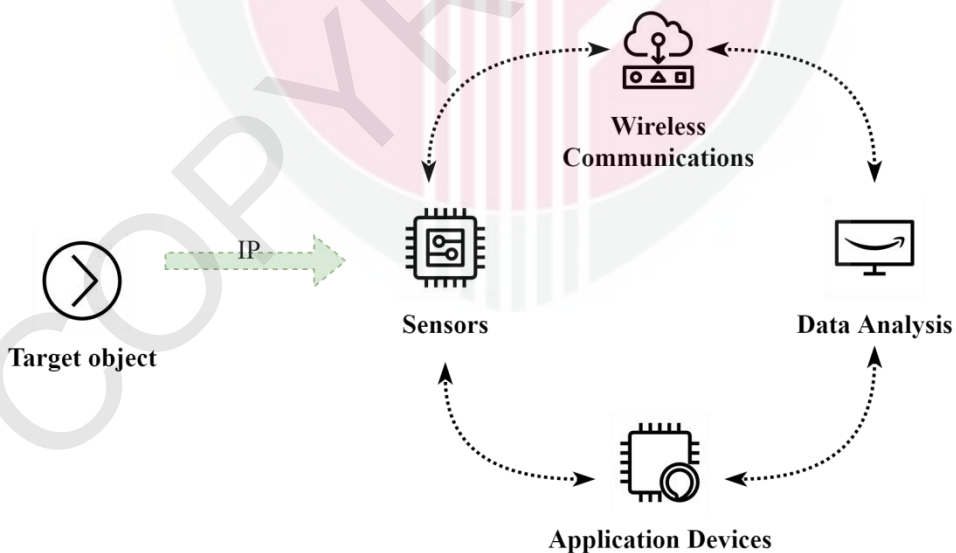


Figure 2.6 : IoT Conceptual Model

With the development of sensors, wireless communication, and the Internet, IoT technology has expanded to fields such as environmental monitoring, biomedicine, and intelligent infrastructure in recent years. The Internet of Things combines computer vision technology and artificial intelligence technology, can accurately and effectively identify the abnormal images of tourist attractions, and can also establish an intelligent decision support system for manufacturing enterprises, making the decision-making of manufacturing enterprises more effective and scientific [95]. The Internet of Things for environmental monitoring has established a high-density and intelligent remote real-time monitoring system through various technological means. In addition to providing high-density and intelligent remote real-time monitoring of various ecological elements, the Internet of Things can also achieve intelligent diagnosis and efficient maintenance of monitoring system status, as well as automatic control, storage, and online processing of massive monitoring data.

2.3.2 Information Perception

The perception layer is the source of object recognition and information collection in the Internet of Things, and its primary function is to recognize objects and collect information. The Internet of Things perceives water environment information through sensors, which are devices that can convert specific measured signals into usable signals according to certain laws [96]. It achieves the transmission, processing, recording, display, and control of information by providing the necessary raw data for the Internet of Things system.

In addition, optical loss wave sensors have advantages such as corrosion resistance, structural intelligence, electromagnetic interference resistance, and low cost, which have been proven to be suitable for online detection and monitoring of various parameters in water. However, these sensors face challenges such as poor sensitivity, selectivity, and high detection limits. Jiao et al. [97] summarized effective methods to improve the sensors' selectivity, sensitivity, detection limit, and response speed in response to these issues.

Hassan et al. [98] designed a new chemical sensor using mesoporous silica nanospheres as the scaffold material and embedding 1,10-Phenanthroline on its surface, which can quickly and conveniently detect the corrosion level of divalent iron ions in different types of water samples. In addition, the sensor can be recycled using acidic ammonium thiocyanate to form a metal-free sensor, which can also be efficiently reused in the detection system. However, traditional sensing systems have single monitoring parameters and lack on-site monitoring capabilities, while electrochemical sensors involve the conversion of water quality parameters, converting chemical signals into electrical signals, which can effectively solve this problem. Table 2.1 shows the comparison of different sensor sensing technologies.

Table 2.1 : Comparison of Different Sensor Sensing Technologies

Sensors	Chemical Reaction Occurs	Advantages	Disadvantages
Photochemical [97]	Unwanted	Good repeatability and stability	Poor sensitivity and selectivity
Electrochemical [98]	Need	High sensitivity	Single detection object

Compared with electrochemical sensors, optical sensors do not require chemical reactions with the detected substance, and there are no electrode surface passivation, poisoning, or electrode film pollution issues. They have good repeatability and stability, but their sensitivity and selectivity are worse than electrochemical sensing capabilities. The current research focuses on designing low-cost, easy-to-use, and highly sensitive sensor arrays that continuously monitor major water quality parameters such as pH, free chlorine, temperature, emerging pharmaceutical pollutants, and heavy metals. Sensors based on electrochemistry, optics and electricity focus on improving sensing mechanisms and hardware processes and pay attention to combining the advantages of different mechanisms to develop multi-parameter and multi-channel sensors.

2.3.3 Information Transmission

A Wireless Sensor Network (WSN) comprises randomly distributed sensor nodes [99]. Sensor nodes are tiny nodes composed of sensors, data processing units, and wireless communication modules. They can sense changes in the external environment through built-in sensors, convert them into specific physical quantities through data processing units, and finally achieve information exchange and circulation between nodes through wireless communication modules. In the wireless sensor network, sensor nodes are scattered in the area to be monitored. Nodes form a network through wireless communication. Nodes are directly or indirectly connected to the sink node, which is then connected to the Internet through Ethernet, 3G, 4G, 5G, WiFi, etc. [100].

Wireless Sensor Network (WSN) comprises many microsensor nodes with on-chip processing capabilities. The communication distance and coverage can be divided into wireless LAN technology and wireless comprehensive area network technology. Among wireless wide area network technologies, low-power wide area network (LP-WAN, such as LoRa, NB IoT, etc.) technology is one of the hot research directions of the Internet of Things in recent years. Compared with the traditional wireless wide area network cellular mobile communication technology (such as 2G, 3G, 4G, etc.), it has the characteristics

of low cost and low power consumption. The classification of wireless sensor network transmission technologies is shown in Figure 2.7.

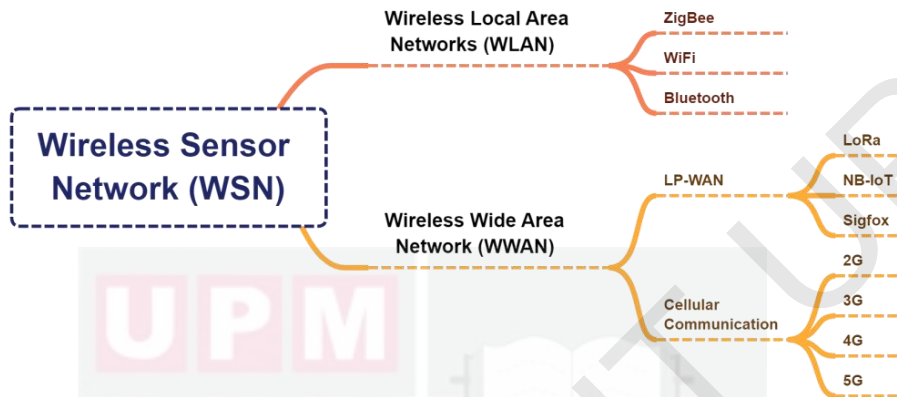


Figure 2.7 : Transmission Technology of Wireless Sensor Network [100]

Wireless communication technology is the transmission foundation of the Internet of Things. With the widespread application of smart cities becoming popular, various technologies are emerging and seizing the Internet of Things market. The most popular LPWAN technologies are LoRa, Sigfox, and NB IoT. In the technical architecture of the Internet of Things, sensing is the most fundamental core source. Whether in agriculture, industry, construction, transportation, medical and other fields, in order to analyze the sensed data through artificial intelligence and form related applications, it is necessary to deploy suitable transmission technologies and network domains in order to collect and return a massive amount of environmental data.

In wireless communication technology, earlier applications such as WI-FI, Bluetooth, and ZigBee have laid the foundation for development in different fields. WI-FI is suitable for the transmission of large amounts of data, such as video and audio transmission or VR, and is also the foundation of general wireless networks, with the disadvantage of high power consumption; Bluetooth is commonly used in personal wearable devices and has a relatively mature application in the field of sound; ZigBee has achieved fruitful results in automatic control applications in industry, construction, and other fields.

Today's communication technology is about to enter 5G, emphasizing larger bandwidth, higher speed, lower latency, and of course, more power consumption. Due to the correspondence between people, data transmission is more intensive, and the exchange volume is also larger. Due to the generally more comprehensive deployment range of devices and the need for wireless devices to avoid frequent battery replacement, LPWAN (Low Power Wide Area

Network) technology has emerged in response to this issue. Its small data volume, long-distance transmission, and power-saving characteristics have made it shine in the field of IoT applications.

Early wireless transmission technologies, such as WI-FI, ZigBee, and Bluetooth, had communication transmission distances of only 300 meters at most. When used in the field of smart homes, additional antennas or relay stations with signal enhancement were necessary. If we want to meet the relevant applications of smart cities, such as environmental monitoring or asset tracking, LPWAN technology with a transmission distance of up to 20 kilometres can significantly reduce the construction cost, as only a few stations can cover a large area. Using batteries as the source of power eliminates wiring issues, making the installation process of sensors easier. At present, the most popular LPWAN technologies are LoRa, Sigfox, and NB IoT, which have their own advantages. Owners can choose the most suitable communication technology based on different fields and usage needs. The specific performance comparison is shown in Table 2.2

Table 2.2 : Performance Comparison of Wireless Sensor Network Transmission Technology [100]

Performance Index		Power Consumption	Speed	Distance
WWAN	Cellular Communication	High (5- Days)	Quick (1.4 Gbps)	Far (Anywhere with BS)
	LoRa	Low (15+ Years)	Slow (50Kbps)	Far (20km)
	NB-IoT	Low (10+ Years)	Slow (60Kbps)	Far (20km)
	Sigfox	Low (5+ Years)	Slow (100bps)	Far (50km)
WLAN	WiFi	High (2+ Hours)	Quick (300Mbps)	Middle (300m)
	Bluetooth	Middle (2+ Days)	Middle (3Mbps)	Short (30m)
	ZigBee	Low (2+ Years)	Slow (250Kbps)	Middle (300m)

The three popular LPWAN technologies mentioned above have different characteristics, and the industry predicts that one will surpass the others and become a standout in the future. However, the coexistence relationship of cooperation is more likely to lead future technology towards new developments. In fact, there are hundreds of applications in the Internet of Things, and the characteristics of these three technologies also correspond to the special needs of different fields.

NB-IoT, whose network does not limit the number of times messages can be transmitted and can carry a higher amount of data, is suitable for smart industrial fields that value network transmission stability and real-time performance or IoT devices that require high data transmissions, such as sound and image files. The power consumption of NB IoT is also higher than the other two LPWAN technologies, resulting in significant battery life loss. The collaborative model with telecom operators will be faster and easier to promote to users. However, from another perspective, it is also limited by hardware costs (chips) and monthly rental costs. Compared with NB IoT, LoRa and Sigfox are more suitable for small data volume and large-scale transmission applications due to their low hardware cost and lower power consumption.

The current development scale of LoRa technology has become mature. Although the transmission distance is lower than Sigfox, the transmission bandwidth is relatively high, and the construction cost and technical difficulty are low. It is suitable for constructing closed network domains in high-tech factories to transmit various sensing data types. From the perspective of global deployment, Sigfox is an up-and-coming technology. As Sigfox provides global domain services, it is more convenient for multinational companies, especially for integrated network solutions. It provides complete and stable cloud services for high-income companies, saving many development and collaboration troubles. Sigfox has the longest transmission distance but has the least transmission times in a day, so it is suitable for application in scenarios that reflect data changes or transmit data in a fixed period, such as pipeline monitoring, smart meter, regional climate monitoring and alarm.

2.3.4 Performance Metrics in IoT

In the domain of the Internet of Things (IoT), the evaluation of system performance is paramount for ensuring the efficacy of deployed solutions. Performance metrics serve as indispensable tools for gauging the efficiency, reliability, and overall functionality of IoT systems. In the context of research focused on forest fire prediction and management in peatland ecosystems, the selection and scrutiny of appropriate metrics become crucial for attaining optimal outcomes.

Data Accuracy and Precision: One fundamental metric revolves around the accuracy and precision of data acquired by IoT sensors. Reliable data collection, especially concerning meteorological parameters such as temperature, humidity, and wind speed, forms the bedrock for accurate fire risk assessments. Recent studies emphasize the importance of precise data in improving the reliability of environmental monitoring systems [101].

Real-Time Responsiveness: The timeliness of data transmission and system responsiveness are pivotal performance metrics, particularly in the context of forest fire prediction. A real-time IoT system allows for swift data analysis and decision-making, contributing to more effective disaster prevention. The significance of real-time monitoring is highlighted in contemporary literature addressing the challenges of environmental sensing [102].

Energy Efficiency: Energy consumption is a critical metric for IoT devices, especially in remote and resource-constrained environments like peatland forests. Optimizing energy usage ensures prolonged sensor lifespans and sustainability. Scholarly works stress the need for energy-efficient IoT solutions in ecological monitoring contexts [103].

Scalability and Adaptability: Scalability and adaptability metrics consider the system's ability to accommodate an increasing number of connected devices and evolving environmental conditions. A scalable IoT architecture is essential for extending the monitoring network across vast peatland areas. Recent literature emphasizes the role of scalable IoT solutions in addressing environmental challenges [104].

By delving into these performance metrics, this research aligns with contemporary IoT principles, aiming to enhance the reliability and efficiency of peatland fire prediction systems. The incorporation of these metrics ensures that the proposed IoT-based solution is not only technologically robust but also well-suited to the dynamic and challenging peatland ecosystem.

2.3.5 Application of IoT Monitoring

The groundwater monitoring system mainly consists of data collection equipment, a data communication system, and a terminal information platform. The data collection equipment is responsible for regularly and automatically collecting parameters such as water level and temperature. The remote transmission system exchanges and communicates information through data collection devices according to agreed protocols to achieve intelligent collection, transmission, monitoring, and management.

Forest resources are mainly composed of forest resources, including forest land resources, forest wildlife resources, forest wild plant resources, forest microbial resources, and forest environmental resources. Forest resource regulation is one of the main functions of the forestry department, and the forestry Internet of Things has been applied in forest resource investigation, management, protection, and other aspects.

Some countries have developed various forestry-specific sensors, which can monitor abnormal conditions of trees, prevent illegal logging of trees, and achieve forest resource protection. For example, Kameswararao et al. [105] fixed tree vibration sensors. When trees are cut down, the vibration sensors will detect vibrations and send abnormal situations to the server through WSN to achieve anti-theft logging of precious trees. Chau et al. [106] can monitor whether trees are crushed through angle tilt and sound sensors.

In wildlife protection, WSN is mainly used to achieve indirect and non-contact perceptions of wildlife information. For example, using various environmental monitoring sensors and audio and video sensors to obtain environmental information of the main activity areas of wild animals, as well as animal information such as their activity images and sounds, to study the living habits and activity patterns of wild animals, and to achieve the goal of protecting wild animals. Xin et al. [107] constructed an Internet of Things system in southwestern China to protect the Amur Tiger and Amur Leopard.

Forestry disasters mainly include forest fires, diseases and pests, and other forest disasters caused by extreme climate change [108]. Using the Internet of Things in forestry to monitor and predict forestry disasters in a timely manner is beneficial for reducing the losses caused by forestry disasters and providing useful references for reconstruction and restoration after forestry disasters. Currently, the forestry Internet of Things has made progress in forest fire monitoring and forest pest and disease monitoring. In forest fire prevention, WSN is mainly used to monitor changes in environmental factors related to forests and fires to predict forest fires.

For example, Peng et al. [109] used the relative humidity, air temperature, wind speed, and pressure of the atmosphere in the forest environment to reflect the moisture content of forest combustibles and monitored the changes in these four environmental factors through wireless sensors to achieve forest fire prediction.

In the forest fire prevention and control system based on a wireless sensor network designed by Liu et al. [110], multiple temperature, humidity, light and smoke sensors are used. These sensors report the collected data to the server through WSN. According to the set threshold, when the reported data exceeds the threshold, the server will send a short message to the forest protection

personnel to inform them of the GPS coordinates of the suspected forest fire area. Forest rangers verify forest fires based on GPS coordinates and take corresponding measures to avoid significant losses caused by forest fires.

The current research aims at the low accuracy and false alarm of forest fire monitoring by relying solely on wireless sensor networks. By taking a snapshot of the suspected fire area and using human or machine learning methods to review the suspected fire area, the false alarm rate can be reduced, and the accuracy of forest fire prediction can be improved. For example, Kinaneva et al. [111] used drones to obtain snapshots of suspected fire areas and manually identify them. Dhiman [112] used robots with 360-degree cameras and machine learning to reduce human involvement and achieve automation in fire prediction. In forest pest and disease monitoring, Potamitis et al. [113] designed a sensor specifically designed to monitor poplar longicorn beetles. This sensor can monitor the vibrations emitted by longicorn beetles when they move and eat on poplar trees, and analyze these vibrations to understand the development period and the number of longicorn beetles, in order to evaluate the erosion status and health status of trees.

Forest ecological monitoring mainly refers to the continuous observation of ecological factors in the forest environment, perception of changes in the local forest environment microclimate, prediction of natural disasters such as sudden changes in the local forest environment and forest fires, and assessment of forest ecosystem health, ecological service functions and values. Using IoT technologies such as WSN to achieve forest ecological monitoring can solve the monitoring difficulties caused by the spatiotemporal heterogeneity and scale complexity of ecosystems through appropriate node deployment. On the other hand, compared to manual and remote sensing methods, it can achieve large-scale, long-term, continuous, and synchronous monitoring. At present, the application of forestry IoT for forest monitoring is shown in Table 2.3.

Table 2.3 : Application of The Internet of Things in Forest Monitoring

Authors	Ref.	Year	Location	Monitoring Indicators	System Performance	Wireless Transmission Protocol
Chau et. al.	[106]	2023	Hong Kong, China	Tilt Angle of trees wind speed	5s/data	LoRa
Krishnamoorthy et. al.	[114]	2023	Shamshabad region, Hyderabad, India,	flame humidity Temperature smog	99.2%	LoRa
Peng et. al.	[109]	2022	Yanbian, China	temperature humidity wind speed pressure	---	LoRa
Liew et. al.	[115]	2021	Selangor, Malaysia	temperature humidity rainfall wind speed pressure soil humidity soil temperature solar radiation	84.3% 94.8% 90.6% 89.7% 97.1% --- --- ---	LoRa
Park et. al.	[116]	2018	Indiana, America	temperature humidity luminance	0.2 °C 1% 1%	LoRa

Table 2.3 : Continued

Authors	Ref.	Year	Location	Monitoring Indicators	Monitoring Performance	Wireless Transmission Protocol
Wang et. al.	[117]	2022	Ganzhou, China	temperature humidity smog	0.4 °C 2% 2%	NB-IoT
Chen et. al.	[118]	2021	Taiwan, China	luminance Pressure Ultraviolet rays carbon dioxide	---	NB-IoT and LoRa
Athanasios et. al.	[119]	2020	Corfu, Greece	Cloud Fog	1160ms /respond 1080ms /respond	ZigBee
Sakawah and Aung	[120]	2019	Mandalay, Myanmar	temperature smog humidity	---	ZigBee
Yan et. al.	[121]	2017	Fujian, China	humidity temperature pressure soil humidity Carbon dioxide concentration	2% 0.4 °C 150 Pa 3% 50 mg/L	ZigBee
Yu et. al.	[122]	2022	Harbin, Yichun, Chengde, Beijing, Hebei, Jiangxi, and Zhejiang, China	temperature humidity wind speed Light intensity Rainfall	±0.5 °C ±0.1 % ±0.1 m/s ±0.1 Lx ±0.1 mm	Bluetooth with satellite

At present, due to the lack of unified monitoring standards in forestry IoT monitoring, there are differences in monitoring indicators, monitoring accuracy and monitoring cycle between different IoT monitoring systems, which makes it difficult for different monitoring systems to integrate and share monitoring data, and information silo phenomenon has formed between different IoT systems. The ZigBee protocol was initially the most commonly used transmission technology in forestry WSN. Although ZigBee has low power consumption characteristics, its effective communication distance in forest environments is only 300m due to its short transmission distance, which limits its application in large-scale forestry ecological monitoring.

At this stage, applying LoRa and other new generation wireless wide area networks (LPWAN) makes up for the previous technical deficiencies, has excellent potential in the forestry Internet of Things application, and is an ideal communication technology for future forestry wireless sensor networks [124]. The forestry Internet of Things system collects a large amount of forestry data in forest monitoring, with a large data volume, high data redundancy, and low information density. It must undergo sufficient data analysis and mining to be effectively applied [125]. However, there needs to be more research on analysing and mining these data, making it challenging to guide forestry production and practice accurately. The practicality of such IoT systems still needs to be improved.

2.3.6 Subsection Summary

Currently, the forest environment situation is still severe, and there are still many problems in environmental monitoring based on Internet of Things technology: weak sensor automation capabilities, the limited functionality of individual sensors; Slow wireless transmission speed; Complex data processing algorithms; Incomplete monitoring points, etc. To further improve environmental quality, it is necessary to enhance the environmental emergency monitoring capacity under the influence of significant events and further strengthen the construction of operation and maintenance automation, gradually achieving remote operation and maintenance of precision monitoring instruments and improving the speed of data transmission. For example, modifying sensor equipment or optimizing data processing algorithms to enable qualitative and quantitative monitoring of various indicators of pollutants; Promoting the integration of Internet of Things technology with other information technologies to improve environmental monitoring technology.

In the design of environmental IoT, emphasis should also be placed on the scientific layout of monitoring points, the accuracy of monitoring equipment performance, and the accessibility of data transmission to achieve authenticity, accuracy, and comprehensiveness. Accelerate the application research of new wireless communication technologies in the forestry Internet of Things. Low power wide area networks (LPWANs), represented by LoRa and NB IoT, with

characteristics such as low power consumption, low cost, and long-distance, are the leading technologies for future forestry information transmission. They have great potential in the application of the forestry Internet of Things, and it is necessary to accelerate their application research and promote the development of the forestry Internet of Things.

In addition, the Forestry Internet of Things gathers much forestry data, which must be thoroughly mined and utilized to guide forestry work better. It is necessary to conduct in-depth research on new data mining and analysis methods, such as machine learning and deep learning, and apply them to processing forestry IoT information to improve the practicality of forestry IoT business models.

2.4 FWI for Peatland Fires Prediction

Forest burning is a phenomenon of combustion in nature. However, fires that have lost human control and spread freely within the forest, causing certain harm and losses to the forest ecosystem and humans, become forest fires. Forest fires occur several hundred thousand times a year worldwide, affecting approximately 0.1% of the total forest area, causing serious harm and loss to forest resources, forest ecosystems, and human life and property [126]. Especially since the 1980s, the global climate has been continuously warming, and forest fires have shown an upward trend [127]. The forest fires that occur yearly cause huge economic losses to countries worldwide. With the rapid development of high-tech represented by computers, the application of forest fire prediction and prediction has become a powerful tool for forest fire management in more and more forested countries worldwide.

Forest fire prediction and prediction is a comprehensive analysis and prediction of the combustion risk of forest fuels based on meteorological factors, terrain, the degree of dryness and wetness of fuels, the characteristics of fuel types, and fire sources. The accuracy of weather forecasting directly affects the accuracy of forest fire prediction [128]. Forest fire prediction and prediction can generally be divided into three types: fire risk weather prediction, forest fire occurrence prediction, and forest fire behaviour prediction [129]. Forest fire risk level prediction only predicts the possibility of fire caused by weather conditions. Forest fire prediction comprehensively considers weather changes, changes in the degree of dryness and wetness of combustibles, types of combustibles, and the hazards of fire sources to predict the likelihood of fire occurrence. Forest fire behaviour prediction refers to predicting the speed of forest fire spread, energy release, fire intensity, and the difficulty of extinguishing a fire after it occurs.

On the other hand, as an important terrestrial ecosystem on the earth, the forest ecosystem of peatland has the functions of regulating climate, conserving water sources, conserving water and soil, preventing wind and fixing sand, but forest fires will cause huge losses and serious hazards to forest resources, ecosystems and human life. For example, on May 6, 1987, a severe forest fire broke out in the Greater Khingan Mountains region of China, burning for 28 days. The affected area of the forest in the area was 10100km², with 211 people killed and more than 50000 people affected. The indirect economic losses amounted to 6.913 billion yuan [130]. On March 30, 2019, a forest fire broke out in Muli County, Liangshan, Sichuan, causing the sacrifice of 30 firefighters [131]. Therefore, conducting forest fire monitoring and early warning plays an important role in forest ecological security and the safety of people's lives and property. Global warming has a significant impact on wildfires, and a large number of studies have shown that the area and incidence of wildfires will increase, and the season of wildfires will become longer [132].

Fire hazard is the assessment of fixed and variable factors (such as combustibles, weather, and terrain) in the fire environment, which determine the fire's difficulty, spread speed, control difficulty, and fire impact. The process of systematically evaluating and integrating various factors that affect fire hazards is called fire hazard classification. The fire hazard level system generates qualitative or quantitative indicators of potential fires, which can serve as guidelines for various fire management activities such as fire prevention, fire detection, deployment and scheduling of firefighting resources, large-scale fire management, strategic planning, and combustible management. These practical fire management activities can reduce the harm of fires.

The Canadian Forest Fire Danger Rating System (CFDDRS) has been widely used worldwide. Its essential component, the Fire Weather Index (FWI), has been applied or calibrated in North America, South America, Europe, and Asia. This section elaborates on the development process of the Canadian Forest Fire Weather Index system, focusing on examining the calibration and application of the FWI system worldwide. These experiences are helpful in applying the FWI system to different environments. Finally, suggestions are made for establishing a more accurate FWI system.

2.4.1 History of FWI

Forest fire prediction and prediction research has a history of over a hundred years since the 1920s and has developed rapidly in various countries worldwide. The United States, Canada, and some Western European countries attach great importance to research on forest fires. For example, in 1914, the United States began studying fire risk levels [133]; The former Soviet Union used cypress branches and wooden columns to estimate the occurrence of forest fires during the Tsarist Russia period [134]; In 1928, Wright in Canada used relative humidity in the air to make fire hazard predictions, with a relative

humidity of 50% as the limit. If the relative humidity is less than 50%, forest fires are possible [135]; In 1936, Gisborn of the United States proposed a multi-factor forecasting method [136].

The above methods all belong to the fire risk weather forecasting category. The fire risk level is divided into five levels: non-combustible, non-combustible, flammable, flammable, and strongly combustible. After the 1950s, more and more countries studied forest fire forecasting, with the United States and Canada developing the fastest.

In the 1970s, Canada and the United States first formed a national-level fire risk prediction system. In 1972, Canada proposed the Canadian Forest Fire Weather Indicator System [137]. This system is based on a large amount of fire and weather data, as well as field experiments, and utilizes the principle of water heat balance to predict the nationwide unified combustible humidity code. It only needs to measure four meteorological factors, such as temperature, relative humidity, wind speed, and precipitation, every day to conduct a three-day forecast. In 1972, the United States also proposed a national fire safety system, which calculated the ignition quantity, spread component, and energy release component. It determined three independent indicators, namely lightning fire occurrence indicator, artificial fire occurrence indicator, and combustion indicator. These three indicators were further summarized as fire load indicators [138]. By 1978, the system had been revised and rapidly developed from qualitative forecasting to quantitative forecasting [139].

The North Forest Fire Laboratory in the United States has also designed a pocket calculator for calculating fire behaviour, which is simple in the program, fast in calculation speed, and high in accuracy. Users can obtain fire characteristic values as long as they input a certain value and use it to predict fire behaviour [140]. In 1974, the former Soviet Union also proposed the method of using electronic computers to develop forest fire prediction programs in individual forest regions [141].

With the rapid development of high-tech such as computers, many forest fire risk level prediction systems have emerged, becoming powerful tools for forest fire management. In 1925, Wright conducted a study on forest fire risk levels in Canada, mainly studying the relationship between weather factors, fuel moisture content, and fire behaviour. By the late 1960s, the ForCan team began establishing a national fire hazard rating system. In 1969 released, a temporary version of the first subsystem of the Canadian Forest Fire Danger Rating System (CFFDRS) - the Canadian Forest Fire Weather Index (FWI) System. Subsequently, the first version was officially released in 1970, and the system was updated in 1976, 1978, and 1984, respectively. The current FWI system retains the best features of early systems and adds new modules, making it more complex than previously released systems [142].

The FWI system is one of the world's most commonly used fire weather hazard level index systems [143]. This index system is based on a large number of ignition tests, weather data, and fire data. The theoretical basis is the time delay equilibrium moisture content theory, which organically connects meteorological conditions, geographical location, sunshine hours, and combustible moisture content. The FWI system needs to input the local temperature, relative humidity, wind speed, and 24-hour precipitation of the day, calculate the change in combustible moisture content through changes in meteorological factors, and then determine the potential fire risk level based on the combustible moisture content of different sizes or locations. This system organically combines the moisture content of combustible materials with the size of fire risk, and its framework has been widely recognized by the world's forest fire prevention community.

2.4.2 Modification of FWI System

The FWI system was initially implemented in the fire hazard level scheme based on the correlation between the FWI system values and fire activity analyzed based on historical fire weather and fire occurrence data. In addition, the fire hazard level must also consider the fire management objectives and explaining the fire level mainly depends on the fire risk value and available fire management resources or tools. The design intention of the FWI system was to prevent fires in Canadian North American short-leaved pine and twisted-leaved pine. However, the principles of fires in different regions are the same, such as combustible materials in fires in different regions obtain and lose moisture according to the same physical principles; When fires occur in different regions, they can respond to combustible materials, weather, and terrain in the same way [144].

Therefore, different ecosystems worldwide can use the three combustible moisture codes in the FWI system, namely FPMC, DMC, and DC, as relevant indicators of combustible moisture. This has made FWI the most commonly used fire weather rating system globally, and some countries have fully or partially implemented FWI systems, including North America (United States), South America (such as Chile and Mexico), Europe (such as Russia), Oceania, and so on. The fire management department uses combustible humidity and fire behaviour index to estimate the daily occurrence of fires, potential fire behaviours, and the difficulty of extinguishing fires in the area. At the same time, it assists in deploying fire extinguishing resources to high-risk areas. These experiences help to apply fire hazard level knowledge from one environment to another.

The climate, types of combustibles, fire conditions, and fire management activities vary in different regions, so many countries need to revise the FWI system when using it. Table 2.4 shows the performance of the FWI system after adapting to regional modifications.

Table 2.4 : Performance of The Modified FWI

Authors	Ref.	Proposed Methods	Performance Results
Viegas et. al.	[145]	Calibrate the fire hazard level based on statistical data of daily FWI, number of fires, and burned area in Portugal.	There is a good relationship between the fire risk level and the fire that occurred in the area on that day.
Wotton and Beverly	[146]	Establish specific equations in FFMCI for estimating actual litter moisture content based on different forest types, stand densities or seasons, and different coefficients, and adjust the litter moisture content.	The correlation between the estimated litter moisture content of daily FFMCI, HFFMCI, and adjusted daily FFMCI and the observed moisture content is higher than that of the original moisture content calculated using standard formulas.
Schiks and Wotton	[147]	A calibration method between moisture and FFMCI was developed through regression modeling, and several corrections were made to the FFMCI model, including the temperature of combustible materials driven by solar radiation.	The hourly FFMCI value is converted into moisture content, greatly reducing prediction bias. The improved FFMCI model is in good agreement with the observation results, with an average error of 10%.

Table 2.4 : Continued

Authors	Ref.	Proposed Methods	Performance Results
Lucas and Guillermo	[148]	Using a logistic regression model to calculate the FFMC for each season, it is recommended to divide it into three fire hazard levels.	When FFMC is correlated with MC, there is a very significant regression, suggesting a highly robust and strong relationship between FFMC and MC variables.
Groot et. al.	[149]	Adjust the sunshine hours or daily combustible drying time to calibrate the region, and use the FBP system and Southeast Asian standard combustible parameters to calibrate ISI.	An ignition potential indicator was developed using FFMC. Developed difficulty indicators for grassland fire control using ISI.
Carlos et. al.	[150]	Establish a model for the combustible temperature, equilibrium moisture content, response time, rainfall without cover, and time intervals between weather observations of open-air grass.	A new model has been developed for FWI to track the moisture content of outdoor combustible materials. Compared to the existing hourly FFMC, it is closer to the actual humidity content.

2.4.3 Application of FWI

As the most commonly used fire weather rating system worldwide, FWI has a wide range of applications and research areas. Many studies have linked the components of the FWI system to the daily, monthly, and annual fire incidence and burning areas in Canada. For example, Kerry [151] found that a model containing FWI system values and lightning strikes correctly predicted 56% of the fires caused by lightning strikes in Saskatchewan, Canada, within five years and correctly predicted 90% of the days of low-risk fires. Waddington et al. [152] found that DMC and DC can predict northern peatlands' overall water status and fire risk.

The output of FWI has been used in many studies, such as developing models for fire occurrence, models for forest shrub charring height and tree mortality, the thickness of ground combustion (model for forest ground consumption during fires), predicting lightning ignition probability, and combustion surface area in various regions of Canada. The system also lays the foundation for studying the impact of climate change on forest fires in Canada. Currently, it is also used in Canada's annual forest carbon budget to estimate carbon losses caused by fires [153]. In 1990 [154], the US Alaska field fire research team also adopted the FWI system because of the similar types of combustibles in Alaska and northern Canada. Since then, other states in the northern United States have also adopted this system. Abatzoglou and Kolden [155] and Jain et al. [156] evaluated fire weather and fire hazards in eight western United States and North American regions, respectively. Jain et al. found that the length of fire seasons in most parts of North America increased. Although the environment in the United States and Canada is similar, the FWI system did not consider latitude factors such as sunlight duration and permafrost. Therefore, Wilmore [157] and Jandt et al. [158] studied the impact of permafrost on DMC and DC during the wetting and drying processes. They believe that automated electronic devices such as frequency domain reflectometry (FDR) can be used to estimate the moisture content of moss and turf.

In Argentina, the National Fire Management Department began using the FWI system in three pilot areas in 2000 and found that the FWI system can accurately represent fires in different ecosystems throughout Argentina. Wadelich et al. [159] added FWI to their designed forest fire visualization simulator, displaying FWI values in a table format and displaying fire risks on a colour map. It can also calculate FWI values during meteorological data updates, making it easier for firefighters to monitor fire risks in the area, and is expected to be used for fire management, training, and communication. Silva et al. [160] used the FWI system in Serrado, Brazil, to evaluate the meteorological level of fires, and the results obtained confirmed the universality of the FWI system in simulating global fire situations. However, Lucas and Guillermo believe that there are significant differences in combustible types between Argentina and Canada and that the output values of the FWI system still need

to be calibrated to better display fire risk. A logistic regression model is applied to calculate the Fine Fuel Moisture Code (FFMC) for each season, and correlation analysis is conducted with the measured Moisture Content (MC). Based on ignition tests and regression results, an FFMC classification was proposed for evaluating fire hazards in the Patagonia forest [148].

New Zealand [161] adopted the FWI system in 1980 to assess the fire risk of artificial pine forests. Part of the reason why New Zealand adopted the FWI system is that it is simple, with climate and terrain conditions similar to those in British Columbia, Canada, and there are decision-support tools associated with the FWI system [162]. In the application process in New Zealand, in addition to the impact of changing the length of sunlight in low-latitude areas, the FWI system was not well utilized due to a lack of technology transfer and research on how to adapt to the local environment. In 1992, fire research and technology transfer programs were launched to address these issues. For example, when applying the system in areas with different climate and vegetation environments, two methods were proposed to improve the drought coding DC of the New Zealand FWI system. The first method employed a potential evaporation scheme considering wind speed, surface air stability, and water vapour mixture gradient. The second method calculates DC by observing soil moisture, where DC represents the actual situation of the soil [163].

In Europe, the FWI system has been calibrated to describe different fire activities. For example, Viegas et al. [164] calibrated the fire risk level based on FWI statistical data for each region and the number and burning area of fires per day. In addition, research has shown that the FWI system is particularly suitable as a fire risk rating system in Europe. Fox et al. [165] found that 73% of the 99 fires in southeastern France occurred within weeks with an FWI value of ≥ 90 , and 97% of the burning area occurred within weeks with an average FWI value of ≥ 90 . Therefore, in Europe, FWI has been used to study the relationship between FWI and fire activity (fire frequency, combustion area) at different spatiotemporal scales or to simulate fire activity, and to evaluate the likelihood, characteristics, and fire emissions of large-scale fires [166].

The FWI system was first introduced in China in the 1980s. From 1984 to 1991, a project team from China and Ontario, Canada, implemented the Gadagchi project in the Greater Khingan Mountains region of China, improving the local ability to protect forest resources and demonstrating the application of the FWI system in other regions of China. Although the FWI system was not widely used after being introduced into the Northeast China forest region, some scholars have conducted relevant research on the applicability of the FWI system in China, modifying the relevant parameters and calculation methods of the system or dividing forest fire risk levels according to local conditions for use in China [168-170]. It can even be directly applied in the Greater Khingan Mountains region, Yunnan Province, Fujian Province [171].

China has a complex and diverse terrain with numerous mountains, and slope, aspect, and location can affect forest fire behaviour. Among them, slope and aspect affect the speed of forest fire spread and the direction of forest fire spread. Another subsystem of the Canadian Forest Fire Risk Rating System, the Canadian Forest Fire Behavior Prediction System, incorporates terrain factors such as slope and uphill direction. China should also consider the impact of terrain on forest fire behaviour when applying the FWI system, adding factors such as terrain and altitude. Currently, most fire risk rating systems used worldwide do not fully consider human factors in the occurrence of fires. Some provinces in Canada have developed prediction systems for fires caused by humans and lightning, while in China, human activities are intense. Therefore, when applying FWI systems, human and lightning-induced fire prediction systems should be included.

Many studies have been conducted in Southeast Asia to calibrate the FWI to adapt to the fire environment and fire issues in Southeast Asia. By adjusting the sunshine hours or daily combustible drying time, the FWI was directly calibrated to the equatorial region, and then three components of the FWI were further calibrated to provide early warning of severe haze events caused by peat fires (using the DC index) Potential warning for a large number of fires (using FPMC index) and potential warning for grassland fire spread (using ISI index). On grasslands, fire intensity can only be estimated using ISI, but it is necessary to use the Fire Behavior Prediction (FBP) system and Southeast Asian standard combustible parameters to calibrate ISI as a grassland fire control indicator [172].

Southeast Asia is a region with a unique environment and weather patterns, which require modification of the FWI system to make it more suitable for use in this region. Several studies have been conducted to modify the FWI system for use in Southeast Asia [173, 174]. These studies demonstrate that modifying the FWI system for use in Southeast Asia can improve the accuracy of fire danger assessment and facilitate more effective fire management strategies. However, challenges remain, such as the lack of accurate weather data and trained personnel to operate and interpret the results of the modified FWI system. Overall, modifying the FWI system for use in Southeast Asia is an ongoing research area with great potential for improving fire management and protecting the environment and human lives in the region.

In addition to the Fire Weather Index (FWI), the Forest Fire Danger Rating System (FDRS) is also used in Southeast Asia for fire danger assessment and management. The FDRS is a comprehensive system that considers various factors such as fuel type, slope, and weather conditions to assess fire danger. The FDRS has been modified for use in Southeast Asia to make it more suitable for the region's unique environmental conditions. For example, the FDRS has been modified in Malaysia to include additional factors such as topography and vegetation type [175]. The modified FDRS system was found to be more effective in predicting fire danger compared to the standard FDRS

system. Similarly, in Indonesia [176], the FDRS has been modified to include additional factors such as forest type and land cover and was found to be more accurate in predicting fire danger compared to the standard FDRS system. These modifications to the FDRS system demonstrate the importance of adapting fire danger assessment systems to regional conditions and the potential benefits of doing so in terms of more accurate predictions of fire danger and more effective fire management strategies. Overall, using both FWI and FDRS systems in Southeast Asia highlights the need for customized fire danger assessment systems that consider the region's unique environmental conditions and fuel types. These modified systems can help reduce the incidence and severity of forest fires, protect the environment, and promote the safety of human lives and property.

2.4.4 Subsection Summary

The FWI system is based on the time-delay equilibrium moisture content theory, which organically combines combustible materials' moisture content with the fire risk size. It tracks the diurnal variation of combustible materials in three layers of forest under different drying rates, which is crucial for the occurrence, spread, and control difficulty of fires. As the FWI system only requires parameters such as temperature, relative humidity, wind speed, and 24-hour precipitation, real-time meteorological data can be combined to calculate fire risk levels and timely release forecasts. When applying the FWI system, on the one hand, the relevant parameters and calculation methods of the system should be modified. On the other hand, the forest fire risk level can be divided according to the actual situation of different regions to adapt to the situation. In addition, the complex and diverse terrain, numerous mountainous areas, and strong human activities can all affect forest fire behaviour. Therefore, when applying FWI systems, factors such as terrain, altitude, human activities, and lighting should also be considered.

The FWI system has been successfully applied in many parts of the world, including Canada, the United States, Australia, and parts of Europe. However, the system needs to be modified for use in different regions because the fuel types, weather patterns, and environmental conditions vary widely across different regions. Several studies have modified the FWI system for use in different regions. However, modifying the FWI system is not without challenges. One challenge is the need for more accurate weather data, especially in developing countries. Another challenge is the need for trained personnel to operate the system and interpret the results. Despite these challenges, the FWI system remains an essential tool in fire management. Its wide adoption and successful application in different regions demonstrate its versatility and effectiveness. With continued research and development, the FWI system can be further improved to meet the specific needs of different regions, making it an even more valuable tool in fire management.

2.5 Predictive Models for Fire Risk Assessment

Wildfires pose significant threats to ecosystems, human lives, and property, necessitating advanced strategies for risk assessment and prediction. Predictive models play a crucial role in this domain, offering insights into fire behavior, spread patterns, and potential impacts. This introduction delves into the academic landscape of predictive models for wildfire risk assessment, highlighting the evolution of methodologies and their applications in addressing the complex challenges posed by wildfires. From traditional linear and power models to sophisticated machine learning techniques, the review explores the depth and breadth of approaches employed in understanding and forecasting wildfire dynamics. Emphasizing the need for accurate and dynamic risk assessment, this introduction sets the stage for an in-depth exploration of the advancements, nuances, and emerging trends in the field of predictive modeling for wildfire risk assessment.

2.5.1 Application of Curve Fitting in Fire Prediction

Curve fitting, a statistical technique, plays a pivotal role in wildfire prediction, enabling the identification of intricate patterns within datasets [177]. This overview delves into the applications of curve fitting, focusing on three prominent models: Linear, Power, and Linear Mixed models, each offering unique advantages in understanding and forecasting wildfire behavior.

Linear Model: The Linear model, a fundamental approach, assumes a linear relationship between variables [178]. In wildfire prediction, it proves valuable in capturing straightforward trends, especially in scenarios where fire behavior exhibits consistent patterns over time [179]. Linear models excel in cases where a direct proportional relationship between factors is evident, providing a clear and interpretable representation of the data [180].

Power Model: Power models, characterized by nonlinear relationships, are adept at capturing complex, exponential patterns inherent in wildfire dynamics [181]. This model accommodates scenarios where the influence of certain factors on fire behavior is not constant but follows a power-law distribution [182]. In the context of wildfires, power models enhance predictive accuracy by addressing the nonlinearity intrinsic to factors like fuel moisture content and environmental conditions [182].

Linear Mixed Model: The Linear Mixed model combines elements of both fixed and random effects, accommodating variations in data that may not conform to a single fixed curve [183]. This flexibility is crucial in wildfire prediction, where factors influencing fire behavior can exhibit both consistent trends and random fluctuations. The Linear Mixed model's adaptability

makes it suitable for capturing the nuanced relationships within diverse datasets, providing a more comprehensive understanding of wildfire patterns [184].

Curve fitting techniques contribute significantly to the advancement of wildfire prediction. Linear, Power, and Linear Mixed models offer complementary strengths, allowing researchers to tailor their approach based on the nature of the data. These models facilitate a nuanced understanding of the relationships between various factors, ultimately enhancing the precision and reliability of wildfire risk assessments.

In conclusion, the application of curve fitting techniques in wildfire prediction showcases a sophisticated interplay of mathematical models, each offering distinct advantages. This nuanced approach is vital in addressing the multifaceted challenges posed by wildfires and contributes to the continual evolution of predictive methodologies in fire science.

2.5.2 Machine Learning Applications in Fire Prediction

Machine learning (ML) has emerged as a powerful tool in wildfire prediction, leveraging diverse algorithms to enhance the accuracy and efficiency of risk assessments [185]. This overview delves into the applications of ML in wildfire prediction, scrutinizing various techniques and algorithms. Additionally, it highlights the potential advantages of employing Neural Networks (NN) in the proposed wildfire risk assessment system.

Several ML techniques have been applied to wildfire prediction, including Decision Trees [186], Random Forests [187], Support Vector Machines [188], and Neural Networks [189]. Decision Trees offer interpretability and are effective in capturing complex decision-making processes. Random Forests leverage an ensemble of decision trees, enhancing predictive performance through aggregation. Support Vector Machines excel in handling high-dimensional datasets and nonlinear relationships. Neural Networks, inspired by the human brain, demonstrate exceptional capability in learning complex patterns and nonlinear dependencies.

Neural Networks, specifically deep learning architectures, present inherent advantages for wildfire prediction [190]. Their ability to automatically learn hierarchical features from data makes them well-suited for capturing intricate relationships within environmental variables, fuel conditions, and historical fire patterns [191]. Neural Networks excel in discerning nonlinear patterns, essential for modeling the dynamic and multifaceted nature of wildfires [192].

Wildfires exhibit complex and nonlinear behaviors influenced by a myriad of factors [193]. Neural Networks excel in recognizing intricate patterns within datasets, allowing them to adapt and learn from diverse environmental conditions. This adaptability is crucial for accurate predictions in dynamic and evolving wildfire scenarios.

Neural Networks, particularly recurrent architectures, are adept at handling temporal dependencies and spatial relationships in wildfire data [194]. They can capture how environmental variables evolve over time and discern patterns that may vary across different geographic locations, contributing to a more robust predictive model.

In conclusion, the application of machine learning techniques in wildfire prediction represents a sophisticated approach to address the challenges posed by the dynamic nature of wildfires. Among these techniques, Neural Networks stand out for their potential to automatically learn and adapt to complex patterns, providing a promising avenue for improving the precision and reliability of wildfire risk assessments.

2.5.3 Performance Metrics for Prediction Models

Evaluating the performance of wildfire prediction models is paramount to ensure their accuracy and reliability in mitigating the impact of forest fires. This review provides a comprehensive overview of key performance metrics commonly employed in assessing wildfire prediction models, including Mean Squared Error (MSE) [195 - 197], Root Mean Squared Error (RMSE) [195 - 197], Mean Absolute Error (MAE) [197 - 199], and R-squared (R^2) [199, 200].

MSE stands for Mean Squared Error and is a common metric used to evaluate the performance of machine learning models. It measures the average of the squared differences between the predicted values and the actual values. The equation for MSE is:

$$\text{MSE} = \frac{\sum_i^N (y_{\text{predicted}(i)} - \overline{y_{\text{actual}}})^2}{N} \quad (2.1)$$

Where: N is the number of samples in the dataset; $y_{\text{predicted}(i)}$ is the i -th predicted value; $\overline{y_{\text{actual}}}$ is the mean of the actual values.

The MSE value is always positive, and a smaller value indicates a better fit between the predicted and actual values. However, MSE has the disadvantage of being sensitive to outliers, as the squared differences amplify their effects on the overall error.

RMSE stands for Root Mean Squared Error, and it is a popular performance metric used in regression analysis to measure the difference between predicted values and actual values. It is similar to MSE but takes the square root of the average of squared errors, making it more interpretable in the same unit as the target variable. The equation for RMSE is:

$$\text{RMSE} = \sqrt{\frac{\sum_i^N (y_{\text{predicted}(i)} - \overline{y_{\text{actual}}})^2}{N}} \quad (2.2)$$

Where: N is the number of samples in the dataset; $y_{\text{predicted}(i)}$ is the i -th predicted value; $\overline{y_{\text{actual}}}$ is the mean of the actual values.

MAE stands for Mean Absolute Error, which is another commonly used metric for evaluating the performance of a regression model. It measures the average absolute difference between the predicted values and the actual values. The lower the value of MAE, the better the model's performance. The formula for MAE is:

$$\text{MAE} = \frac{\sum_i^N |y_{\text{predicted}(i)} - \overline{y_{\text{actual}}}|}{N} \quad (2.3)$$

Where: N is the number of samples in the dataset; $y_{\text{predicted}(i)}$ is the i -th predicted value; $\overline{y_{\text{actual}}}$ is the mean of the actual values.

The dimensions of the error indicators calculated by RMSE and MAE are consistent with the target variable, but after obtaining the results, it will be found that RMSE is slightly larger than MAE. This is because RMSE first accumulates the squared errors before square root, which actually amplifies the difference between larger errors.

The coefficient of determination (R-squared or correlation), denoted as R^2 , is a statistical measure that represents the proportion of the variance in the dependent variable that is explained by the independent variables in a regression model. It ranges from 0 to 1, where a value of 1 indicates a perfect fit and 0 indicates no linear relationship between the dependent and independent variables. The formula for R^2 is:

$$R^2 = 1 - \frac{SS_{\text{residual}}}{SS_{\text{total}}} \quad (2.4)$$

$$SS_{residual} = \sum_i^N (y_{actual(i)} - y_{predicted(i)})^2 \quad (2.4-a)$$

$$SS_{total} = \sum_i^N (y_{actual(i)} - \overline{y_{actual}})^2 \quad (2.4-b)$$

Where: $SS_{residual}$ is the sum of squared residuals; SS_{total} is the total sum of squares; N is the number of samples in the dataset; $y_{actual(i)}$ is the i -th actual value; $y_{predicted(i)}$ is the i -th predicted value; $\overline{y_{actual}}$ is the mean of the actual values. $SS_{residual}$ represents the sum of the squared differences between the actual and predicted values of the dependent variable. It measures the variability that is not explained by the model. SS_{total} represents the total variability of the dependent variable. It is the sum of the squared differences between the actual values and the mean of the dependent variable.

In general, an R^2 value of 0.8 or higher is considered to be a good fit for a regression model, indicating that 80% or more of the variance in the dependent variable can be explained by the independent variables. However, the interpretation of the R^2 value depends on the context and the purpose of the analysis. In some cases, a lower R^2 value may still be useful or meaningful, especially if the goal is prediction rather than explanation. It is also important to consider other factors such as the sample size, the significance of the individual independent variables, and the potential presence of outliers or non-linear relationships.

Selecting an appropriate performance metric depends on the specific objectives of the wildfire prediction model. MSE and RMSE are suitable for scenarios where large errors should be penalized [195 - 197], while MAE may be preferred when robustness to outliers is crucial [198, 199]. R^2 provides an overarching assessment of the model's explanatory power [200].

In conclusion, understanding and appropriately applying performance metrics are critical for evaluating the efficacy of wildfire prediction models. Each metric serves a distinct purpose, allowing researchers and practitioners to tailor their assessments based on the specific requirements of their predictive modeling endeavors.

2.6 Chapter Summary

Peatland is easy to burn, and in many places where it is abundant, it is usually used as a fuel in daily life. It is also sold as potted soil by horticultural centres and can be used for brewing whiskey. When peat is drained of water, it can be used as agricultural land. At present, the growing global demand for palm oil has driven palm oil suppliers to develop peatland on a large scale, which has

largely led to the destruction of peatland and forest fires, and further exacerbated climate change, pushing many precious species to the brink of extinction. In view of its importance and multiple uses, the EU has introduced laws to restrict the use of peatland, ASEAN has adopted a regional peatland management strategy, and Ireland, Scotland and other countries have also formulated national peat strategies.

This chapter provides an overview of the carbon loss caused by forest fires in peatlands and discusses the advantages and challenges of using Internet of Things (IoT) technology to monitor and manage forest environments in these areas. The chapter suggests that machine learning and other data mining and analysis techniques can be introduced to better handle the large datasets generated by IoT systems in peatland forests. The chapter also delves into the development and application of the Fire Weather Index (FWI) system for predicting forest fires, emphasizing the need to consider factors such as topography, altitude, human activity, and lightning when applying the FWI system. Overall, the chapter highlights the importance of integrating advanced technologies and methodologies in forest fire monitoring and management to mitigate the environmental and social impacts of forest fires in peatlands.

In summary, this literature review has provided a comprehensive examination of various methodologies employed in wildfire prediction, including the application of curve fitting models to ground and atmospheric parameters. As we transition towards the implementation of our study, it is imperative to underscore the pivotal role of the Internet of Things (IoT) system. The sensors embedded in this system will diligently capture real-time data on ground and atmospheric conditions, enabling precise modeling through curve fitting techniques. Moreover, the integration of machine learning algorithms, notably neural networks, will empower our predictive models with the ability to discern intricate patterns within the collected data. Together, the amalgamation of IoT-based sensing and advanced machine learning constitutes the cornerstone of our forthcoming research, poised to contribute significantly to the realm of wildfire risk assessment.

CHAPTER 3

METHODOLOGY

The causes of forest fires in peatlands are complex, and the regional and randomness are significant. Therefore, the traditional Canadian prediction model must achieve ideal results in predicting forest fires in tropical areas. However, the related theories of the Internet of Things system and machine learning can provide a new method for monitoring and forecasting forest fires in peatlands in tropical areas and effectively improve the accuracy of predicting forest fires. This chapter focuses on the prediction of forest fires in tropical peatlands, mainly introducing the relevant parameters of the peatland IoT system and fire weather index system deployed in Raja Musa Forest Reserve, Kuala Selangor, Malaysia.

3.1 Introduction

The Internet of Things (IoT) has emerged as a powerful tool for environmental monitoring and management, offering a range of benefits such as real-time data collection, remote monitoring, and predictive analytics. IoT systems have been increasingly used in environmental applications, including agriculture, forestry, water management, and air quality monitoring. One area where IoT systems have particular potential is in the monitoring and management of forests, which are vital ecosystems that provide essential ecological services such as carbon sequestration, biodiversity conservation, and water regulation.

The Raja Musa Forest Reserve (RMFR), located in Kuala Selangor, Malaysia, is a tropical peat swamp forest that is home to a diverse range of flora and fauna. The forest is also an important carbon sink, storing large amounts of carbon in its peat soils. However, like many forests around the world, RMFR is under threat from human activities, including illegal logging, forest fires, and land conversion. It is crucial to have an efficient and effective system for monitoring and managing the forest to protect this valuable ecosystem. This project presents an IoT system for monitoring the environmental conditions at Raja Musa Forest Reserve (RMFR). The system utilizes various sensors and devices to collect data on parameters such as temperature, humidity, pressure, and soil moisture. Various methods are used to analyze and process this data, including mathematical models, machine learning algorithms, and data visualization techniques. The implementation of this system provides an efficient and cost-effective way to monitor the environment and understand the ecological processes at Raja Musa Forest Reserve (RMFR), contributing to the sustainable management of ecosystems worldwide. In addition, the methodology used in this project involves four main stages: literature review, system design and implementation, data analysis and modeling, and system evaluation, as shown in Figure 3.1.

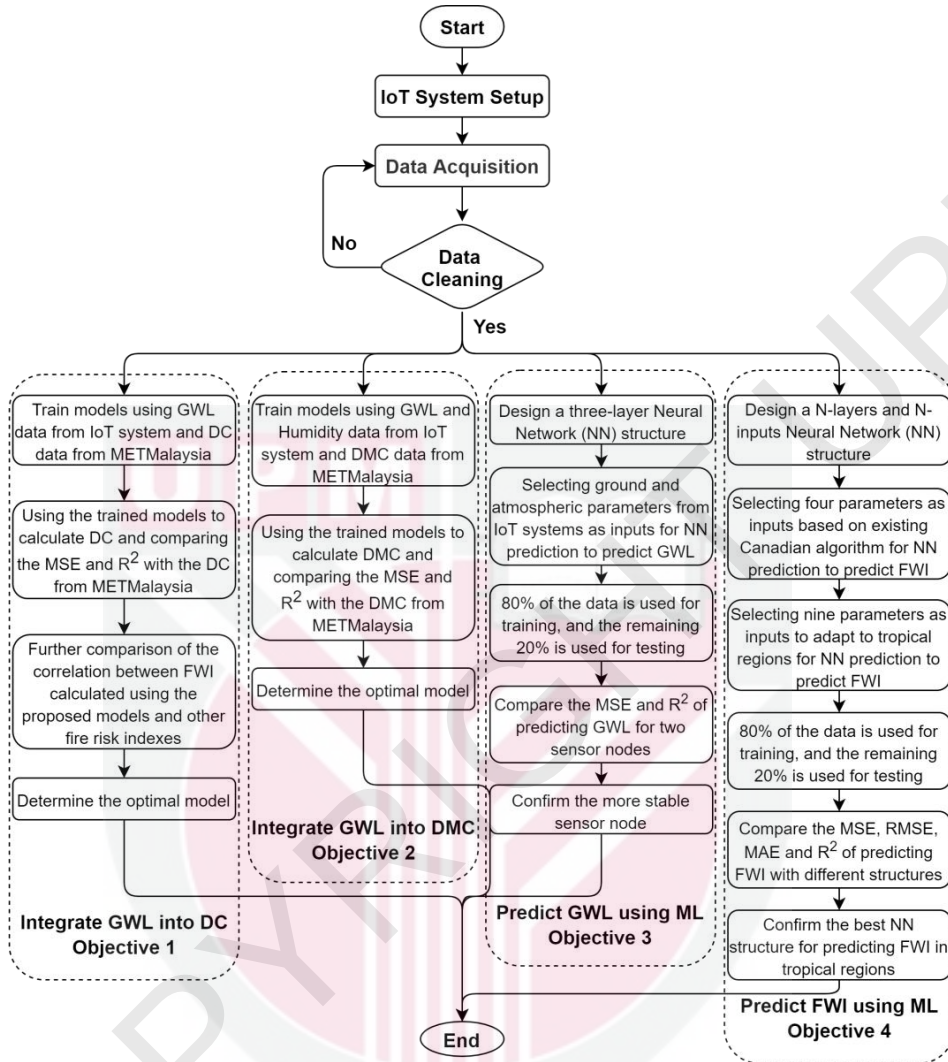


Figure 3.1 : Flowchart of The Proposed System

The first stage of this project involved conducting a comprehensive review of the existing literature on IoT systems for environmental monitoring and forest fire prediction. The literature review aimed to identify the current state of the art in IoT systems for forest fire prediction and environmental monitoring and to identify the research gaps in the existing literature. This stage provided the theoretical foundation for the development of the IoT system and the selection of appropriate sensors and devices.

The second stage of this project involved the design and implementation of the IoT system for monitoring environmental conditions and predicting the risk of forest fires. The system was designed to collect data on various environmental parameters, including temperature, humidity, pressure, and soil moisture. The system was implemented using a LoRa-based wireless communication protocol to transmit the data collected by the sensors to a cloud-based server for processing and analysis. The system also incorporated machine learning algorithms and mathematical models to predict the risk of forest fires based on the collected data.

The third stage of this project involved the analysis and modeling of the data collected by the IoT system. The data collected was analyzed using statistical methods to identify trends and patterns in the data. Mathematical models and machine learning algorithms were used to develop predictive models for forest fire risk based on the collected data.

The final stage of this project involved the evaluation of the effectiveness of the IoT system in predicting the risk of forest fires. The system's performance was evaluated based on its ability to accurately predict forest fire risk and its ease of use and scalability. The models were evaluated using various performance metrics, including mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and correlation (R^2). The system's performance was compared to the standards set by the Malaysian Meteorological Department, and the results showed that the developed system had a high degree of accuracy and was reliable for predicting forest fire risk. Overall, the methodology used in this project provided a comprehensive approach to the design and implementation of an IoT system for environmental monitoring and forest fire prediction. The methodology highlighted the importance of a thorough literature review, system design and implementation, data analysis and modeling, and system evaluation to develop an effective and reliable IoT system for environmental monitoring and management.

3.2 IoT System

This section presents an Internet of Things (IoT) system for monitoring environmental conditions and predicting the risk of forest fires in the Raja Musa Forest Reserve, located in Kuala Selangor, Malaysia. The system utilizes various sensors and devices to collect data on parameters such as temperature, humidity, pressure, and soil moisture. The implementation of this system provides an efficient and cost-effective way to monitor the environment and understand the ecological processes at RMFR, contributing to the sustainable management of ecosystems worldwide. This section highlights the potential of IoT systems in environmental monitoring and management and provides valuable insights for future research and implementation.

3.2.1 Location

The location of an Internet of Things (IoT) system is an essential aspect that can significantly influence its effectiveness and usefulness. The IoT system's location refers to the physical area where the sensors and devices that collect data are installed and where the data is analyzed and processed. The IoT system referred to in this project is located at longitude 101°26'31" east and latitude 3°27'58" north in the Selangor region of Malaysia, specifically in the Raja Musa Forest Reserve, as shown in Figure 3.2.

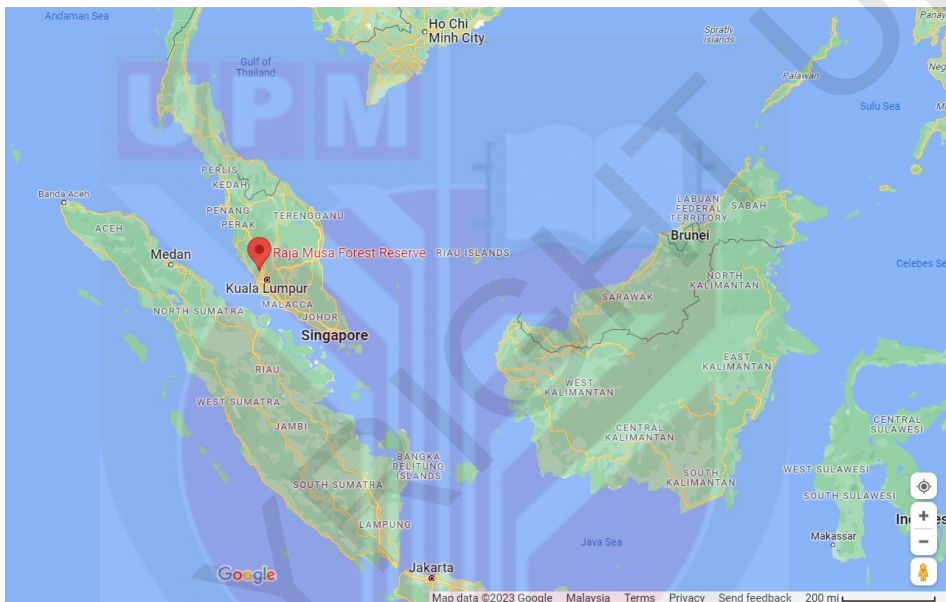


Figure 3.2 : Location of IoT System

The Raja Musa Forest Reserve is a vital peatland ecosystem in Malaysia, covering approximately 8,600 hectares [201]. The area's unique hydrology and soil characteristics make it particularly susceptible to fires, especially during prolonged dry spells. Therefore, the deployment of an IoT system in this location provides a valuable opportunity to monitor and predict the occurrence of peatland fires using real-time data collection and analysis. This system's location is critical to ensuring the timely detection of potential fire outbreaks and taking prompt measures to prevent their escalation. Additionally, the location of the IoT system provides a wealth of data that can be used to understand peatland ecosystems' functioning and help in their conservation and sustainable management. Figure 3.3 shows the distribution map of the peatlands.

The location of this IoT system at the heart of the peatland distribution in Malaysia provides valuable insight into the management of peatland ecosystems, including permanent forest reserves and protected areas. The distribution map of peatlands, permanent forest reserves, and protected areas indicates the urgent need for effective management practices to prevent the risk of wildfires, especially in areas with high peatland coverage. Overall, the implementation of an IoT system in this location can serve as a model for other regions facing similar environmental challenges, helping to improve the management and conservation of precious ecosystems.

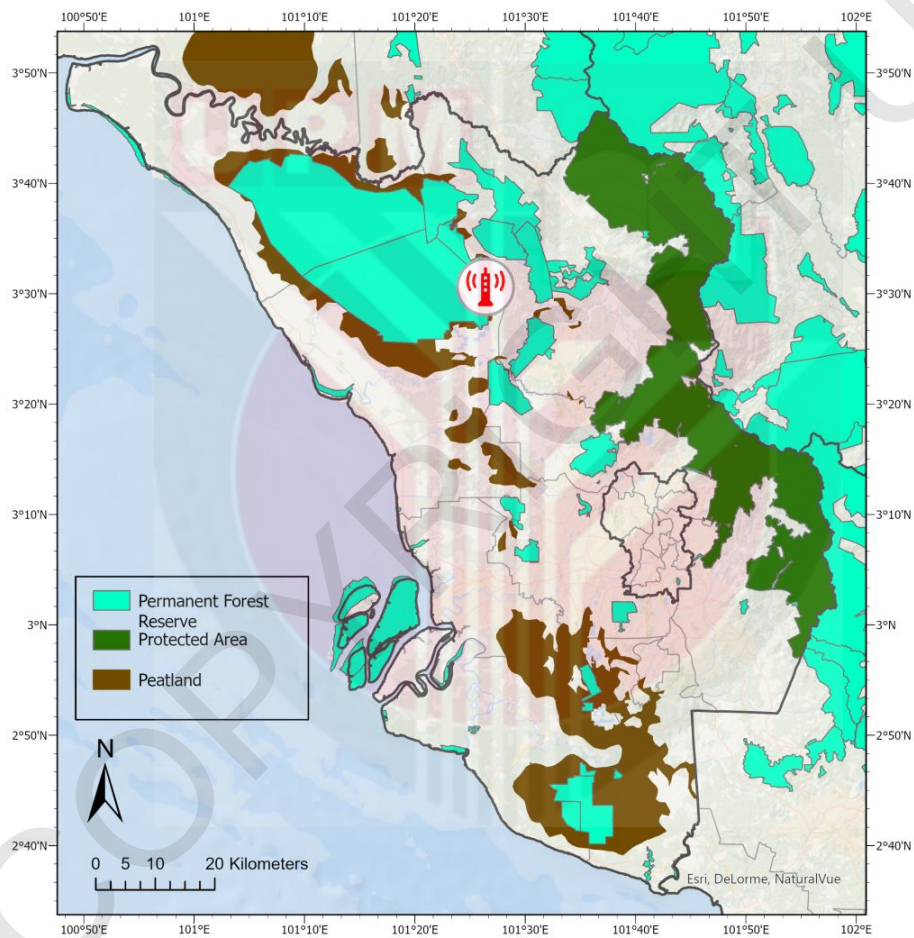


Figure 3.3 : Distribution of The Peatlands in Raja Musa Forest Reserve

This location was chosen for several reasons. First, the Raja Musa Forest Reserve, where the system is installed, is a vital ecosystem that supports numerous plant and animal species, some of which are endangered. Therefore, it is crucial to monitor the environmental conditions in the reserve to ensure

their preservation. Second, the reserve has a history of peatland fires, which can have severe ecological and economic consequences. Therefore, it is necessary to monitor the conditions that can lead to these fires, such as temperature, humidity, and moisture levels in the soil. Finally, the location was chosen because it is a remote area that can be difficult to access, making it challenging to monitor manually. An IoT system provides a solution to this problem, enabling real-time monitoring and remote data collection. Overall, the location of an IoT system is critical to its success, and the selection of the Raja Musa Forest Reserve was based on ecological, economic, and practical considerations.

Peatlands contain large amounts of organic matter that can ignite and burn for long periods, making them particularly challenging to extinguish. Therefore, monitoring peatlands with IoT technology is crucial in preventing and predicting the occurrence of wildfires. The Raja Musa Forest Reserve, where the IoT system is located, is one of the largest peat swamp forests in Malaysia, making it an ideal location for the project. By monitoring various parameters such as temperature, humidity, wind speed, pressure, solar radiation, and soil moisture and temperature of the peatlands, the IoT system can provide valuable data for predicting the likelihood of wildfires and preventing their occurrence. Overall, the IoT location at the Raja Musa Forest Reserve plays a critical role in mitigating the risk of wildfires and ensuring the sustainability of the peatlands in the region.

3.2.2 Architecture

Peatlands are valuable ecosystems that are under threat due to climate change and human activities such as drainage for agriculture, forestry, and mining. Monitoring peatland water level and temperature is crucial for understanding peatland hydrology and carbon dynamics. The groundwater level and peatland temperature and humidity in the tropical peatland ecosystem are critical indicators of the ecosystem's health [202]. Therefore, we describe a IoT System that uses LoRa technology to monitor ground water level, temperature, humidity and other indexes in peatlands, and transmit the data to a gateway located at a nearby observation tower in a tropical peatland reserve.

Figure 3.4 shows the overall structure of the monitoring system, with sensor nodes on the far right using LoRa transmission technology to send the measured groundwater level and peatland temperature and humidity to a gateway on the observation tower located between 150-300 meters away. The observation tower houses a weather station, which monitors meteorological parameters such as rainfall, atmospheric pressure, temperature, humidity, and solar radiation, and a solar panel for backup power. A gateway receives the data from the observation tower and sends it to the cloud server.



Figure 3.4 : Structure of The Proposed IoT System

The architecture of the IoT system is structured into multiple interconnected layers, encompassing ground sensor nodes, gateways, a central server, and data processing algorithms. The ground sensor nodes are responsible for acquiring environmental data, which is subsequently transmitted to the gateways for aggregation. The central server serves as the focal point for receiving and processing the collected data. This comprehensive architecture enables seamless integration and efficient management of the IoT system, facilitating accurate monitoring and analysis of environmental parameters.

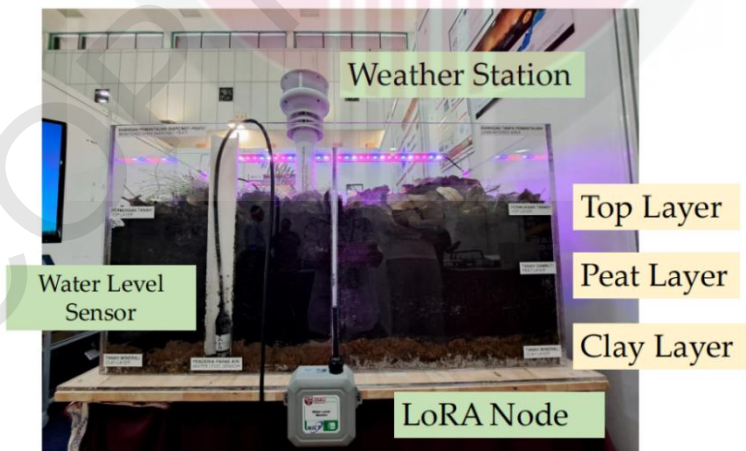


Figure 3.5 : Physical Model of IoT System

The IoT system consists of several sensor nodes placed in strategic locations within the peatland, which are responsible for measuring the water level, temperature and others at their respective locations. In addition, the scaled down physical model of this IoT system is shown in Figure 3.5. It can be seen that the groundwater level sensor is located at the junction of the peat layer and the clay layer.

3.2.3 Transmission Technology

LoRa (Long Range) transmission technology, a prominent low-power wide area network (LPWAN) technology, has gained significant attention for its suitability in long-range and low-data-rate communication applications. In this study, the IoT system incorporates LoRa technology as the preferred wireless communication protocol for transmitting data from the sensor nodes to the base station. The adoption of LoRa offers several advantages for efficient and reliable data transmission. It leverages the long-range capabilities of LoRa Radio Frequency (RF) modulation, enabling seamless communication over extended distances. Moreover, LoRa's low power consumption characteristics contribute to prolonged battery life for the sensor nodes, ensuring long-term and sustainable monitoring. The IoT system is designed with LoRa transceivers integrated into the sensor nodes, facilitating bi-directional communication between the nodes and the base station. These allow for the reliable transmission of various environmental parameters, such as groundwater level measurements, from the remote sensor nodes to the central data processing unit. By employing LoRa technology, the IoT system achieves robust and energy-efficient wireless data transmission, enabling real-time monitoring and analysis of crucial environmental data.



Figure 3.6 : Observation Tower

Figure 3.6 shows the observation tower, which is approximately 20 meters tall, consists of a six-story steel frame structure and is equipped with five sections of pedestrian stairs. At the top of the tower, there is a weather station, a LoRa gateway, an LTE 4G gateway, and solar panels. The tower provides a bird's eye view of the surrounding area and allows for the installation of various monitoring equipment. With the weather station, the tower can gather real-time data on environmental factors such as temperature, humidity, and wind speed. The LoRa gateway and LTE 4G gateway enable wireless communication with the sensor nodes in the network, while the solar panels provide backup power for the system. Overall, the observation tower serves as a critical component of the monitoring system, facilitating data collection and communication among the various components of the network.



Figure 3.7 : LoRa Gateway

Figure 3.7 shows the LoRa gateway, which is located on the observation tower's roof. LoRa (Long Range) is a wireless technology that enables long-range communication between devices with low power consumption. It operates in the unlicensed sub-gigahertz radio frequency bands, which can penetrate through obstacles such as buildings and vegetation. LoRa technology is ideal for IoT applications that require long-range connectivity, low power consumption, and reliable data transmission. In the case of the Raja Musa Forest Reserve peatland monitoring system, LoRa technology is a suitable choice due to the large area of the peatland and the difficulty of accessing certain areas. The LoRa gateway can be placed at a central location within the peatland, and the sensor nodes can be deployed at different locations to monitor various environmental parameters. Since LoRa technology has a long communication range, the sensor nodes can transmit data back to the gateway even if they are located far away. Additionally, the low power consumption of LoRa technology ensures that the sensor nodes can operate for an extended period, reducing the need for frequent battery replacements.

Furthermore, the use of LoRa technology reduces the need for expensive infrastructure such as cellular towers or wired connections. This makes it a cost-effective solution for monitoring remote areas such as the Raja Musa Forest Reserve peatland. Overall, the use of LoRa technology in the IoT system for monitoring the Raja Musa Forest Reserve peatland provides a reliable and efficient way to collect environmental data, which can be used to better understand and protect the peatland ecosystem.

3.2.4 Weather Station

A weather station is a crucial component in our IoT system, designed to collect accurate and real-time meteorological data for environmental monitoring and analysis. The weather station comprises a set of instruments and sensors that measure various atmospheric parameters such as temperature, humidity, wind speed, precipitation, and air pressure. These sensors are strategically placed in the study area to ensure representative and comprehensive data collection. Integrating the weather station into the IoT system enables seamless data acquisition and transmission. The collected meteorological data from the weather station are processed and transmitted to the central data processing unit via wireless communication protocols. This integration enables continuous monitoring and analysis of weather conditions, timely detection of potential fire risks and accurate prediction of fire weather indices. The weather station's high-quality and reliable data serves as a valuable input for the machine learning algorithms employed in the system, enhancing the accuracy and effectiveness of fire risk assessment and prediction models. Integrating the weather station into the IoT system can gain valuable insights into the complex interactions between weather patterns and fire behavior, contributing to improved forest fire management and mitigation strategies.



Figure 3.8 : Weather Station

Figure 3.8 shows the weather station which is fixed beside the observation tower's top staircase. It used to monitor the weather conditions in the area. The weather station is equipped with sensors that measure temperature, humidity, wind speed, and wind direction. This data is important because it can help researchers understand the impact of weather on the water level in the underground water system. The weather station installed in the Raja Musa Forest Reserve peatland is designed to measure various meteorological parameters that are important for monitoring the environmental conditions in the area. The weather station typically consists of a set of sensors that are placed at various heights above the ground, as well as a data logger and a communication module that sends the collected data to the central monitoring system. The sensors used in the weather station can include instruments to measure temperature, humidity, barometric pressure, wind speed, wind direction, rainfall, and solar radiation.

The data collected by the weather station sensors is usually processed by the data logger, which records the measurements at regular intervals, typically every few minutes. The data logger can be configured to store the data locally, or it can be programmed to send the data to the central monitoring system in real-time. The communication module used in the weather station can be based on a range of wireless technologies, such as cellular networks, Wi-Fi, or LoRa. In the case of the Raja Musa Forest Reserve peatland monitoring system, a LoRa communication module is used, as it provides long-range and low-power connectivity, which is ideal for transmitting data from remote areas. Overall, the weather station plays a crucial role in providing important environmental data that can help to monitor the conditions in the Raja Musa Forest Reserve peatland and inform decision-making related to the conservation and management of the area.

3.2.5 Sensor Nodes

Ground sensor nodes are fundamental components of the IoT system, designed to collect and transmit ground-level environmental data for comprehensive monitoring and analysis. These sensor nodes are strategically deployed throughout the study area to capture spatially distributed information. Each sensor node has sensors that measure vital parameters such as soil moisture, temperature, and groundwater level. The sensor nodes are powered by low-power and long-range communication technologies, enabling efficient and reliable transmission of the collected data to the central data processing unit. The integration of ground sensor nodes into the IoT system facilitates real-time and continuous monitoring of ground conditions, providing valuable insights into the dynamics of the study area. The collected data from the ground sensor nodes serve as essential inputs for fire risk assessment and prediction models, enabling accurate evaluation of the moisture content in the soil and vegetation, which plays a crucial role in determining fire susceptibility.

Figure 3.9 illustrates the spatial layout of the sensor nodes and the observation tower on the peatland reserve. Sensor node 1 is located 174 meters west of the observation tower, and Sensor node 2 is located approximately 262 meters southwest of the observation tower. The straight-line distance between Sensor node 1 and Sensor node 2 is about 200 meters, and Sensor node 1 is located near a water channel shown in Figure 3.10. Sensor nodes monitor groundwater level and soil temperature and humidity, while the weather station on the observation tower monitors meteorological parameters.

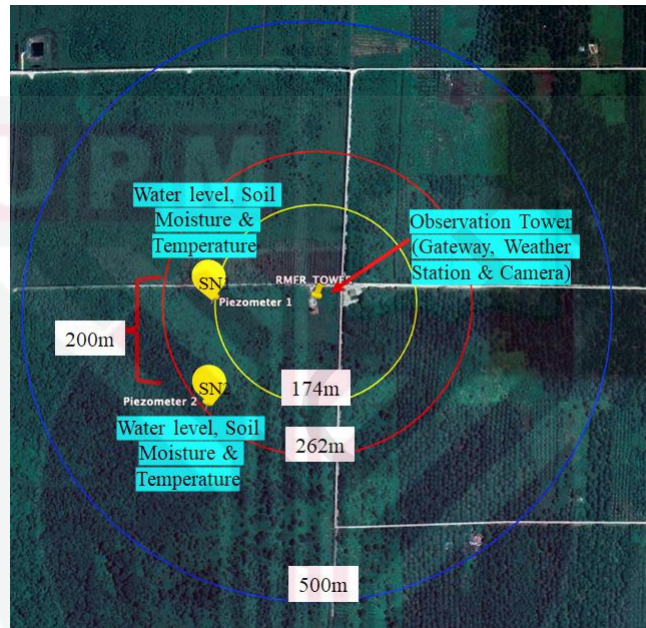


Figure 3.9 : Spatial Layout of Sensor Nodes and Observation Tower



Figure 3.10 : Water Canal Near Sensor Node 1

The sensor nodes are protected with a red iron pipe, and the transmission line is placed inside to protect it and connect it to the peatland, as shown in Figure 3.11. The black LoRa antenna transmits the data, and the entire node is powered by a 3.4V DC battery. The external one-meter-high iron net prevents wild animals from entering and damaging the sensor node equipment. The sensor node is the device that is responsible for measuring the water level in the underground water system. The sensor node is also equipped with a temperature and humidity sensor that is used to measure the temperature and humidity of the soil environment.



Figure 3.11 : Sensor Node

Figure 3.12 shows the internal sensors of the sensor node, which includes a piezometer to monitor groundwater level and a temperature and humidity sensor to monitor soil temperature and humidity.

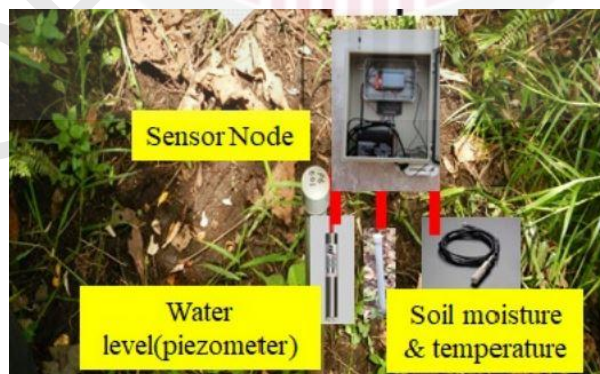


Figure 3.12 : Internal Sensors of The Sensor Node

The internal sensors of the sensor node comprise several types of sensors, including a piezometer for monitoring the underground water level, as well as temperature and humidity sensors for monitoring soil temperature and humidity. These sensors are essential components of the monitoring system, providing valuable data on soil and water conditions in real-time. The pressure gauge, in particular, is crucial for monitoring changes in the water level, which can have significant implications for agriculture and water management. By integrating these sensors into the monitoring system, researchers can gain a deeper understanding of the local environment and make more informed decisions regarding resource management.

The theoretical structure diagram in Figure 3.13 describes the placement of the pressure gauge sensor used to monitor the underground water level. The pressure gauge sensor is placed at the bottom of a well that is drilled into the underground water system. The sensor is connected to a data acquisition system that collects the pressure data and sends it to the cloud server for analysis.

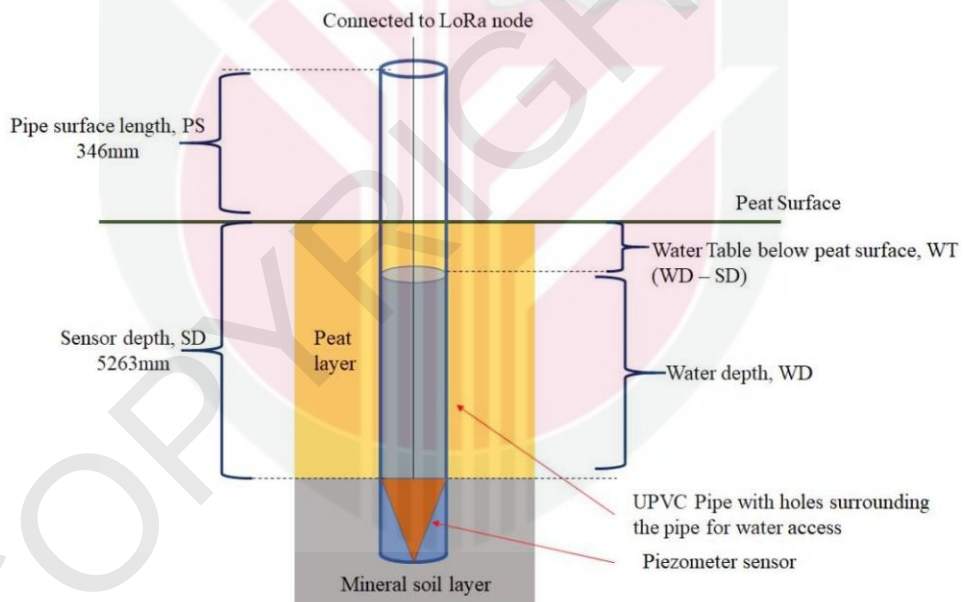


Figure 3.13 : Piezometer Placement on Peatland

The piezometer sensor is placed inside a UPVC pipe with holes to ensure the smooth flow of groundwater. The sensor's upper end is connected to the LoRa node, and the pipe's exposed length is 346 millimeters. The sensor contacts the mineral soil layer at a depth of 5263 millimeters. The groundwater level is calculated by subtracting the sensor's depth from the pressure gauge's monitored water level. In summary, the monitoring system for groundwater level and peatland temperature and humidity in tropical peatland reserves is a

critical tool for monitoring the health of these ecosystems, and the sensor nodes' spatial layout and protection ensure accurate and reliable data collection.

Moreover, the LoRa-based sensor network provides a reliable and efficient method for monitoring water level and temperature in peatlands. The sensor network can be used to collect data for research and monitoring purposes, which can be used to improve our understanding of peatland hydrology and carbon dynamics. With the increasing threat of climate change and human activities, the monitoring and preservation of peatlands are of utmost importance.

3.2.6 Dashboard

The data collected by the IoT system is visualized through a dashboard interface developed with technical and financial support from the National Institute Of Information And Communications Technology (NICT). The interface provides users with a comprehensive overview of the environmental conditions monitored by the system, including real-time measurements of temperature, humidity, and water level. In addition, users can access historical data and track changes in environmental conditions over time. The dashboard also includes interactive maps that allow users to visualize the spatial distribution of sensor nodes and observation towers, as well as other relevant features of the Raja Musa Forest Reserve peatland. Overall, the dashboard provides an intuitive and user-friendly interface for visualizing and analyzing the data collected by the IoT system, making it a valuable tool for environmental monitoring and management.

After logging in to the dashboard interface, the image (Figure 3.14) shows the display situation. On the left side of the screen, there is a functional option bar, including options such as Home, Dashboard, Location, Devices, Gateways, Users, and Reports. In the middle of the screen, the geographical location of the monitoring site and all the monitored parameters of ground sensors are displayed. On the right side of the screen, there are three taskbars: Alarm, Event, and Legend. The Alarm taskbar is used to display abnormal alert information, the Event taskbar is used for event reminders, and the Legend taskbar is used for message notifications related to other events. This user-friendly interface enables users to easily navigate and access the relevant information they need.

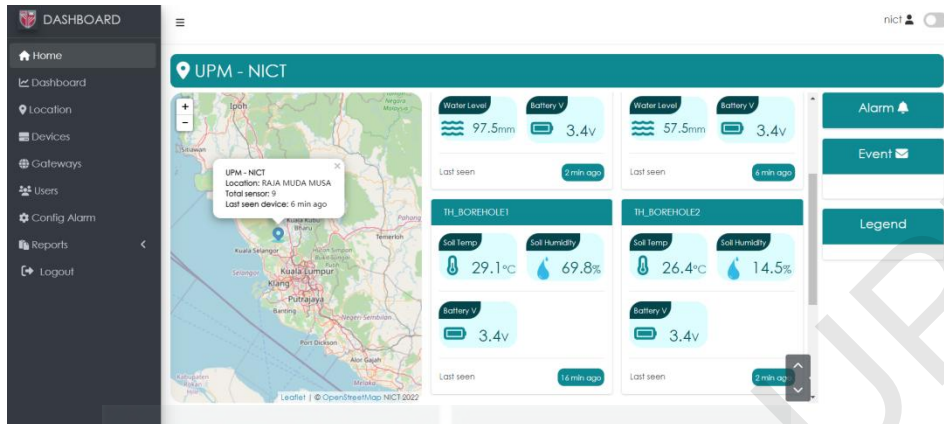


Figure 3.14 : Dashboard Overview Display for The Proposed System

This Figure 3.14 displays the real-time parameters monitored by ground sensor nodes 1 and 2. Each sensor node is powered by a 3.4V DC battery. The underground water level is displayed in millimeters, while the soil temperature and humidity are displayed in degrees Celsius and percentage, respectively. It is worth noting that these parameters are continuously updated and can be viewed in real-time using the dashboard interface.

The IoT system collected meteorological data from the weather stations throughout the entire year of 2020, recording data every second, while ground sensor nodes logged information every minute. However, post-April 2020, the sensor nodes encountered disruptions due to the COVID-19 pandemic, preventing on-site maintenance and resulting in considerable anomalies and missing values caused by wildlife interference. To maintain the scientific rigor and objectivity of the study, subsequent modeling and machine learning endeavors utilized data exclusively from January 17 to March 31, 2020. This carefully selected timeframe ensures the reliability and integrity of the dataset, mitigating the impact of disruptions and anomalies caused by unforeseen circumstances.

IoT systems, while promising, exhibit certain limitations that warrant consideration in the context of this study. One notable constraint is the relatively short duration of data collection, spanning a period of only three months. This temporal constraint introduces a potential small-size bias, which may impact the robustness and generalizability of the obtained results. The limited time frame may not fully capture seasonal variations and long-term trends, restricting the comprehensive understanding of the dynamic interplay between ground and atmospheric parameters in peatland fires. Additionally, the condensed data collection duration may hinder the model's ability to discern subtle patterns or anomalies that might emerge over more extended periods. It is imperative to acknowledge these temporal constraints when interpreting the

outcomes and recognize the need for longer-term data acquisition to enhance the reliability and applicability of the predictive models derived from the IoT system. Future endeavors should aim to address these limitations by extending the temporal scope of data collection for a more comprehensive analysis and prediction of peatland fire dynamics.

3.3 Fire Weather Index System

The Fire Weather Index (FWI) is a meteorological index that represents the potential behavior of a wildfire under certain weather conditions. The FWI system is used to rate the fire danger and determine the appropriate level of fire suppression resources required. It is used by land management agencies, firefighters, and the public in making decisions about fire prevention, preparedness, and response. Moreover, the FWI system is widely used in Canada, where it was developed, as well as in many other countries around the world. The Figure 3.15 shows the structure of the Canadian FWI system.

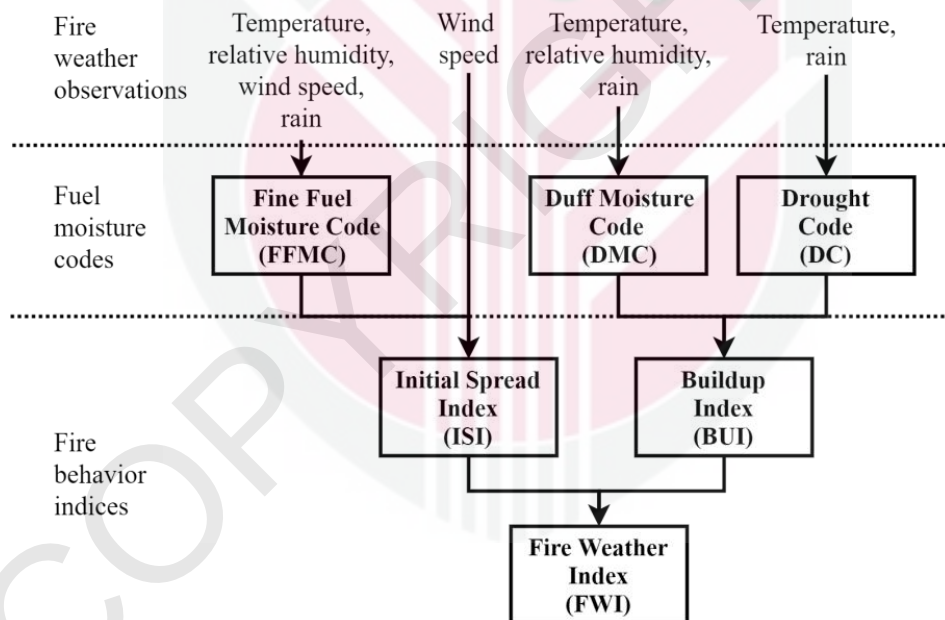


Figure 3.15 : Structure of The Canadian FWI System [203]

The Canadian FWI system structure includes the FFMC, DMC, DC, ISI, and BUI. The FFMC is the Fine Fuel Moisture Code, which is used to rate the moisture content of litter and other fine fuels. The DMC is the Duff Moisture Code, which is used to rate the moisture content of the decomposing organic material beneath the litter. The DC is the Drought Code, which is used to rate the moisture content of the larger fuels. The ISI is the Initial Spread Index,

which is a rating of the potential rate of fire spread, and it is calculated from the FFMC and wind speed. The BUI is the Buildup Index, which is a rating of the total amount of fuel available for combustion and is calculated from the DMC and DC. The FWI is an indicator of the ease of ignition and the potential spread of fire, and it is calculated using temperature, relative humidity, wind speed, and precipitation data.

The FWI system can be implemented using various programming languages, and the Jupyter Notebook has been used to develop the code for this FWI system in this project. Jupyter Notebook is an open-source web application that allows users to create and share documents that contain live code, equations, visualizations, and narrative text. It is commonly used in data science and scientific research to analyze and visualize data, and it can be a useful tool for implementing and testing the FWI calculations.

3.3.1 Fine Fuel Moisture Code (FFMC)

Fine Fuel Moisture Code (FFMC) is a component of the Canadian Forest Fire Weather Index (FWI) system and is an important indicator of fire danger in forests. FFMC is a measure of the moisture content of surface fuels and is primarily influenced by recent weather conditions, such as temperature, relative humidity, wind speed, and precipitation. FFMC is calculated based on the drying time of a small fuel particle, such as a dead leaf, with a one-hour time lag. The FFMC value ranges from 0 to 101 [204], with higher values indicating drier conditions and higher fire danger. Moreover, FFMC is an important component of the FWI system as it provides a baseline indication of fire danger that can be used to supplement other fire behavior prediction systems. It can be used to assess potential fire behavior and to support fire management decisions. The Jupyter Notebook code may be used to calculate FFMC values based on input parameters such as temperature, relative humidity, rainfall, and wind speed, as shown in Algorithm 1. This can be a valuable tool for researchers and forest management professionals in predicting and managing wildfire risk.

Algorithm 1 is a pseudo-code of Python function that calculates the Fine Fuel Moisture Code (FFMC) used in forest fire danger rating systems. The FFMC is an index that represents the moisture content of fine fuels such as grass, needles, and small twigs. The function takes in arrays of temperature, rainfall, wind speed, and humidity, as well as the previous value of the FFMC, and returns the updated value of the FFMC.

Algorithm 1:	FFMC model of Canadian FWI system [205]
Input:	Rainfall as R , Temperature as T , Humidity as H , Wind Speed as W , FFMC of the previous value as $ffmc0$.
Output:	FFMC
<pre> if $R > 0.5$ $Re = R - 0.5$ $Mo = (147.2 * (101.0 - ffmc0)) / (59.5 + ffmc0)$ if $Mo > 150.0$ $Mo = (Mo + 42.5 * Re * np.exp(-100.0 / (251.0 - Mo)) * (1.0 - np.exp(-6.93 / Re))) + (0.0015 * (Mo - 150.0) ** 2) * np.sqrt(Re)$ elseif $Mo \leq 150.0$ $Mo = Mo + 42.5 * Re * np.exp(-100.0 / (251.0 - Mo)) * (1.0 - np.exp(-6.93 / Re))$ If $Mo > 250.0$ $Mo = 250.0$ $Ed = (0.942 * (H ** 0.679) + (11.0 * np.exp((H - 100.0) / 10.0)) + 0.18 * (21.1 - T) * (1.0 - 1.0 / np.exp(0.1150 * H)))$ if $Mo < Ed$ $Ew = (0.618 * (H ** 0.753) + (10.0 * np.exp((H - 100.0) / 10.0)) + 0.18 * (21.1 - T) * (1.0 - 1.0 / np.exp(0.115 * H)))$ if $Mo < Ew$ $Kw = (0.581 * np.exp(0.0365 * T)) * (0.424 * (1.0 - ((100.0 - H) / 100.0) ** 1.7) + (0.0694 * np.sqrt(w)) * (1.0 - ((100.0 - H) / 100.0) ** 8))$ $M = Ew - (Ew - Mo) / 10.0 ** Kw$ elseif $Mo > Ew$: $M = Mo$ elseif $Mo == Ed$: $M = Mo$ else $Kw = (0.581 * np.exp(0.0365 * T)) * (0.424 * (1.0 - (h / 100.0) ** 1.7) + (0.0694 * np.sqrt(w)) * (1.0 - (h / 100.0) ** 8))$ $M = Ed + (Mo - Ed) / 10.0 ** Kw$ $FFMC = (59.5 * (250.0 - M)) / (147.2 + M)$ if $FFMC > 101.0$ $FFMC = 101.0$ elseif $FFMC \leq 0.0$: $FFMC = 0.0$ return $FFMC$ </pre>	

In Algorithm 1, Re refers to the effective rainfall, Mo refers to the fine fuel moisture content from previous value, Ed refers to the equilibrium moisture content from drying phase, Ew refers to the equilibrium moisture content from wetting phase, Kw refers to the affect of temperature on wetting rate, and M refers to the fine fuel moisture content after drying.

3.3.2 Duff Moisture Code (DMC)

DMC stands for Duff Moisture Code and is one of the components used in the Canadian Forest Fire Weather Index (FWI) system to estimate the potential fire behavior. It estimates the moisture content of decomposed organic material

beneath the litter layer, which is commonly referred to as the "duff" layer. The moisture content of the duff layer is critical in determining the rate of spread and intensity of a forest fire. The DMC is calculated based on the drying and wetting of the duff layer. The drying and wetting are influenced by temperature, humidity, and precipitation.

Algorithm 2:	DMC model of Canadian FWI system [205]
Input:	Rainfall as R , Temperature as T , Humidity as H , DMC of the previous value as $dmc0$.
Output:	DMC
<pre> if $R > 1.5$ $Re = 0.92 * R - 1.27$ $Mo = 20.0 + 280.0 / \exp(0.023 * dmc0)$ if $dmc0 \leq 33.0$ $b = 100.0 / (0.5 + 0.3 * dmc0)$ elseif $dmc0 > 33.0 \ \& \ dmc0 \leq 65.0$ $b = 14.0 - 1.3 * \log(dmc0)$ else $b = 6.2 * \log(dmc0) - 17.2$ $Mr = Mo + (1000 * Re) / (48.77 + b * Re)$ $Pr = 43.43 * (5.6348 - \log(Mr - 20.0))$ $K = 1.894 * (T + 1.1) * (100 - H) * 12 * 0.0001$ $DMC = Pr + 100 * K$ else $K = 1.894 * (T + 1.1) * (100 - H) * 12 * 0.0001$ $DMC = dmc0 + 100 * K$ return DMC </pre>	

In Algorithm 2, Re refers to the effective rainfall, Mo refers to the moisture content of the previous value, Mr refers to the moisture content after rainfall, b refers to the reaction factor of DMC after rainfall, Pr refers to the DMC after rainfall, and K refers to the drying rate.

3.3.3 Drought Code (DC)

Drought Code (DC) is a critical component of the Canadian Forest Fire Weather Index (FWI) System, which is widely used to predict forest fire behavior and assess fire danger in Canada and many other countries. The DC is a numerical rating that represents the moisture content of deep, compact organic layers in forest litter. It is calculated based on changes in moisture conditions caused by temperature, and precipitation.

The DC is crucial for predicting the potential spread rate and intensity of forest fires, as well as for assessing fire danger and supporting fire management decisions. Therefore, understanding the concept and application of the DC is essential for professionals involved in forest fire management and those who live in areas prone to forest fires.

Algorithm 3:	DC model of Canadian FWI system [205]
Input:	Rainfall as R , Temperature as T , DC of the previous value as $dc0$.
Output:	DC
<pre> if $T < -2.8$: $T = -2.8$ $Pe = (0.36 * (t + 2.8) + Df) / 2$ if $Pe < 0.0$: $Pe = 0.0$ If $R > 2.8$: $Re = 0.83 * R - 1.27$ $Mi = 800.0 * np.exp(-dc0 / 400.0)$ $Dr = dc0 - 400.0 * np.log(1.0 + ((3.937 * Re) / Mi))$ if $Dr > 0.0$: $DC = Dr + Pe$ else $DC = Pe$ else $DC = dc0 + Pe$ return DC </pre>	

In Algorithm 3, Pe refers to the potential evapotranspiration, Df refers to the drying factor, Re refers to the effective rainfall, Mi refer to the moisture equivalent of the previous DC, Dr refers to the DC after rain. The drying factor based on the latitude of a specific location [205].

3.3.4 Initial Spread Index (ISI)

The Initial Spread Index (ISI) is a measure of the potential rate of fire spread in a forest fuel bed, based on wind speed and fine fuel moisture content. It is one of the primary components of the Canadian Forest Fire Weather Index (FWI) system, which is widely used in Canada and other countries for assessing the risk of forest fires.

ISI is important because it provides a measure of the initial rate of fire spread, which is critical in the early stages of a fire when suppression efforts are most effective. The index is based on the concept that as wind speed increases, fire spread rate will increase exponentially, and as fuel moisture content decreases,

fire spread rate will increase linearly. By combining these factors, ISI provides a quantitative estimate of the potential rate of fire spread, allowing fire managers to make informed decisions about fire suppression resources and tactics.

The calculation of ISI is based on empirical relationships between fuel moisture content, wind speed, and the rate of fire spread observed in field experiments. This makes the index sensitive to local conditions and fuel types, allowing it to be adapted to a wide range of forest ecosystems.

Algorithm 4:	ISI model of Canadian FWI system [205]
Input:	FFMC, Wind Speed as W ,
Output:	ISI
$Mo = 147.2 * (101.0 - FFMC) / (59.5 + FFMC)$ $Ff = 19.1152 * np.exp(Mo * -0.1386) * (1.0 + (Mo ** 5.31) / 49300000.0)$ $ISI = Ff * np.exp(0.05039 * W)$	
return ISI	

In Algorithm 4, Mo refers to the moisture content, Ff refers to the fine fuel moisture. This function calculates the initial spread index using the wind speed and the Fine Fuel Moisture Code (FFMC) as inputs. The function calculates the moisture content and the fine fuel moisture. Finally, the function computes the initial spread index by applying a formula that takes into account the ff and the wind speed.

3.3.5 Buildup Index (BUI)

The Buildup Index (BUI) is a parameter used in fire danger rating systems that reflects the moisture content of deep, compact organic layers of forest floors. The BUI represents the moisture content of the forest floor fuels and is a key parameter in the Canadian Forest Fire Weather Index (FWI) System. It is calculated based on the Duff Moisture Code (DMC) and the Drought Code (DC), which represent the moisture conditions of the upper and lower forest floor layers, respectively.

The BUI is important in wildfire management because it provides an indication of how much energy would be available for combustion in the forest floor fuels. High BUI values indicate that the forest floor fuels are dry and susceptible to ignition, while low BUI values indicate that the fuels are moist and less likely to burn. The BUI, along with other FWI System parameters, is used to predict the potential for wildfire ignition, spread, and intensity. In addition to its use in fire danger rating systems, the BUI can also be used to evaluate the effectiveness of prescribed burning and other forest management practices aimed at reducing fuel loads and mitigating wildfire risk. By monitoring BUI values, forest

managers can determine when it is safe to conduct prescribed burns and other fuel reduction activities, as well as evaluate the effectiveness of these activities over time. Overall, the BUI plays an important role in understanding and managing wildfire risk in forested ecosystems.

Algorithm 5:	BUI model of Canadian FWI system [205]
Input:	DMC, DC
Output:	BUI
<pre> if DMC <= 0.4 * DC BUI = (0.8 * DC * DMC) / (DMC + 0.4 * DC) else BUI = DMC - (1.0 - 0.8 * DC / (DMC + 0.4 * DC)) * (0.92 + (0.0114 * DMC) ** 1.7) if BUI < 0.0: BUI = 0.0 return BUI </pre>	

Algorithm 5 is the pseudo code based on Jupyter Notebook for calculating BUI. This function calculates the Build Up Index (BUI) which is an indicator of the amount of fuel available for combustion. The BUI is related to the Duff Moisture Code (DMC) and the Drought Code (DC), which are two other fire danger indicators. The BUI is calculated based on two different scenarios.

3.3.6 Fire Weather Index (FWI)

The Fire Weather Index (FWI) is a key component of the Canadian Forest Fire Danger Rating System (CFFDRS) and is widely used internationally to estimate the potential severity of wildfires. It is a numerical rating of fire intensity that takes into account the moisture content of the forest floor, the availability of fuels, and the weather conditions that may contribute to the spread of a fire. The FWI is a composite index to provide a comprehensive measure of wildfire risk.

The FWI is important because it allows fire managers to assess the level of risk posed by a wildfire and make informed decisions about how to respond. By providing an objective and standardized measure of fire intensity, the FWI enables fire managers to allocate resources effectively and efficiently, which can help to minimize the damage caused by wildfires. The FWI is also important for forecasting the potential severity of wildfires, which can help to mitigate their impact and reduce the risk of loss of life and property damage.

Overall, the FWI is an essential tool for managing the risk of wildfires, which are a significant threat to forests, wildlife, and human populations around the world. By providing a standardized and objective measure of fire intensity, the FWI helps to ensure that fire managers can respond effectively to wildfires and minimize their impact on the environment and communities.

Algorithm 6:	FWI model of Canadian FWI system [205]
Input:	BUI, ISI
Output:	FWI
<pre> if $BUI \leq 80.0$ $Fwii = 0.1 * ISI * (0.626 * BUI^{0.809} + 2.0)$ else $Fwii = 0.1 * ISI * (1000.0 / (25.0 + 108.64 / np.exp(0.023 * BUI)))$ if $Fwii \leq 1.0$: $FWI = Fwii$ else $FWI = np.exp(2.72 * (0.434 * np.log(Fwii))^{0.647})$ return FWI </pre>	

In Algorithm 6, *Fwii* refers to the intermediate form of FWI. This function calculates the Fire Weather Index (FWI) based on the Initial Spread Index and the Build Up Index. The FWI is a numerical rating of the fire intensity potential, and it is widely used to assess the risk of forest fires.

3.4 Performance Evaluation

The Fire Weather Index (FWI) system is an important tool for assessing the risk of forest fires. However, the accuracy of the FWI system depends on various factors, such as the inputs used, the algorithm used, and the calibration of the system. Therefore, evaluating the performance of the FWI system is essential to ensure its reliability and effectiveness in predicting forest fire risk.

In this thesis, the performance evaluation of the FWI system will be performed by using machine learning techniques. Specifically, the performance of the FWI system will be evaluated by using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (or correlation or coefficient of determination) (R^2) metrics. These metrics are commonly used in machine learning to evaluate the accuracy and precision of predictive models. Jupyter Notebook, a popular platform for data analysis and machine learning, will be used to train and test the data of the FWI system. Using machine learning techniques improves the accuracy and reliability of the FWI system, which can ultimately help prevent and mitigate the risks of forest fires.

3.5 Simulation Parameters

This section lists the different parameters involved in the simulation, including the lab where it was conducted, the type of computer used, the software used for the simulation, and the specific details of the computer used for the simulation. The Table 3.1 provides an organized and concise way to present this information for readers to easily understand the experimental setup.

Table 3.1 : Hardware and Software Specification for Simulation

Parameter	Value
Lab	WiPNET (Wireless and Photonic Networks Research Centre of Excellence), UPM
Computer support	SHYFTE 4.0
Computer model	Dell OptiPlex 5070
Operating system	Windows 10
Processor type	x64-based Intel Core i7-9700
Processor speed	3.00 GHz
Memory (RAM)	16.0 GB (15.8 GB available)
Software	Jupyter Notebook from Anaconda3, MATLAB R2016b

These parameters provide important information about the hardware and software used in the simulation. The 64-bit operating system and x64-based processor indicate that the computer is capable of running 64-bit software and handling large amounts of data. The 16 GB of memory available is also a significant factor in the performance of the simulation. The software listed, Anaconda3, Jupyter Notebook, and MATLAB, are all commonly used in scientific and engineering applications. Anaconda 3 is a distribution of Python that includes many popular scientific packages, Jupyter Notebook is an interactive notebook environment for Python, and MATLAB is a numerical computing environment for data analysis and visualization. Overall, these parameters indicate that the computer used in the simulation is a high-performance machine capable of running complex simulations and data analysis tasks.

Utilizing a Neural Network (NN), the model consists of three layers. Rectified Linear Unit (ReLU) serves as the activation function for both input and hidden layers, fostering non-linearity. The output layer employs a Linear Activation Function, suitable for regression tasks. The number of neurons varies per layer, with input neurons adapting to features. Employing Mean Squared Error as the loss function and the Adam Optimizer, the model's learning rate of 0.001, batch

size of 64, and 100 epochs. Validation split reserves 20% of data for model validation during training, ensuring robustness. These configurations strike a balance between training efficiency and convergence, ensuring effective model performance.

3.6 Data Acquisition

The IoT system collected meteorological data from the weather stations throughout the entire year of 2020, recording data every second, while ground sensor nodes logged information every minute. However, post-April 2020, the sensor nodes encountered disruptions due to the COVID-19 pandemic, preventing on-site maintenance and resulting in considerable anomalies and missing values caused by wildlife interference. To maintain the scientific rigor and objectivity of the study, subsequent modeling and machine learning endeavors utilized data exclusively from January 17 to March 31, 2020.

Moreover, the verification of the accuracy of the IoT system's monitoring data and the precision of the predictive results in this study relies on data obtained from METMalaysia. It is crucial to note that these data are classified as confidential and not publicly shared. To access the requisite information, a formal request must be submitted to the responsible authorities at the Malaysian Meteorological Department. The provision of data, whether on a fee basis or free of charge, is contingent upon the discretion of the Malaysian Meteorological Department, taking into consideration the specifics of the request and the prevailing circumstances. This established protocol ensures the confidentiality and controlled dissemination of meteorological data, underscoring the importance of respecting data privacy and security standards in collaborative research efforts

The histogram displays the distribution of six different atmospheric parameters monitored by the IoT system in the Raja Musa peat swamp forest reserve, as shown in Figure 3.16. The parameters include atmospheric temperature (in Celsius), atmospheric humidity (in percentage), rainfall (in millimeters), wind speed (in meters per second), air pressure (in hectopascals), and solar radiation (in watts per square meter). Figure 3.16 is organized into a 2x3 grid, with each parameter having its own subplot. The x-axis represents the magnitude of the parameter value, while the y-axis represents the total number of occurrences of the respective parameter value. From the histogram, it is clear that atmospheric temperature is mainly distributed between 25 and 30 degrees Celsius, atmospheric humidity is concentrated around 90%, and rainfall values are mostly below 20 mm. Wind speed shows a relatively distribution between 0 and 2 m/s, while air pressure is concentrated around 1004 hPa to 1008 hPa. Finally, solar radiation values show a maximum at around 25000W/m², indicating strong solar radiation during the monitoring period.

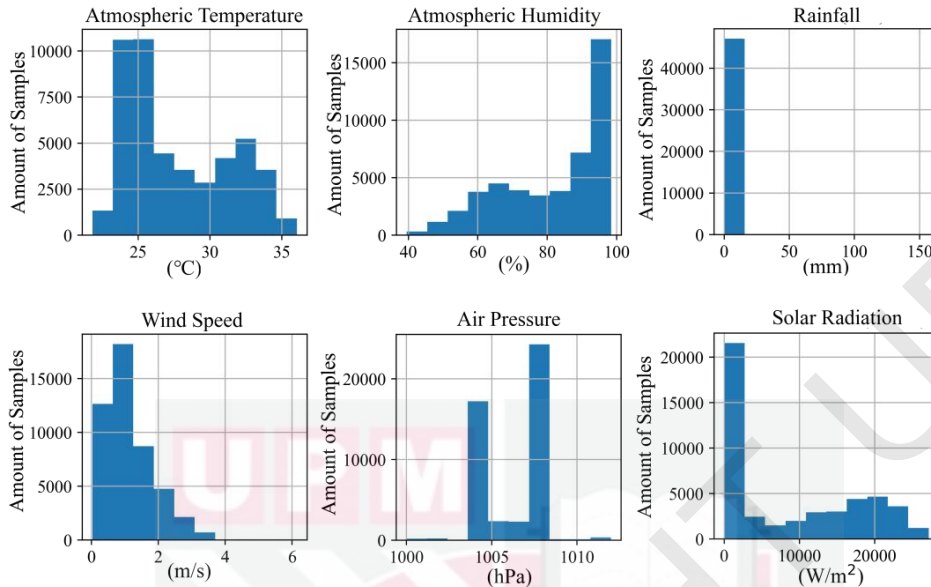


Figure 3.16 : Histogram of Atmospheric Parameters

Table 3.2 presents the descriptive statistics of six meteorological parameters monitored by an IoT system, namely Atmospheric Temperature, Atmospheric Humidity, Rainfall, Wind Speed, Air Pressure, and Solar Radiation. The table includes six columns, each representing a meteorological parameter, and six rows indicating various statistical measures, such as count, mean, standard deviation, minimum, 25th percentile, median, 75th percentile, and maximum. The count row shows that the system has recorded 47,306 observations for each parameter. The mean values indicate that the average Atmospheric Temperature is 27.695 degrees Celsius, the average Atmospheric Humidity is 81.418%, the average Rainfall is 0.388 mm, the average Wind Speed is 1.149 m/s, the average Air Pressure is 1006.301 hPa, and the average Solar Radiation is 8725.699 W/m². The standard deviation values reveal the degree of variation in the data, while the minimum and maximum values denote the range of each parameter. Overall, this table provides a comprehensive summary of the meteorological data collected by the IoT system, which can be useful for further analysis and decision-making.

Table 3.2: Descriptive Statistics of Atmospheric Parameters

	Atmospheric Temperature	Atmospheric Humidity	Rainfall	Wind Speed	Air Pressure	Solar Radiation
count	47306.000	47306.000	47306.000	47306.000	47306.000	47306.000
mean	27.695	81.418	0.388	1.149	1006.301	8725.699
std	3.594	14.652	4.712	0.724	1.986	9010.301
min	21.811	39.534	0.000	0.029	1000.000	0.000
25%	24.653	68.971	0.000	0.619	1004.000	0.000
50%	26.382	87.417	0.000	0.979	1007.933	5181.073
75%	31.132	94.359	0.001	1.514	1008.000	17693.440
max	36.059	98.414	157.000	6.142	1012.000	27174.400

The acquisition of 47,306 samples within a relatively short timeframe (January 17, 2020, to March 31, 2020) was facilitated by the high-frequency data recording capabilities of the weather stations and ground sensor nodes integrated into the IoT system. The weather stations, operating at a remarkable speed, recorded data every second, providing a dense temporal coverage. Simultaneously, the ground sensor nodes contributed by recording data at a minute interval, ensuring a complementary dataset to capture variations at a broader timescale. The meticulous synchronization of time points across all collected parameters was rigorously maintained to ensure the scientific integrity of the study.

To uphold the scientific rigor of the dataset, a stringent data cleaning process was implemented. Any time point exhibiting anomalous or missing values in any parameter underwent systematic removal, ensuring that the retained data points remained consistent and reliable. This meticulous approach not only preserved the temporal coherence of the dataset but also contributed to the elimination of potential biases arising from irregularities in the recorded data. The combination of high-frequency data collection and rigorous data cleaning procedures enhances the reliability and precision of the dataset, laying a robust foundation for subsequent analyses and predictive modeling in the study of peatland fires.

Figure 3.17 presents a histogram of ground soil parameters monitored by two ground sensor nodes (i.e. SN1 and SN2) in the IoT system. The histogram includes soil temperature measured in Celsius, soil humidity measured in percentage, and ground water level measured in millimeters. The figure is displayed in a 2x3 grid corresponding to the three soil parameters measured by two groups of sensor nodes. The x-axis represents the size of the parameter,

while the y-axis shows the total number of observations for each parameter value. The figure provides an overview of the distribution of ground soil parameters, which can be useful in understanding the environmental conditions and their impact on plant growth and other related factors.

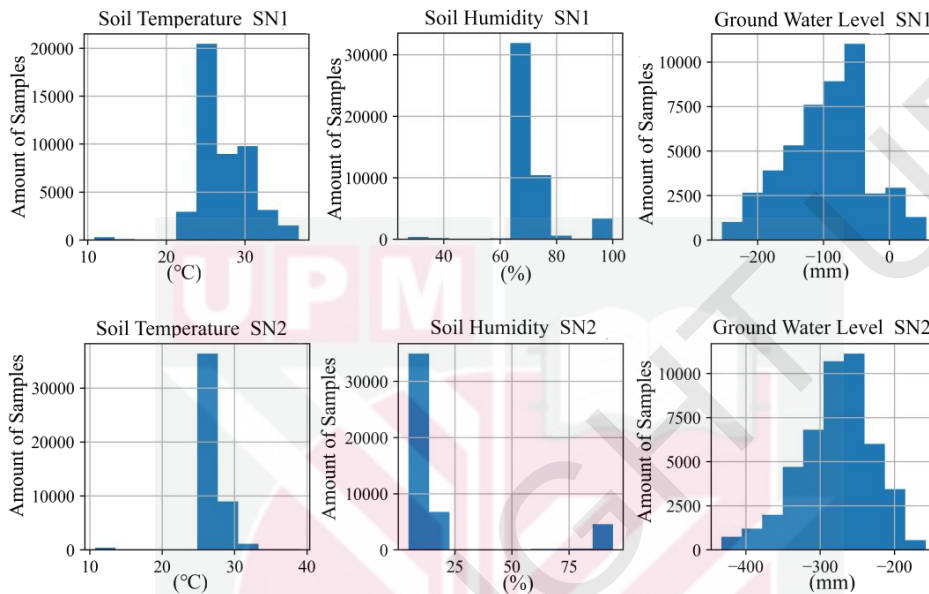


Figure 3.17 : Histogram of Ground Soil Parameters

Table 3.3 provides detailed data descriptions of ground soil parameters monitored by two ground sensor nodes (SN1 and SN2) in the IoT system. The parameters include Ground Water Level (GWL) measured in millimeters, Soil Temperature in degrees Celsius and Soil Humidity in percentage. The table reports the count, mean, standard deviation, minimum, maximum, and 25th, 50th, and 75th percentiles of each parameter for both SN1 and SN2. The mean values for GWL are -92.606 and -278.846 for SN1 and SN2, respectively. The mean Soil Temperature is slightly higher for SN1 than SN2, with mean values of 27.254 and 26.802 degrees Celsius, respectively. On the other hand, Soil Humidity is significantly higher for SN1 than SN2, with mean values of 71.458% and 19.776%, respectively. Overall, the table provides a comprehensive overview of the soil parameters measured by the two sensor nodes.

Table 3.3 : Descriptive Statistics of Ground Soil Parameters

	GWL_SN1	GWL_SN2	Soil Temperature _SN1	Soil Temperature _SN2	Soil Humidity _SN1	Soil Humidity _SN2
count	47306.000	47306.000	47306.000	47306.000	47306.000	47306.000
mean	-92.606	-278.846	27.254	26.802	71.458	19.776
std	63.645	49.330	3.346	2.072	9.196	25.151
min	-254.174	-432.956	10.822	10.730	27.280	4.760
25%	-134.911	-309.349	24.900	25.900	68.117	9.500
50%	-90.553	-274.033	26.383	26.440	69.067	11.500
75%	-42.011	-246.957	30.050	27.433	71.650	13.900
max	55.910	-157.993	36.840	38.950	99.900	94.200

3.7 Methodology of Drought Code (DC) Modeling

The proposed approach of integrating Groundwater Level (GWL) for calculating Drought Code (DC) in the Forest Fire Weather Index (FWI) system is motivated by the limitations of the existing FWI system, which heavily relies on the previous day's values to calculate the DC. This approach aims to develop a model that can directly calculate DC based on current conditions without relying on the previous day's values. To achieve this, the traditional variables used in the FWI system, such as temperature and rainfall, are replaced with groundwater levels. This approach is particularly relevant for tropical peatland forest fires, as groundwater levels can be a critical factor in fire behavior and spread in these ecosystems.

The theoretical framework for this approach is illustrated in Figure 3.18, which outlines the basic structure for integrating groundwater levels into the FWI system. The proposed approach provides a more direct and efficient way to calculate DC, as it eliminates the need to rely on historical data and instead uses real-time groundwater level measurements. This can help improve the accuracy of fire danger assessments and provide more timely and reliable information for forest fire management and prevention efforts.

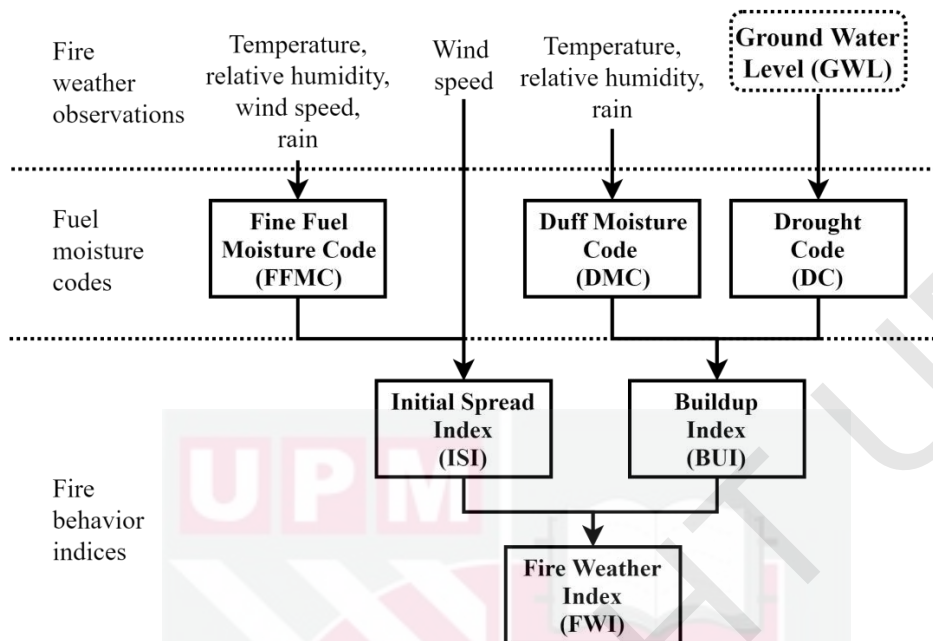


Figure 3.18 : Architecture for GWL-Based DC Calculation

This section aimed to develop a model to predict drought code (DC) using Ground Water Level (GWL) data obtained from the IoT system in a tropical peatland forest. The model was trained by fitting the daily average ground water level data obtained from the IoT system to the corresponding DC data provided by the Malaysian Meteorological Department. Once the model was established, the hourly ground water level data obtained from the IoT system was used to validate the model against the corresponding DC data provided by the Meteorological Department. The ground water level data from sensor node 1 was chosen for model development, as it had both positive and negative values, which was considered to be more representative and universal.

The use of ground water level data to predict DC is a novel approach that offers several advantages over the existing FWI system that relies on temperature and rainfall data. Firstly, ground water level data is readily available from the IoT system and can be easily integrated into the model. Secondly, ground water level data provides a more direct and accurate measure of the water content in the soil than rainfall data, which can be affected by factors such as evaporation and runoff. Thirdly, ground water level data can provide information on the deeper layers of the soil, which can be important in predicting the occurrence of peatland fires that can smolder underground for long periods of time. The results showed that the ground water level data could be effectively used to predict DC, with high correlation coefficients obtained between the predicted DC values and the observed DC values. The developed model has the potential to improve the accuracy of

predicting drought conditions in tropical peatland forests, which can help to prevent and manage peatland fires.

In the process of curve fitting, each data point (X, Y) representing Drought Code (DC) and Ground Water Level (GWL) values at discrete time intervals is meticulously plotted on the graph, with the X-axis denoting DC and the Y-axis representing GWL. For instance, at a specific time, if DC is 1 and GWL is 2, the corresponding data point would be (1, 2).

The resultant fitted curve encapsulates the underlying relationship between DC and GWL. Its shape and trajectory serve as a visual depiction of the intricate dynamics between these variables. Once the optimal fitting curve is derived, it facilitates the inference of trends and mutual dependencies between DC and GWL, providing a nuanced understanding of their dynamic interplay. This graphical representation enhances the comprehension of how changes in Drought Code correspond to fluctuations in Ground Water Level, contributing to a comprehensive analysis of their temporal relationships.

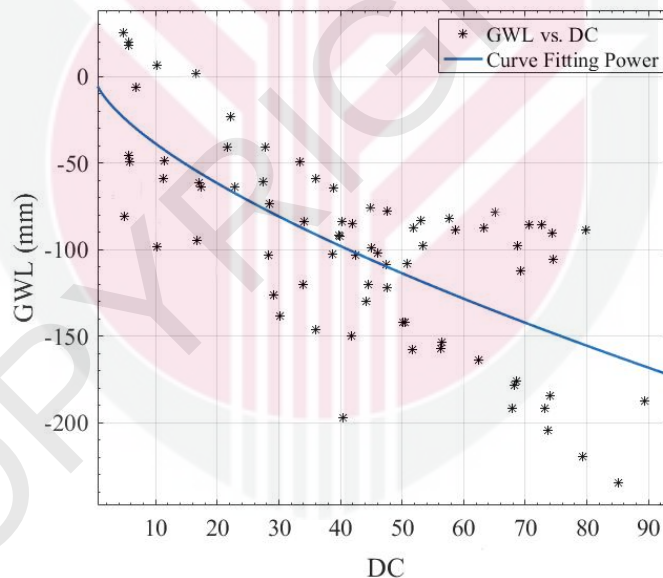


Figure 3.19 : Power Curve Fitting of Groundwater Level and Drought Code

Figure 3.19 displays the power curve fitting between the daily average groundwater level monitored by sensor node 1 and the corresponding Drought Code (DC) data published by the Malaysian Meteorological Department during the same period. The curve-fitting equation obtained from this model is presented in Equation 3.1.

$$DC = -8.39 * GWL^{0.6664} \quad (3.1)$$

The power model is widely used in hydrology and has been proven to fit various hydrological variables well. The equation obtained from the curve fitting can be used to estimate the DC based on the monitored groundwater level data, providing a more efficient and accurate way to calculate the DC for tropical peatland forest fires. This model is crucial for improving the accuracy of wildfire risk assessment and management.

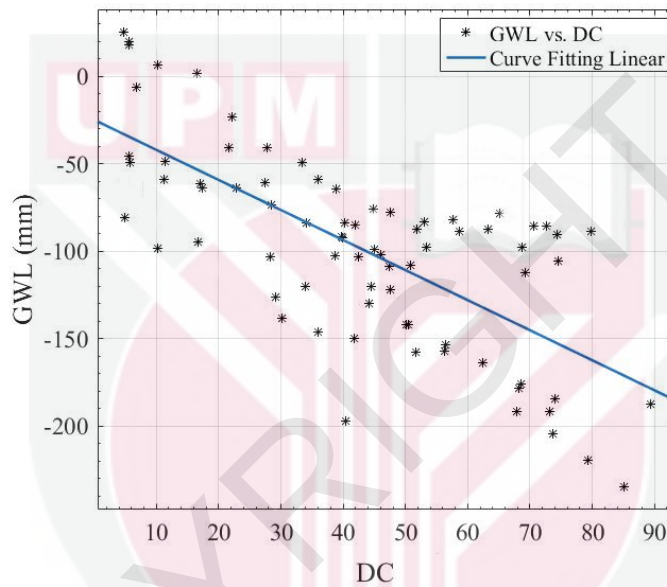


Figure 3.20 : Linear Curve Fitting of Groundwater Level and Drought Code

Based on the data collected from Sensor Node 1 and the corresponding DC values published by the Malaysian Meteorological Department during the same period, a linear regression model was developed to estimate the DC values using the groundwater level (GWL). The results are presented in Figure 3.20, where the blue line shows the linear regression fit. The model equation obtained from the linear regression analysis is shown in Equation 3.2.

$$DC = -1.719 * GWL - 24.95 \quad (3.2)$$

This equation suggests that there is a negative linear relationship between GWL and DC, with an intercept of -24.95 and a slope of -1.719.

The linear regression model provides a straightforward and simple approach to estimate DC values using GWL data, which can be easily collected using IoT sensors. This approach eliminates the need for complex calculations based on temperature and rainfall data, which are often subject to high levels of uncertainty and variability. Moreover, the use of GWL data directly reflects the availability of water for plants and can provide more accurate estimates of the moisture content of the forest floor, which is an important factor in determining the risk of forest fires. The linear model developed in this study can be used to estimate DC values in real-time, providing valuable information for forest fire prevention and management.

3.8 Methodology of Drought Code (DC) Modeling

The idea of using groundwater level (GWL) and humidity to calculate the Duff Moisture Code (DMC) stems from the limitations of using temperature, rainfall, and humidity data, which are commonly used to calculate DMC. Temperature data, for example, may not accurately reflect the temperature conditions in the forest or bushland where DMC is measured, as it is usually measured at a standard height above the ground. Furthermore, rainfall data may not be sufficient to accurately estimate soil moisture, as it may not account for the amount of water stored in the soil, which can have a significant impact on DMC.

To address these limitations, the use of GWL and humidity to calculate DMC has been proposed. GWL is a more accurate measure of soil moisture as it accounts for water stored in the soil, and humidity provides an additional measure of atmospheric moisture, which affects the rate at which fuels dry out. This approach has the potential to improve the accuracy of DMC calculations and better reflect the actual moisture conditions of the fuel.

To illustrate this approach, a proposed architecture diagram has been presented, which replaces temperature, rainfall, and humidity data with GWL and humidity to calculate DMC, as shown in Figure 3.21. The use of GWL and humidity to calculate DMC represents an innovative and potentially significant advancement in the field of forest fire prediction and management.

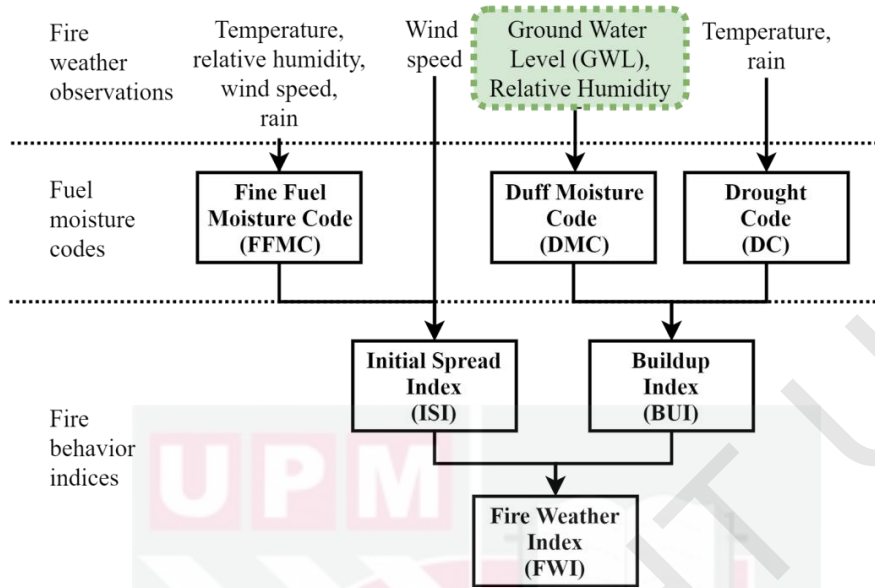


Figure 3.21 : Architecture for GWL and Humidity-Based DMC Calculation

In this section, the single-day average groundwater level and atmospheric humidity data collected by the IoT system, along with the corresponding DMC data published by the Malaysian Meteorological Department (METMalaysia), were used to develop a three-dimensional curve fitting model. Two models were trained: a linear model and a linear mixed triangular function model. Using the hourly GWL and humidity data collected by the IoT system, hourly DMC values were calculated and compared to the DMC values published by METMalaysia for the same time period. The results of the validation showed good agreement between the calculated and published DMC values, indicating the effectiveness of the models in using GWL and humidity data to calculate DMC.

Figure 3.22 shows the result of linear curve fitting between the daily average groundwater level (GWL) and atmospheric humidity measured by an IoT system, and the daily DMC published by METMalaysia. The X-axis represents the GWL range from 50 to -250 mm, the Y-axis represents the atmospheric humidity range from 65% to 95%, and the Z-axis represents the DMC values. The fitted model (referred to as Linear_DMC Model) equation obtained is shown in Equation 3.3.

$$\begin{aligned}
 \text{DMC} = \text{GWL} \times & (1.182 - 0.03258 \times \text{humidity} \\
 & + 0.0002108 \times \text{humidity}^2) - 1647 \\
 & + 0.003829 \times \text{humidity}^3 - 0.8782 \\
 & \times \text{humidity}^2 + 66.44 \times \text{humidity}
 \end{aligned}
 \quad (3.3)$$

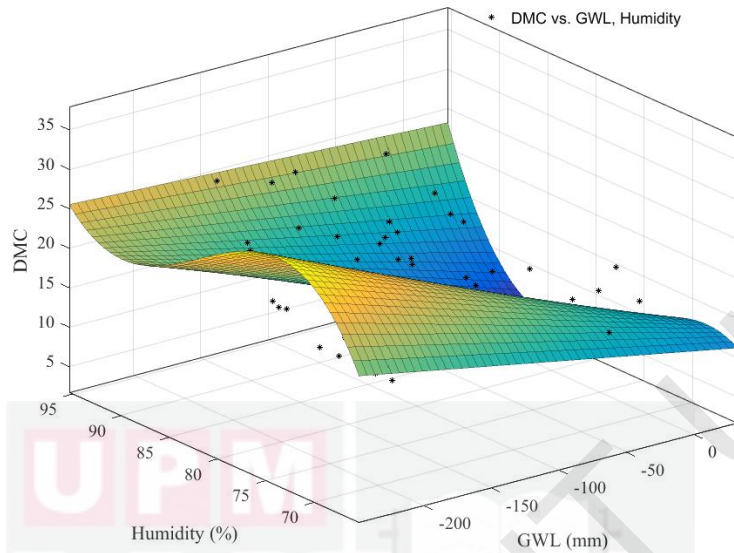


Figure 3.22 : Linear Curve Fitting between GWL, Humidity, and DMC

The linear curve fitting approach provides a simple and effective way to estimate DMC using groundwater level and atmospheric humidity data measured by an IoT system. The equation derived from the curve fitting can be used to predict DMC in real-time, which is essential for wildfire management and prevention.

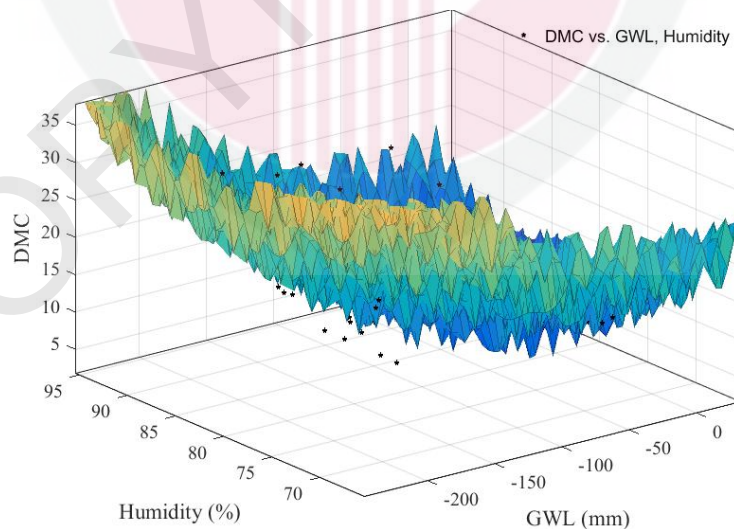


Figure 3.23 : Linear Mixed Curve Fitting between GWL, Humidity, and DMC

Figure 3.23 shows the results of linear mixed trigonometric function curve fitting. The X-axis represents the single-day average GWL monitored by the IoT system in the range of 50 to -250 millimeters. The Y-axis represents the single-day average atmospheric humidity monitored by the IoT system, ranging from 65% to 95%. The Z-axis represents the single-day DMC obtained from METMalaysia. The model (referred to as Linear_Mixed_DMC Model) obtained from the fitting is expressed as shown in Equation 3.4.

$$\begin{aligned} DMC = & 346.2 - 0.02627 \times GWL + 0.0002559 \times GWL^2 - 8.094 \\ & \times humidity + 0.0484 \times humidity^2 - 2.452 \\ & \times \cos(0.7233 \times GWL) + \cos(0.9087 \times humidity) \\ & + 2.776 \times \sin(0.3306 \times GWL \times humidity) \end{aligned} \quad (3.4)$$

This model is obtained by combining linear regression with trigonometric functions, which provides better accuracy in capturing the complex nonlinear relationships between the variables. By incorporating both linear and nonlinear components, the model can fit the data more accurately and better capture the dynamics of the system. The use of the linear mixed trigonometric function curve fitting allows for more accurate prediction of DMC based on GWL and humidity data, which can be useful for forest fire prevention and management.

3.9 Methodology of Predicting Ground Water Level (GWL)

The presented neural network structure with six inputs and three layers is designed to predict groundwater level (GWL) using machine learning, as shown in Figure 3.24. The six inputs are soil temperature, solar radiation, soil humidity, atmospheric pressure, wind speed, and rainfall. These inputs are chosen as they are known to have a significant impact on GWL dynamics in tropical peatlands. Soil temperature and humidity affect the water-holding capacity of the peat, while solar radiation, atmospheric pressure, and wind speed influence the evapotranspiration rate, which affects the water balance of the system. Rainfall is a critical input that affects the water table level directly. Other parameters, such as air humidity and air temperature, are also important but are often correlated with the six inputs used in this neural network. Therefore, they are not included to avoid multicollinearity issues.

With the availability of IoT systems, a large amount of data can be collected on various environmental parameters, including soil temperature, solar radiation, soil humidity, atmospheric pressure, wind speed, and rainfall. In this section, these six parameters were selected as inputs to predict groundwater level (GWL) using a neural network model. A total of 47,306 data samples were collected from the IoT system, of which 80% (37,844 samples) were used for training the neural network model, and the remaining 20% (9,462 samples) were used for testing the model. By training the neural network model on this large dataset, it is possible to accurately predict GWL, which is important for

understanding the water balance of the ecosystem and its impact on vegetation, as well as for predicting the occurrence and spread of tropical peatland fires. The successful implementation of this neural network model can serve as a valuable tool for water resource management and fire prevention in tropical peatlands.

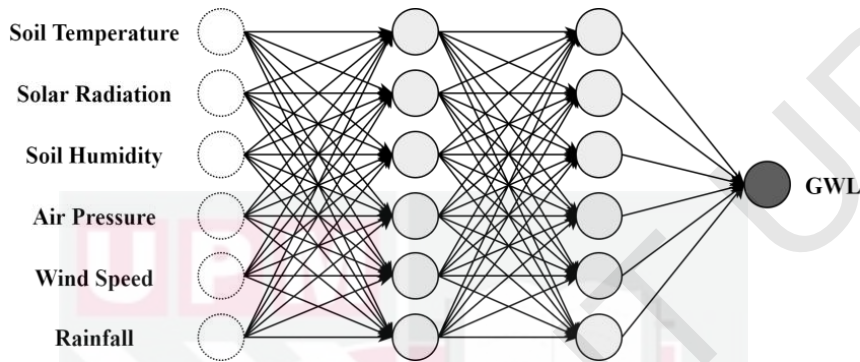


Figure 3.24 : Neural Network for GWL Prediction in Tropical Peatlands

This neural network is used to predict GWL for two sensor nodes (i.e. sensor nodes 1 and 2), with the aim of exploring the differences in predictions made by sensor nodes in different geographical locations. Understanding the distribution of groundwater levels can help managers make informed decisions about water usage, conservation, and sustainability.

3.10 Methodology of Predicting Fire Weather Index (FWI)

A neural network structure with four inputs and N layers, used for predicting the Fire Weather Index (FWI) through machine learning, as shown in Figure 3.25. The four inputs are atmospheric temperature, atmospheric humidity, wind speed, and rainfall. These parameters are chosen because they are used in the existing Canadian model for predicting FWI. The neural network is designed to test the optimal number of hidden layers for achieving the best performance. The performance of the model can be evaluated based on its ability to accurately predict FWI values, which can have significant implications for fire risk management in peatlands.

The four parameters are atmospheric temperature, atmospheric humidity, wind speed, and rainfall, which are all monitored by a IoT system that can record data every minute. The data for FWI output layer is provided by METMalaysia for the same period. By analyzing these data, researchers can gain insight into the range and distribution of each parameter, which can help inform the design of the machine learning model.

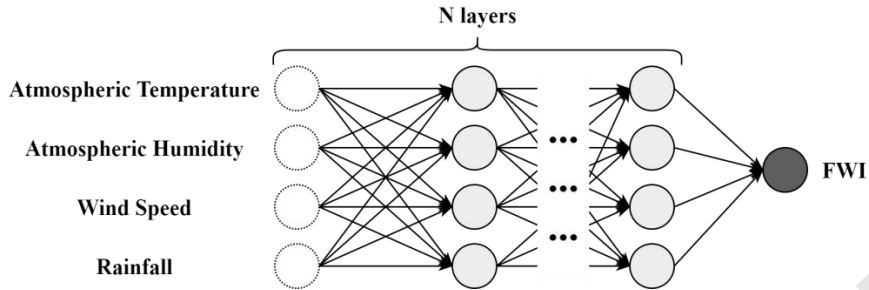


Figure 3.25 : 4-Input and N-Layer Neural Network for FWI Prediction

Figure 3.26 depicts a neural network structure with 9 input parameters for predicting the FWI based on machine learning. The nine inputs include atmospheric temperature, atmospheric humidity, wind speed, precipitation, groundwater level, soil temperature, soil humidity, atmospheric pressure, and solar radiation. These parameters were selected based on their known influence on FWI as well as their availability through monitoring systems. Other parameters may also be relevant, but they were not included in this model due to limitations in data availability or uncertainty in their relationship with FWI.

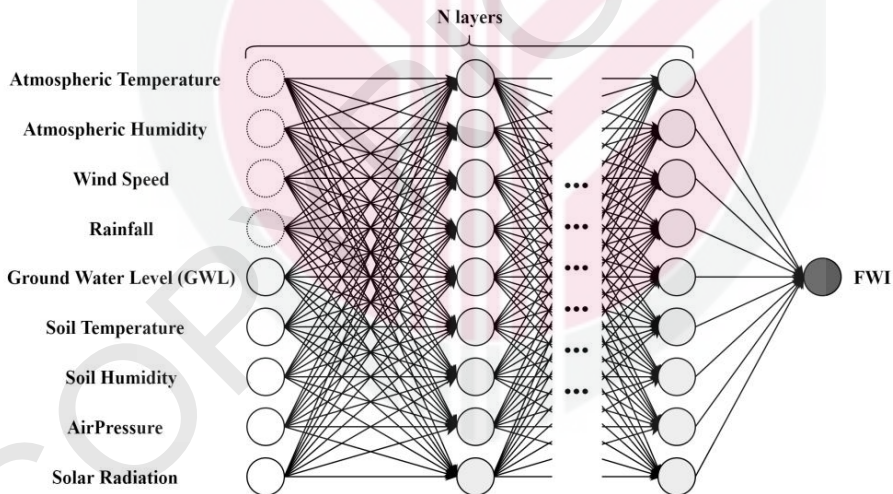


Figure 3.26 : 9-Input and N-Layer Neural Network for FWI Prediction

The data were collected by an IoT system that records measurements every minute. And the measurement result of the sensor node 2 is selected for the underground soil parameters, because the verified measurement value for neural network prediction is more stable and accurate than that of the sensor node 1.

3.11 Summary

In this chapter, an IoT system that collects weather data from various sensors and sends it to a central server has been designed. The location of the sensors is in a forest area, and the data collected includes temperature, humidity, wind speed, rainfall, pressure, solar radiation and other meteorological parameters. The implementation involves the use of low-power wireless sensors and a cloud-based platform to collect and analyze data. A dashboard has also been developed to provide a user-friendly interface for visualizing the data. The FWI system is an important tool for predicting wildfire behavior and aiding in firefighting efforts. The system is based on a set of equations that take into account various weather and fuel parameters. A Python code has been developed to implement the equations and calculate the FWI. Performance evaluation of the FWI system has been carried out using various metrics such as MSE, RMSE, MAE, and R^2 . The evaluation has been conducted using Jupyter Notebook and machine learning techniques to train the model. Moreover, the simulation was carried out at the WiPNET lab using a Dell OptiPlex 5070 computer with the x64-based processor, 16.0 GB RAM, and Windows 10. The software used includes Python 3.5 environment in Jupyter Notebook by Anaconda 3 and MATLAB R2016b.

Overall, this chapter presents a comprehensive study on the implementation of an IoT-based location tracking system, the development and implementation of an FWI system, performance evaluation of the FWI system, and the simulation parameters used in the thesis.

CHAPTER 4

RESULTS AND DISCUSSION

Forests are among the most essential resources for human beings, as they provide a vast array of goods and services that sustain human livelihoods and support the Earth's ecological balance. However, forest fires have become a major threat to forest resources, causing significant loss of life and property. Therefore, developing effective methods for predicting forest fire risk is of great practical importance for avoiding forest fires and protecting forest resources. This chapter demonstrated the effectiveness of an IoT-based peatland monitoring system for real-time data validation, mathematical modeling, and prediction of groundwater level and fire weather index. The finding has important implications for peatland management and fire prevention.

4.1 Validation of IoT System

This section presents the data collected by an IoT system for monitoring the peatlands of Raja Musa Forest Reserve. The IoT system captured various environmental parameters such as temperature, humidity, and soil moisture. These data were then validated with the weather data published by the nearest Malaysian Meteorological Department station, located approximately 8 kilometers away.

The purpose of this validation was to verify the accuracy and reliability of the IoT system in capturing and reporting environmental data. The results of this validation showed that the IoT system was highly effective in capturing environmental data and the data obtained from the IoT system was consistent with the weather data published by the Malaysian Meteorological Department. The findings demonstrate the potential of IoT technology in environmental monitoring and management, and highlights the importance of accurate and reliable data for making informed decisions about the management of natural resources.

Figure 4.1 compares the correlation between the daily average atmospheric humidity monitored by the IoT system and the daily average atmospheric humidity published by the Malaysian Meteorological Department in 2020. The daily average humidity is calculated from 12 am to 12 am and represents the mean value of all humidity data sets. The Malaysian Meteorological Department's data is collected from a weather station located approximately 8 kilometers away from the IoT system. The correlation between the two datasets is shown to be high, with an R^2 value of 0.94797289 throughout the year, which suggests that the IoT system's humidity monitoring is accurate and reliable.

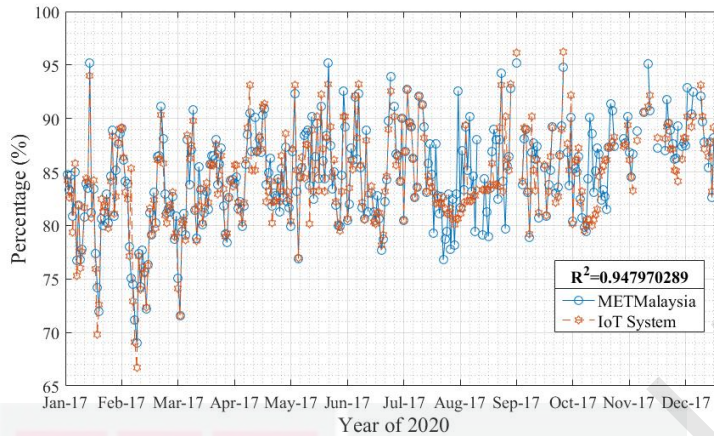


Figure 4.1 : Comparison of Daily Average Atmospheric Humidity

Figure 4.2 compares the correlation between the total daily rainfall measured by the IoT system and the total daily rainfall published by the Malaysian Meteorological Department in 2020. The total daily rainfall is calculated based on the Malaysian Meteorological Department's standard, which is the amount of rainfall collected from 8:00 am to 8:00 am the next day. The plot displays a chart of the two datasets with a correlation coefficient (R^2) of 0.906650511. This indicates a strong positive correlation between the two datasets. The IoT system can be used as a reliable tool to monitor and predict rainfall in the region, contributing to the improvement of flood control and water management. The comparison of the rainfall measured by the IoT system and the data published by the Malaysian Meteorological Department provides insights into the accuracy of the IoT system and validates its use in monitoring rainfall.

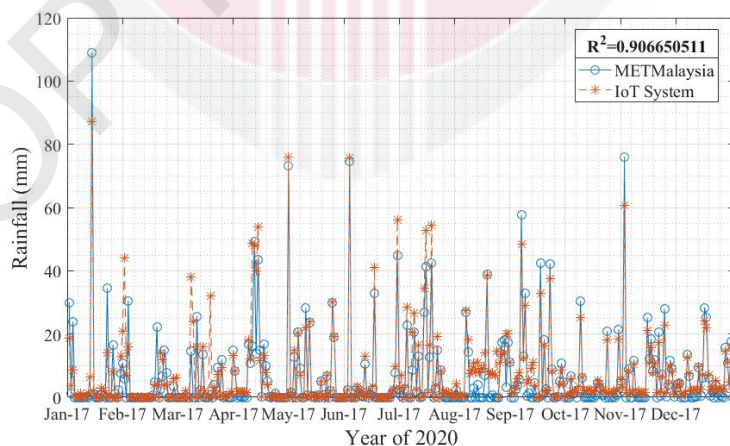


Figure 4.2 : Comparison of Total Daily Rainfall

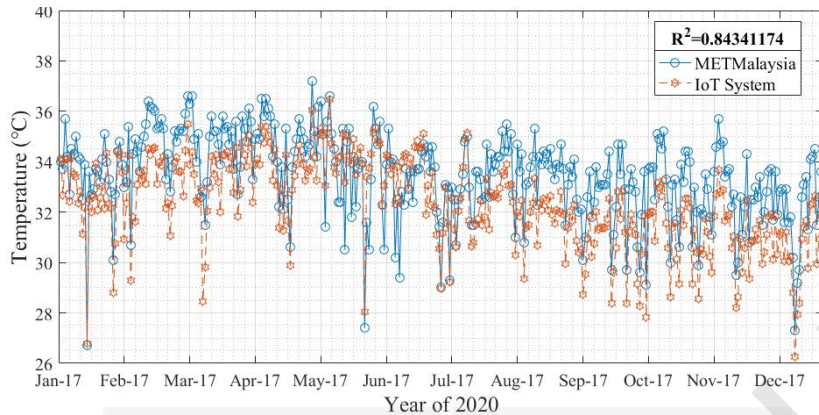


Figure 4.3 : Comparison of Daily Maximum Atmospheric Temperature

The presented Figure 4.3 compares the daily maximum atmospheric temperature measured by an IoT system and the data published by the Malaysian Meteorological Department for the year 2020. The comparison shows a high correlation between the two datasets with an R-squared value of 0.84341174. It is interesting to note that the METMalaysia data shows consistently higher temperatures than the IoT system measurements. This can be attributed to the fact that the IoT weather station is located on a 20-meter observation tower, while the METMalaysia station is situated on the ground. The results demonstrate the potential of IoT systems for accurately monitoring atmospheric temperature in peatland areas. The findings could also help understanding the differences in temperature measurements between ground-based weather stations and those located at higher elevations.

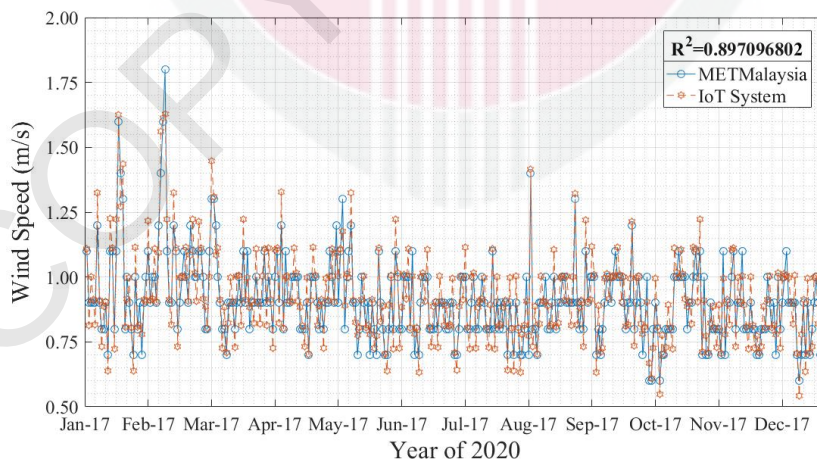


Figure 4.4 : Comparison of Daily Average Wind Speed

Figure 4.4 presented shows a comparison of the daily average wind speeds measured by an IoT system and those reported by the Malaysian Meteorological Department in 2020. The daily average wind speed was calculated as the mean value of all wind speed measurements collected from 00:00 to 24:00 hours. The results indicate a high correlation between the two datasets, with an R^2 value of 0.897096802. This indicates that the IoT system is capable of accurately measuring and monitoring wind speeds. These findings could be of great use for various industries, such as agriculture, construction, and transportation, which rely on accurate wind speed data.

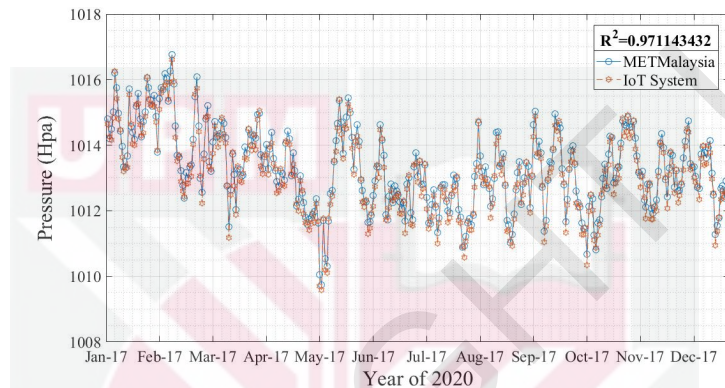


Figure 4.5 : Comparison of Daily Mean Atmospheric Pressure

Figure 4.5 compares the correlation between the daily mean atmospheric pressure measured by an IoT system and that reported by the METMalaysia in 2020. The daily mean atmospheric pressure was calculated as the average of all pressure measurements taken from 00:00 to 24:00. The results indicate that the daily mean atmospheric pressure measured by the IoT system is highly correlated with that reported by the METMalaysia, with an R^2 value of 0.971143432 for the whole year. The high correlation coefficient suggests that the IoT system can provide reliable atmospheric pressure data for various applications.

Figure 4.6 presents a comparison of the correlation between the daily total rainfall, daily maximum air temperature, daily average atmospheric humidity, daily average wind speed, and daily average atmospheric pressure, as measured by both the IoT system and the Malaysian Meteorological Department in 2020. The results indicate that all parameters show strong correlations, with coefficients above 0.8. It is worth noting that the temperature shows the lowest correlation among all the parameters, with a coefficient of 0.82, due to the difference in the height of the meteorological stations used by the IoT system and the Malaysian Meteorological Department. Nevertheless, the figure highlights the reliability and consistency of the IoT system in capturing and monitoring weather data, which can be a valuable tool for climate studies and weather forecasting.

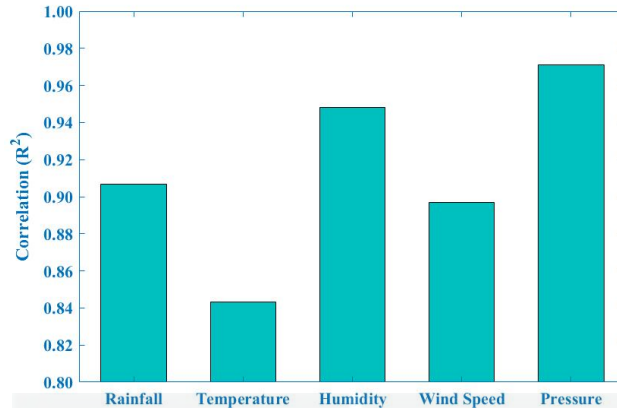


Figure 4.6 : Comparison of Correlation on Different Weather Parameters

Figure 4.7 shows the groundwater level (GWL) data recorded by sensor node 1 in the IoT system throughout 2020. The data collection started from January 17th, which was the day the IoT system was officially launched. From January 17th to March 31st, the groundwater level recorded by sensor node 1 (SN1) remained relatively stable, ranging from -250mm to 50mm. However, the groundwater level became unstable and dropped below -1000mm from April onwards, with many data losses, as shown in the graph split into two parts: January 17th to March 31st and April to December. This was due to the implementation of the Malaysian movement control order (MCO) from April [206], which restricted the travel of technical staff to maintain and repair the IoT system. Furthermore, wild animals, such as monkeys near the IoT system, could potentially damage the sensor nodes. After April, the data collected by SN1 did not possess scientific value and was discarded in subsequent research.

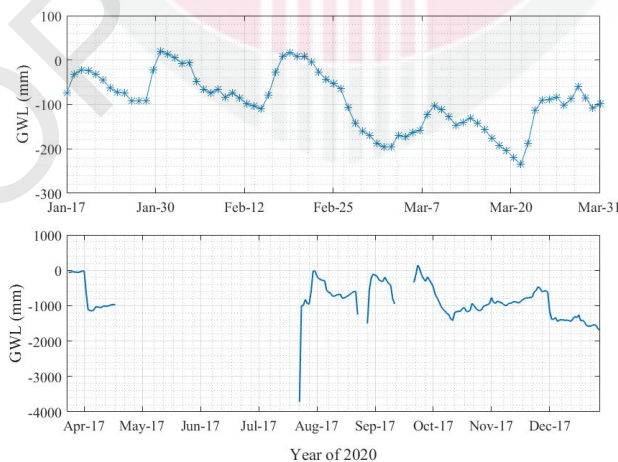


Figure 4.7 : Groundwater Level (GWL) Data Recorded By SN1 in 2020

Figure 4.8 illustrates the groundwater level (GWL) data collected by sensor node 2 (SN2) in the IoT system in 2020. The data were stable between January 17 and March 31, with levels ranging from approximately -450mm to -150mm. However, the sensor node stopped working from April onwards, and no data were recorded. This was due to damage caused by wild animals during the MCO period, and technical personnel were unable to conduct on-site repairs. To ensure data consistency, all subsequent data used in this thesis were obtained before April 2020. The loss of data highlights the challenges of using IoT systems in the field, particularly in areas with wildlife that can cause damage to equipment. Despite this setback, the data obtained from SN2 before April 2020 will still be valuable for groundwater analysis and management. The findings will contribute to a better understanding of groundwater dynamics and inform decision-making for sustainable water resource management.

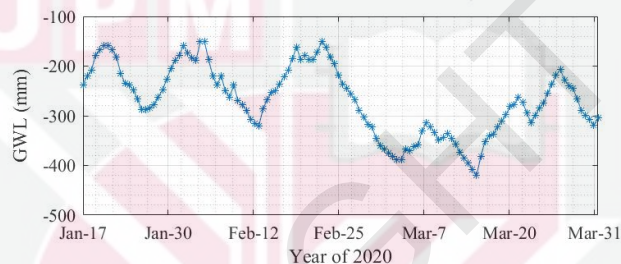


Figure 4.8 : Groundwater Level (GWL) Data Recorded By SN2 in 2020

Based on the GWL data manually measured by Julia and Parish from 2014 to 2016 in the Raja Musa peat swamp forest, the range of GWL is between -500 mm to 250 mm [207]. The GWL data obtained from the IoT system sensors at nodes 1 and 2 show a similar range of GWL. Specifically, the GWL data obtained from node 1 ranged from -250 mm to 50 mm, while the data from node 2 ranged from -450 mm to -150 mm. These results suggest that the GWL data collected by the IoT system is reliable and can be used for further analysis and modeling. The ability of the IoT system to provide accurate and reliable data on GWL can be highly beneficial for the study of wetland ecosystems and their responses to environmental changes.

The Internet of Things (IoT) is a rapidly growing field that has the potential to revolutionize the way we interact with technology and our environment. As the number of connected devices continues to increase, it is important to ensure that the data they generate is accurate and reliable. In this context, validation of IoT data becomes crucial to ensuring that it can be used in meaningful ways. In conclusion, validation of IoT data is crucial to ensure its accuracy and reliability. The presented figures in this section provide an example of the high level of validation achieved by an IoT system in Malaysia in 2020, as well as the potential challenges that can arise in maintaining such systems. This highlights the need for continued research and development in the field of IoT to address these challenges and ensure that the potential of IoT can be fully realized.

4.2 Drought Code (DC) Modeling

The integration of Groundwater Level (GWL) data into the Forest Fire Weather Index (FWI) system for calculating the Drought Code (DC) is an innovative approach to improving forest fire prediction and prevention. The DC is an essential component of the FWI system that measures the dryness of organic layers in forests, which is one of the primary factors affecting the risk of forest fires.

Conventionally, the DC is calculated based on temperature and precipitation data, but this approach has been criticized for its inability to capture the dynamic and complex nature of the moisture regime in tropical peatland forests, where the water table is a significant determinant of fire risk. The integration of groundwater level data into the FWI system addresses this limitation by providing a more comprehensive and accurate assessment of the moisture conditions in the peatland forests. Groundwater level data can better capture the moisture content of the soil, which is critical for maintaining a healthy forest ecosystem and preventing forest fires.

By incorporating groundwater level data into the FWI system, forest managers can more effectively monitor and predict forest fire risks and take appropriate actions to prevent or mitigate forest fires. Therefore, the integration of groundwater level data into the FWI system is a significant advancement in forest fire prediction and prevention, particularly for tropical peatland forests. This new approach provides a more comprehensive and accurate assessment of the moisture conditions in the forests, which is critical for maintaining healthy forest ecosystems and reducing the risk of forest fires.

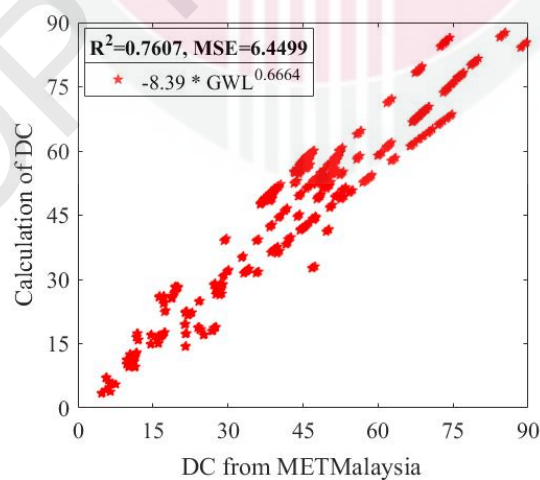


Figure 4.9 : Performance Evaluation of Power Model for DC Calculation

Figure 4.9 shows the performance evaluation of the proposed Power Model for calculating DC using the groundwater level data collected by IoT sensors and the corresponding DC data provided by the Malaysian Meteorological Department. The DC values range from 0 to 90, and the plot displays the comparison of the calculated DC values with the actual DC values. The results indicate that the proposed Power Model achieves a Correlation (R^2) of 0.7607 and a Mean Squared Error (MSE) of 6.4499, which demonstrates the model's capability to accurately estimate DC values based on groundwater level data. The high correlation and low mean squared error values suggest that the proposed model is a reliable and efficient method for estimating DC values for tropical peatland forest fire risk assessment. Further, the use of IoT sensors for monitoring ground water levels provides real-time data that can improve the accuracy and timeliness of DC calculations, allowing for more effective forest fire management and prevention strategies. Overall, the results of this study demonstrate the potential of integrating IoT technology with existing forest fire management systems to improve their accuracy and effectiveness.

Figure 4.10 depicts the validation performance of the proposed linear model for calculating the drought code (DC) using the groundwater level (GWL) data monitored by the IoT system and the corresponding DC data published by the Malaysian Meteorological Department at the same time. The DC values range from 0 to 90, and the linear model achieves a correlation of 0.7868 and a Mean Squared Error (MSE) of 4.3868. The validation results indicate that the proposed linear model can accurately predict DC based on GWL data, and it outperforms the power model in terms of both correlation and mean squared error. The linear model can be used as an efficient tool for early detection and monitoring of peatland forest fires in tropical regions, as it provides a more reliable and direct estimation of DC compared to the existing FWI system. The model can also be useful for developing early warning systems and decision-making strategies to prevent and mitigate forest fires in these regions.

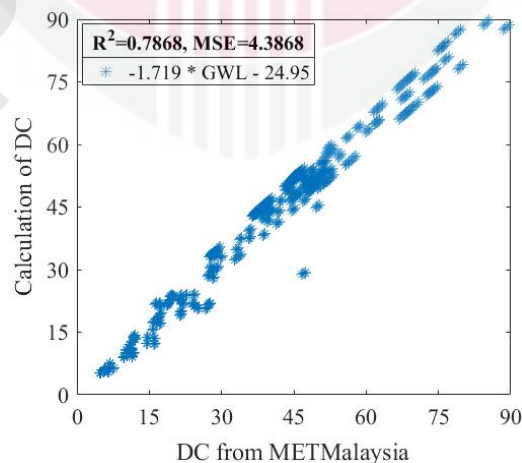


Figure 4.10 : Performance Evaluation of Linear Model for DC Calculation

The linear and power models achieved correlations of 0.75 or higher, indicating relative reliability. However, further verification was carried out to demonstrate the validity of the models. Table 4.1 presents the correlation values between the fire indices (FFMC, DMC, DC, ISI, and BUI) and FWI values calculated using the linear and power models. The FWI was calculated using the DC values from the linear and power models according to Figure 3.18, and correlations were computed between the FWI and the fire indices published by Malaysian Meteorological Department. The correlation values are compared to the reference standard of the correlation between the fire indices and FWI published by the Malaysian Meteorological Department (METMalaysia). The correlation values ranged from 0.348 to 0.957, with ISI having the highest correlation values with both linear and power models, followed by DMC and BUI. The FFMC had the lowest correlation values with both models. These results suggest that both the linear and power models can be used to predict the FWI for the Raja Musa Forest Reserve. However, the correlation between DC and FWI calculated using the power model is lower compared to the correlation between DC and FWI calculated using the linear model. This finding suggest that the Linear Model may be a more reliable approach for calculating DC in the proposed FWI system architecture. Therefore, the Linear Model can be considered as a better model for predicting forest fires in Malaysia.

Table 4.1 : Correlation Values between Fire Indices and FWI

Fire indices from METMalaysia	FWI from METMalaysia	FWI Calculated by Linear_DC_Model	FWI calculated by Power_DC_Model
ISI	0.9575762	0.955882	0.955212
DMC	0.8353773	0.802142	0.790926
BUI	0.7838499	0.801688	0.790630
FFMC	0.6938313	0.660601	0.646227
DC	0.5053826	0.412702	0.348317

Figure 4.11 illustrates a bar chart that compares the correlation values between the FWI using the Linear and Power models and various parameters (ISI, DMC, BUI, FFMC, and DC) published by Malaysian Meteorological Department. In this context, the assessment of acceptability focuses on the correlation values between the modeled FWI and the corresponding METMalaysia values for other fire indices. The primary criterion is to ensure that the selected linear model yields correlation values within an acceptable range when compared to the METMalaysia reference values. Therefore, the emphasis is on the consistency and reliability of the model in capturing the relationships observed by METMalaysia, rather than achieving a perfect correlation with a theoretical maximum of 1. The chart clearly visualises the correlation values and shows that both models produced similar results for ISI, DMC, BUI, and FFMC. The correlation values for these parameters were also similar to those of the reference standard published by the Malaysian Meteorological Department.

However, the correlation value between FWI and DC was significantly lower than the other parameters, and the Linear model showed a closer correlation value to the reference standard than the Power model. Overall, the chart provides a clear and concise summary of the correlation results, which can be helpful in further validating the model's accuracy.

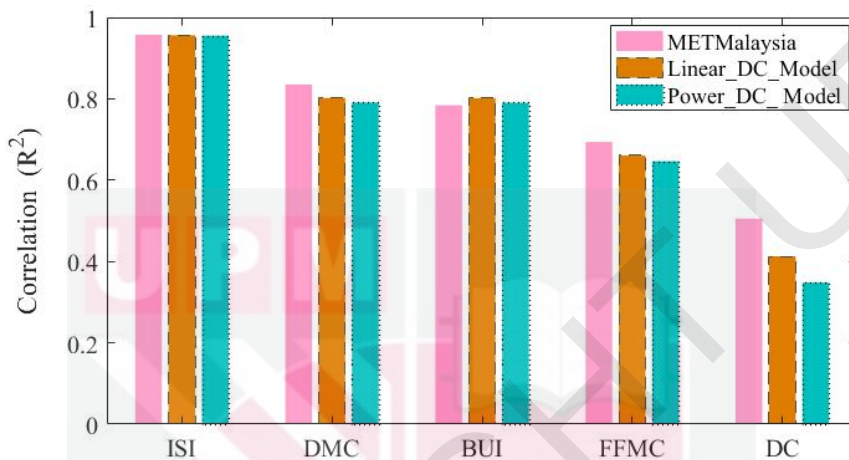


Figure 4.11 : Correlation between Fire Indices and FWI in Different Models

This section developed a DC modeling approach using the average daily groundwater level data from sensor node 1 of an IoT system and the corresponding DC data from the Malaysian Meteorological Department. Two different curve fitting models were used, the linear and power models, to estimate DC values. The performance of both models was tested by comparing the calculated DC values with the DC data from the Malaysian Meteorological Department. The results showed that the linear model achieved a higher correlation and lower mean square error compared to the power model. Additionally, the calculated DC values were used in a fire weather index system to calculate the FWI, and the correlation between FWI and different parameters was analyzed. The results showed that the linear model performed better than the power model in predicting FWI values. This finding provides a promising approach for estimating DC values using IoT data, which could be useful for fire management and prevention.

4.3 Duff Moisture Code (DMC) Modeling

The integration of groundwater level (GWL) data into the Fire Weather Index (FWI) system provides a more accurate estimation of the Duff Moisture Code (DMC). Traditionally, the DMC is calculated using temperature, rainfall, and relative humidity. However, this approach does not account for the effects of groundwater on the moisture content of the forest floor. By including GWL data

and relative humidity in the calculation, the moisture content of the forest floor can be more accurately estimated, improving the overall accuracy of the FWI system. Furthermore, the inclusion of GWL data allows for the identification of areas with elevated fire risk due to low groundwater levels, which can help inform fire management decisions. Therefore, the use of GWL and humidity to calculate DMC provides a more comprehensive approach for estimating fire danger and assessing fire risk in forested areas.

In this section, the proposed Linear_DMC and Linear_Mixed_DMC models were used to calculate the DMC using hourly data of groundwater level and humidity collected by IoT monitoring system, as shown in Figure 4.12. The results were plotted as green solid line with circle markers and pink solid line with star markers, respectively. Additionally, the DMC calculated using the Canadian model (Section 3.3.2) with hourly data of rainfall, temperature, and humidity collected by the IoT system was plotted as red solid line with hexagonal markers. The gray dashed line represents the DMC values published by METMalaysia for the same period. These lines were compared to validate the feasibility of the proposed models. The Canadian model showed a correlation of 0.7824 with the DMC published by METMalaysia, but had a high mean square error of 7.2021 and underestimated the DMC values. The Linear_DMC model showed a correlation of 0.6846 and a MSE of 4.5846. The Linear_Mixed_DMC model had the highest correlation of 0.9071 with the DMC values published by METMalaysia and the lowest MSE of 2.5633. These findings suggest that the Linear_Mixed_DMC model is a more accurate and reliable approach for calculating DMC using groundwater level and humidity data.

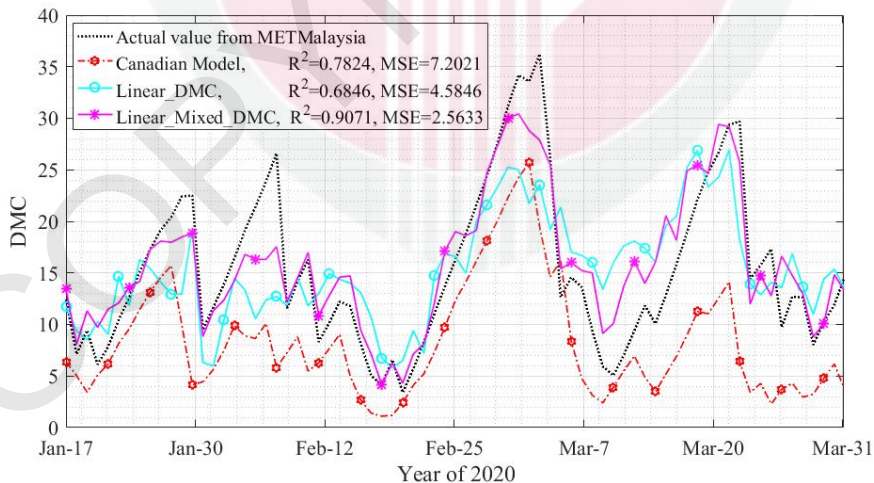


Figure 4.12 : Comparison between Different DMC Calculation Models

Figure 4.13 presents a comparison of the three models - the Canadian model, Linear_DMC model, and Linear_Mixed_DMC model - based on their R^2 and MSE values. The left Y-axis shows the R^2 values represented by blue and gray solid line borders, while the right Y-axis shows the MSE values represented by orange and gray dashed line borders. The X-axis shows the three groups of data from left to right, which come from the Canadian model, Linear_DMC model, and Linear_Mixed_DMC model. The figure shows that all three models have a correlation with the actual values published by the Malaysian Meteorological Department of over 0.6. However, the Linear_Mixed_DMC model has the highest bar for correlation, while the Linear_DMC model has the lowest. In terms of MSE, the Linear_Mixed_DMC model has the lowest bar, and the Canadian model has the highest. Overall, the figure highlights the performance of the three models and provides a useful comparison of their accuracy in predicting DMC values.

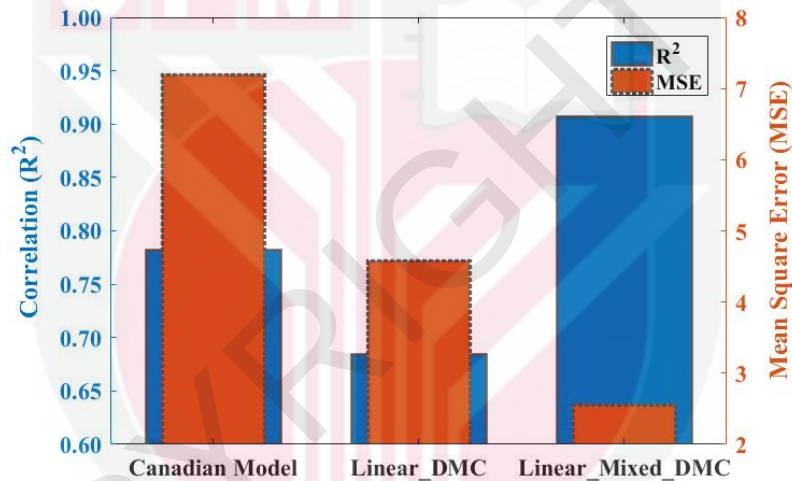


Figure 4.13 : Comparison of DMC Models Based on R^2 and MSE Values

This modeling study aimed to develop a reliable method for calculating the Duff Moisture Code (DMC) using data from IoT sensors measuring groundwater level (GWL), and atmospheric humidity. Two models, Linear_DMC and Linear_Mixed_DMC, were proposed and tested against actual DMC values published by the Malaysian Meteorological Department (METMalaysia). The results showed that both models had a correlation of over 0.6 with actual DMC values, with Linear_Mixed_DMC performing the best in terms of both correlation and mean squared error (MSE). In addition, the Canadian model was also tested and showed a correlation of 0.7824 with actual DMC values, but with a higher MSE compared to the two linear models. These findings suggest that the proposed models could be useful for accurately calculating DMC and could aid in drought monitoring and prediction efforts. The comparison of the models' performance is summarized in a bar chart with R^2 and MSE values.

4.4 Predicting Ground Water Level (GWL)

Peatlands in the tropics are important ecosystems that are under threat due to climate change and human activities such as land-use change and fire. These peatlands store a significant amount of carbon and provide vital ecosystem services such as water regulation, biodiversity conservation, and local livelihoods. However, when peatlands are drained or degraded, they become highly flammable and can experience prolonged and intense fires that release massive amounts of carbon into the atmosphere. Predicting GWL in these peatlands is important because it is a critical factor that affects the fire risk and carbon emissions from these ecosystems. GWL influences the water content and oxygen availability in peat [208], which in turn affects its flammability and decomposition rates. Therefore, accurate predictions of GWL can help to identify areas that are vulnerable to fires and guide management strategies for preventing and controlling peatland fires, as well as reducing their carbon emissions. Machine learning techniques can provide a useful tool for predicting GWL in tropical peatlands, as they can capture complex relationships between hydrological variables and environmental factors that affect GWL dynamics in these ecosystems.

Both predictions for sensor node 1 and 2 show a high degree of accuracy with low mean square error and high R^2 values, indicating good model performance. However, it's important to note that the location of sensor node 1 near a channel may result in more fluctuations in groundwater levels compared to sensor node 2, which may impact the accuracy of the prediction.

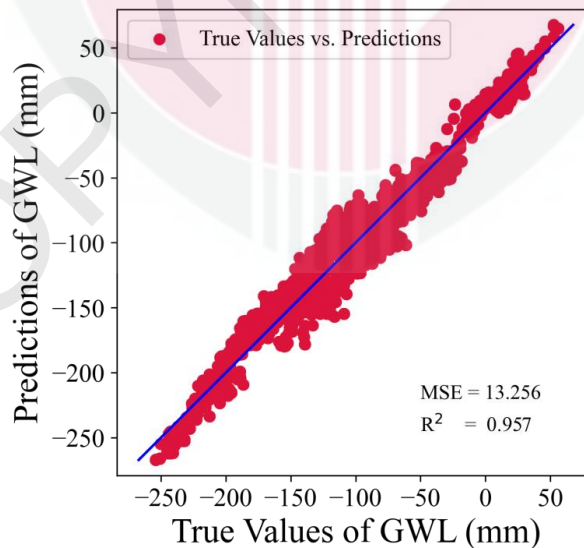


Figure 4.14 : Predicted Versus Actual Values for GWL at SN1

Figure 4.14 displays the prediction results for sensor node 1, where each red dot represents a predicted and true value, with the x-axis representing the true value and the y-axis representing the predicted value. The blue solid line represents the perfect prediction where all predicted values would fall exactly on the diagonal line. It can be observed that all the red dots are close to the diagonal line, indicating a high level of accuracy in the predictions. The mean square error (MSE) of the predictions is 13.256, and the coefficient of determination (R^2) is 0.957. The high R^2 value indicates that the model can explain 95.7% of the variation in the data. The figure suggests that the machine learning model used for predicting the groundwater level at sensor node 1 is robust and accurate, and the predictions can be used for various applications such as groundwater management and agricultural irrigation.

The accurate prediction of groundwater level (GWL) is crucial for efficient water resource management, particularly in areas such as tropical peatlands that are susceptible to fires and droughts. Figure 4.15 depicts the predicted results for sensor node 2, where each point represents the predicted value plotted against the actual value, with red circles denoting the predicted and actual values. The horizontal axis represents the true value, while the vertical axis represents the predicted value. Ideally, if the predictions were 100% accurate, all points would fall on the blue line that represents $y=x$. However, the red circles are clustered closely around this line, indicating high accuracy of the predictions. The mean squared error (MSE) for the model is 11.069, while the coefficient of determination (R^2) is 0.953, suggesting that the model has a good fit to the data.

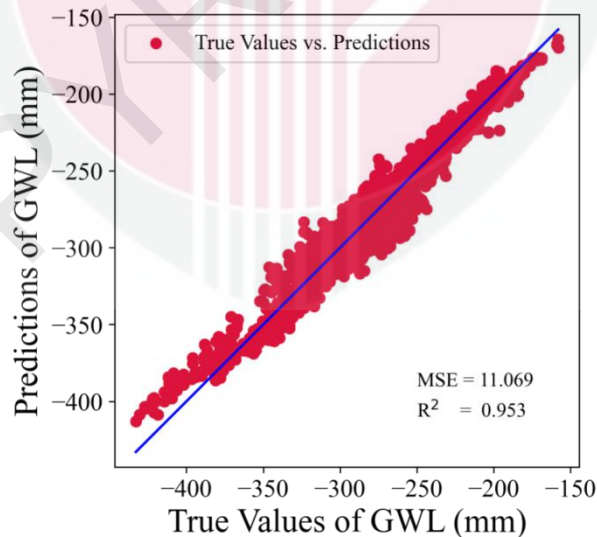


Figure 4.15 : Predicted Versus Actual Values for GWL at SN2

This section employed machine learning techniques to predict GWL using six input parameters, namely soil temperature, solar radiation, soil humidity, atmospheric pressure, wind speed, and rainfall. The data for these parameters and GWL were collected through an Internet of Things (IoT) system, with 80% of the data used for training the neural network model, and the remaining 20% for testing. The neural network architecture comprised of a three-layer structure with six input nodes and one output node representing GWL. Two sensor nodes, SN1 and SN2, were used for GWL prediction, and their results were compared. The performance of SN2 showed better prediction accuracy with a mean squared error of 11.069 and a correlation coefficient (R^2) of 0.953. In contrast, SN1 had a smaller GWL range (-250 to 50 mm), but a higher mean squared error of 13.256, which could be due to its proximity to a channel. Overall, accurate GWL prediction can aid in sustainable water management, and the results from this study could assist in future research and policy decisions.

4.5 Predicting Fire Weather Index (FWI)

Machine learning has been increasingly used in predicting the Forest Fire Weather Index (FWI) for peatland fires. FWI is an index that quantifies the potential for fire growth by taking into account weather variables such as temperature, humidity, wind speed, and precipitation. Peatlands, which are wetland ecosystems with a thick layer of peat soil, are highly susceptible to fires that can burn for extended periods and cause significant damage to the environment and human health. Accurate predictions of FWI can help prevent and control peatland fires by enabling early warning systems and effective firefighting strategies. Overall, the use of machine learning in predicting FWI for peatland fires has shown promising results and can significantly improve our ability to prevent and control peatland fires [209]. However, more research is needed to further improve the accuracy and reliability of these models, especially in the context of changing climate patterns and increasing pressures on peatland ecosystems.

The performance of a 4-input, 3-layer neural network and a 4-input, 4-layer neural network was displayed in Figure 4.16. The red dots represent the predicted and actual FWI values, while the horizontal axis represents the valid FWI values obtained from METMalaysia. The vertical axis represents the predicted FWI values obtained through machine learning. The figure indicates a good fit between the predicted and actual values, as most of the red dots are close to the blue line, which represents the line of perfect prediction. In a 4-input, 3-layer neural network, the Mean Squared Error (MSE) is 1.573, the Root Mean Squared Error (RMSE) is 1.254, the Mean Absolute Error (MAE) is 0.992, and the R-squared (R^2) value is 0.845. While as for the 4-layer neural network, the results show that the MSE is 1.543, RMSE is 1.242, MAE is 0.989, and R^2 value is 0.848. These results indicate that the neural network model can predict FWI values with relatively high accuracy.

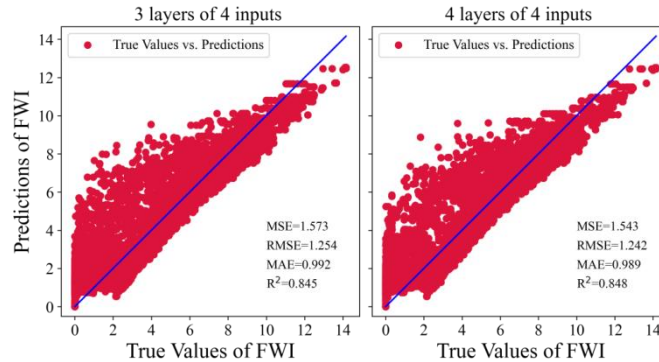


Figure 4.16 : Performance of 4-Input, 3 (and 4)-Layer Neural Networks

Figure 4.17 presents a plot showing the prediction results of a 4-input, 5-layer (6 and 7-layer) neural network for predicting FWI using machine learning. The horizontal axis represents the actual FWI values obtained from METMalaysia, while the vertical axis represents the predicted FWI values. In the case of a 5-layer, the MSE is 1.537, RMSE is 1.239, MAE is 0.975, and R^2 is 0.852. The MSE, RMSE, MAE, and R^2 for the 6-layer neural network are 1.599, 1.265, 1.006, and 0.846, respectively. Moreover, the evaluation metrics of the 7-layer include an MSE of 1.605, RMSE of 1.267, MAE of 1.003, and an R^2 of 0.845. The lower values of MSE, RMSE, and MAE indicate that the predictions made by the model are closer to the true FWI values, while the higher R^2 value indicates a better fit of the model to the data. The results suggest that the 4-input 5-layer neural network is a promising approach for accurately predicting FWI using machine learning techniques. The increasing number of hidden layers in the model has resulted in higher complexity and more abstract feature representation. However, it is observed that the performance of the 7-layer neural network has not improved significantly compared to the 5 or 6-layer model, which indicates that increasing the number of layers beyond a certain threshold may not always result in improved performance.

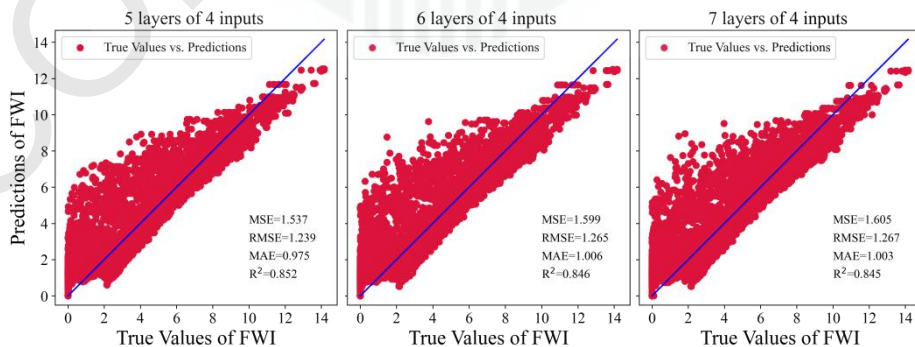


Figure 4.17 : Performance of 4-Input, 5 (6 and 7)-Layer Neural Networks

Table 4.2 summarizes the performance of four-input neural networks with varying numbers of layers for predicting FWI. The evaluation metrics used to compare the models are mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and R-squared (R²). The MSE values for the networks with 3, 4, 5, 6, and 7 layers are 1.573, 1.543, 1.537, 1.599, and 1.605, respectively. The RMSE values are as follows: 1.254, 1.242, 1.240, 1.265, and 1.267 for 3, 4, 5, 6, and 7 layers, respectively. The results show that the MAE values range from 0.975 to 1.006, with the lowest MAE value obtained for the neural network with 4 input parameters and 5 layers. The R² values for the 4-input neural networks with 3 to 7 layers were 0.845, 0.848, 0.852, 0.846, and 0.845, respectively. From the table, it can observe that the neural network with five hidden layers achieved the best, while the neural network with the fewest number of layers, i.e., three layers, produced the worst performance in terms of all evaluation metrics. Interestingly, the performance of the neural network model with six and seven layers is slightly worse than the model with five layers in terms of all evaluation metrics. This observation suggests that increasing the number of layers beyond a certain threshold may not always result in better model performance. In fact, adding too many layers can lead to overfitting, where the model becomes too complex and starts to fit the noise in the data, resulting in poor generalization performance on new data. Therefore, it is important to carefully balance the number of layers and other neural network hyperparameters to achieve the best possible performance.

Table 4.2 : Performance Comparison of 4-Input Neural Networks with Different Numbers of Layers for FWI Prediction

	3 Layers	4 Layers	5 Layers	6 Layers	7 Layers
MSE	1.573	1.543	1.537	1.599	1.605
RMSE	1.254	1.242	1.239	1.265	1.267
MAE	0.992	0.989	0.975	1.006	1.003
R ²	0.845	0.848	0.852	0.846	0.845

Figure 4.18 illustrates a four-bar chart that compares the performance in MSE, RMSE, MAE, and R² of the neural networks with different numbers of layers, ranging from 3 to 7. This figure provides insight into the optimal number of hidden layers required to accurately predict the FWI based on the four input parameters used in this study. The best-performing model is the one with 5 layers, which achieved the lowest MSE, RMSE, and MAE value, and the highest R² value. This result suggests that increasing the number of layers beyond a certain point may lead to overfitting, resulting in reduced predictive accuracy. Therefore, the 5-layer neural network is recommended for predicting FWI based on input parameters.

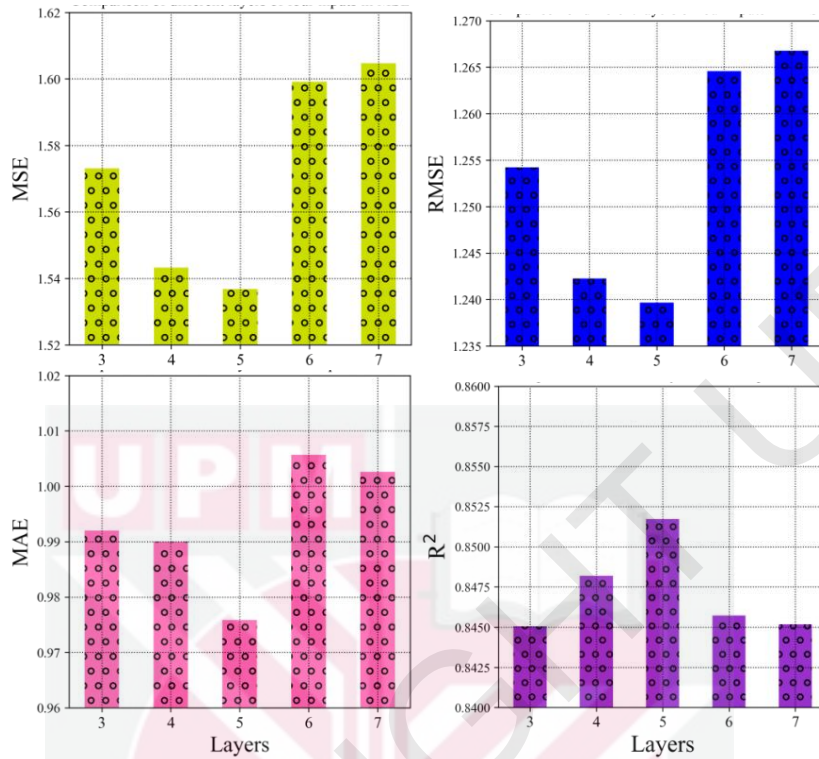


Figure 4.18 : Performance Evaluation of Different 4-Input Neural Networks

On the other hand, based on the machine learning prediction results, Figure 4.19 shows the performance of a three-layer (and four-layer) neural network in predicting the FWI using nine input parameters. The mean squared error (MSE) of the three-layer neural network is 1.144, indicating that the predicted values are, on average, 1.144 units away from the true values. The three-layer neural network's root mean squared error (RMSE) and mean absolute error (MAE) are 1.069 and 0.833, respectively. The R^2 value of the three-layer neural network is 0.889, indicating that the model explains 88.9% of the variance in the data. As for the 4 layers, the mean squared error (MSE) is 1.122, the root mean squared error (RMSE) is 1.059, the mean absolute error (MAE) is 0.826, and the coefficient of determination (R^2) is 0.889. Compared to the 3-layer network, the 4-layer network achieved a slightly lower MSE, RMSE, and MAE, but the R^2 value remained the same. This suggests that increasing the number of layers did not significantly improve the prediction accuracy. However, the 4-layer network still outperformed the 3-layer network, indicating that adding more layers could still lead to some improvement in performance. Further investigations are needed to determine the optimal number of layers for this problem.

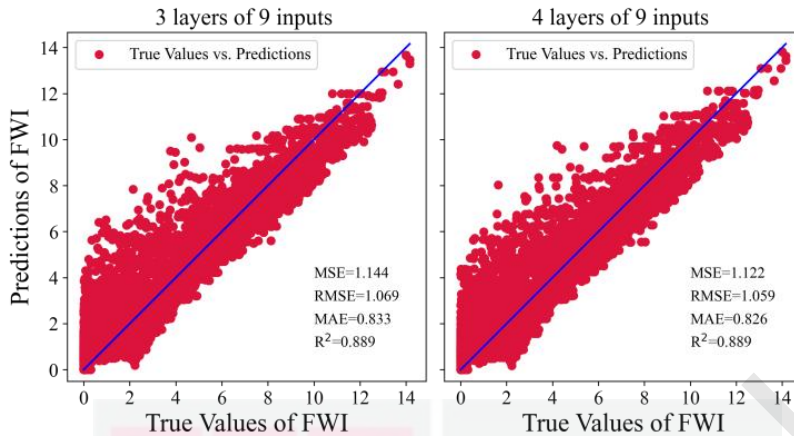


Figure 4.19 : Performance of 9-Input, 3 (and 4)-Layer Neural Networks

Figure 4.20 shows the performance of a neural network machine learning model trained to predict FWI with 9 input features and varying numbers (5, 6, and 7) of layers. The model with 5 layers achieved the best performance with an MSE of 1.116, RMSE of 1.056, MAE of 0.815, and R^2 of 0.890. The neural network with 6 layers achieved the MSE, RMSE, MAE and R^2 values of 1.14, 1.071, 0.826, and 0.886, respectively. Additionally, the model with 7 layers reached a slightly higher MSE of 1.162, RMSE of 1.078, and MAE of 0.833, but the same R^2 value with the 6-layer. It is worth noting that the neural network model's performance did not improve significantly beyond the 5-layer architecture. Specifically, the model with 6 layers achieved slightly worse performance than the model with 4 layers. Therefore, increasing the number of layers in the neural network beyond a certain point can lead to overfitting and reduced performance, which could explain why the performance did not improve with increasing the number of layers beyond 5.

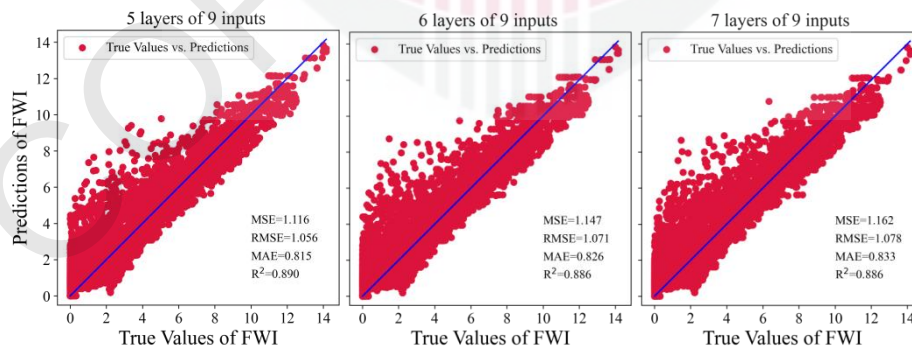


Figure 4.20 : Performance of 9-Input, 5 (6, and 7)-Layer Neural Networks

Table 4.3 summarizes the performance of a neural network model for FWI prediction using nine input features with increasing numbers of hidden layers. The metrics used to evaluate the performance of the model include Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2). The results show that increasing the number of layers from three to five generally improved the model's performance, as indicated by decreasing values of MSE, RMSE, and MAE and increasing values of R^2 . However, increasing the number of hidden layers from six to seven resulted in a slight decrease in performance, as evidenced by the slight increase in MSE and RMSE and the decrease in R^2 . This indicates that there may be a point of diminishing returns in adding more layers to the model beyond a certain threshold. In addition, increasing the number of layers beyond a certain threshold can also lead to overfitting. Therefore, it may be better to use a neural network model with a moderate number of hidden layers for FWI prediction.

Table 4.3 : Performance Comparison of 9-Input Neural Networks with Different Numbers of Layers for FWI Prediction

	3 Layers	4 Layers	5 Layers	6 Layers	7 Layers
MSE	1.144	1.122	1.116	1.14	1.162
RMSE	1.069	1.059	1.056	1.071	1.078
MAE	0.833	0.826	0.815	0.826	0.833
R^2	0.889	0.889	0.890	0.886	0.886

Based on the provided information in Table 4.3, a bar chart was created to display the performance of the 9-input neural network in terms of four different metrics, including MSE, RMSE, MAE, and R^2 , as shown in Figure 4.21. The chart allows for a quick and easy comparison of the performance of the network across different layers. It shows that the 5-layer neural network achieved the best results in terms of all four metrics. The 4-layer network also performed well, with only a slightly higher value for MSE and RMSE compared to the 5-layer network. On the other hand, the performance of the 3-layer network was notably worse than the other architectures. The chart provides a clear visualization of the impact of the number of layers on the performance of the neural network, demonstrating that increasing the number of layers beyond a certain point does not necessarily lead to better performance. Thus, it can help in selecting the best neural network architecture for the given problem.

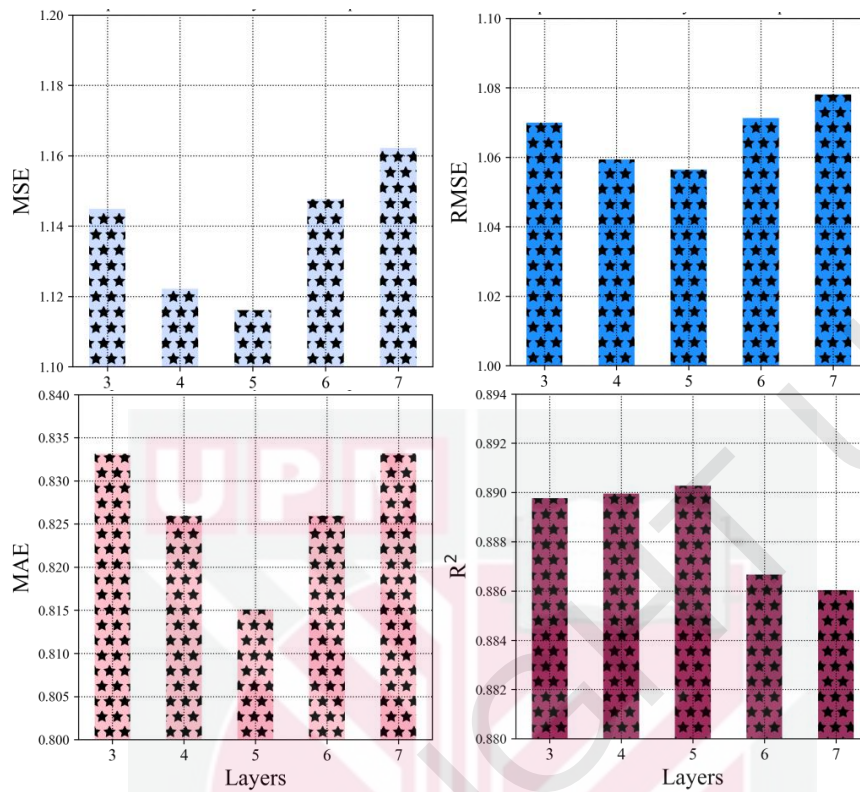


Figure 4.21 : Performance Evaluation of Different 9-Input Neural Networks

Figure 4.22 presents a four-bar chart that compares the performance of a 4-input neural network and a 9-input neural network for predicting FWI using different layers, ranging from 3 to 7 layers. The results indicate that the performance of predicting the Fire Weather Index (FWI) using neural networks is better with nine inputs compared to four inputs, regardless of the number of layers. The evaluation metrics, including mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and R-squared (R^2), consistently demonstrate the superiority of the nine-input models over the four-input models. The MSE values for the four-input models ranged from 1.537 to 1.605, while for the nine-input models, they ranged from 1.116 to 1.162. Similarly, the RMSE values for the four-input models ranged from 1.239 to 1.267, whereas for the nine-input models, they ranged from 1.056 to 1.078. The MAE values showed a similar trend, with the four-input models ranging from 0.975 to 1.006, and the nine-input models ranging from 0.815 to 0.833. Additionally, the R^2 values for the four-input models ranged from 0.845 to 0.852, while for the nine-input models, they ranged from 0.886 to 0.890. These findings highlight the advantage of incorporating more input features in the neural network models to improve the accuracy of FWI prediction. Overall, the results suggest that increasing the number of inputs, specifically from four to nine, enhances the performance of FWI prediction models.

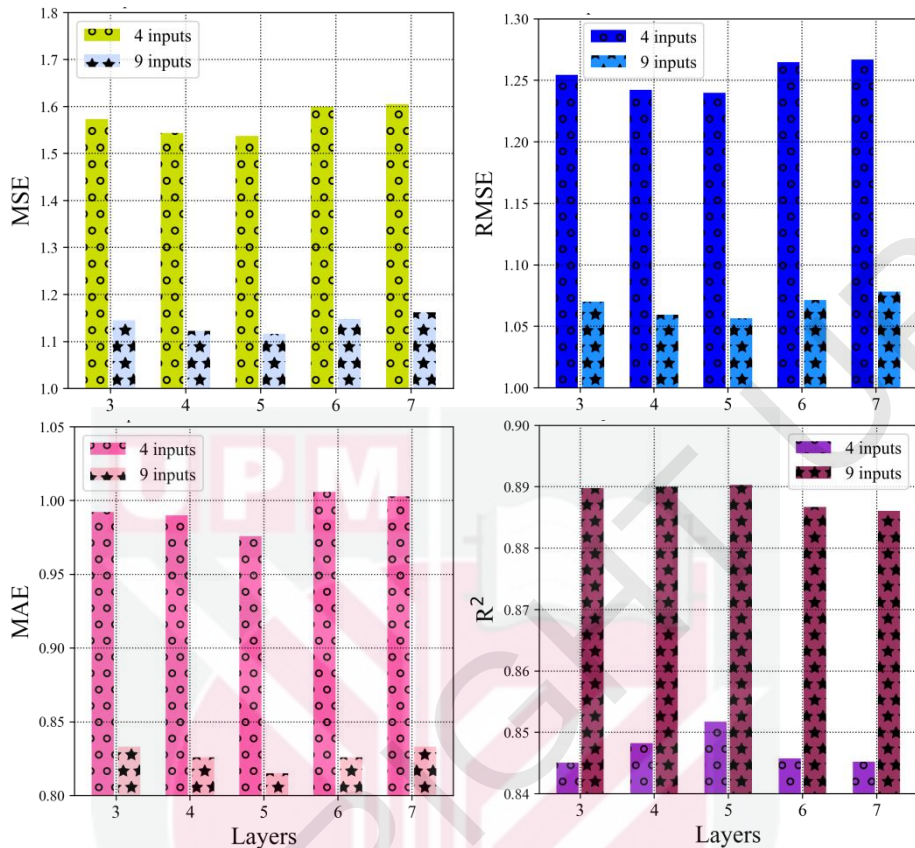


Figure 4.22 : Comparison of 4-Input and 9-Input Neural Networks

In summary, among the different configurations evaluated, the 9-input, 5-layer neural network structure demonstrated the best performance for predicting the Fire Weather Index (FWI). This model exhibited superior accuracy and precision compared to other configurations with varying numbers of inputs and layers. These results suggest that the inclusion of nine input features and the utilization of a five-layer neural network architecture provide the optimal balance between complexity and predictive performance for FWI estimation. Researchers and practitioners can rely on the nine-input, five-layer model as a robust and reliable tool for FWI prediction in forest fire risk assessment and management.

Figure 4.23 compares the Fire Weather Index (FWI) predicted by a 5-layer, 9-input neural network and the FWI published by METMalaysia between January 17th and March 31st, 2020. The upper subplot displays the distribution of FWI published by METMalaysia, while the lower subplot shows the FWI predicted by the neural network. The color bar in the middle of the figure represents the FWI risk level, with blue indicating low risk (0-2), green indicating moderate risk (2-7), yellow indicating high risk (7-13), and red indicating extreme risk (>13).

Overall, the color zones in the upper and lower subplots are similar, except for some discrepancies on January 25th and 27th, where the predicted FWI shifted from green to yellow and on March 6th, where a blue risk level was predicted as green. This suggests that the neural network can effectively predict FWI levels and is in agreement with the published data.

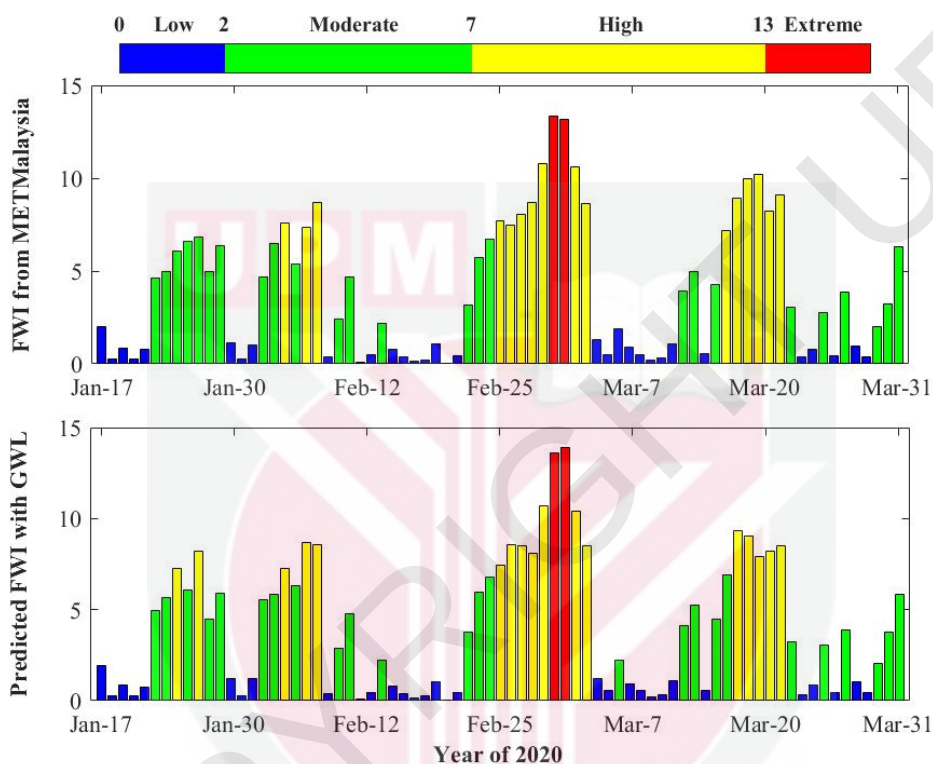


Figure 4.23 : Comparison of FWI Predictions by 9-Input, 5-Layer Neural Network with The Data from METMalaysia

The prediction of Fire Weather Index (FWI) is a critical task for forest management and fire prevention. Furthermore, the predicted FWI values were compared to the FWI data published by METMalaysia for the period of January 17 to March 31, 2020. The comparison revealed a high degree of similarity between the predicted and actual FWI values, with the exception of a few discrepancies in the color-coded risk categories. Overall, this study demonstrates the effectiveness of using a neural network machine learning approach for predicting FWI and its potential for supporting forest management and fire prevention efforts.

4.6 Summary

This chapter demonstrates the effectiveness of IoT systems in environmental monitoring and their ability to provide accurate and reliable data that can inform management practices and improve the resilience of ecosystems. The IoT system provides an efficient and cost-effective way to monitor the environment and understand the ecological processes at Raja Musa Forest Reserve. By implementing this system, the vital ecosystem can be better protected and ensure that it continues to provide essential ecological services such as carbon sequestration, biodiversity conservation, and water regulation. The work presented in this thesis can inspire further research and development in the field of environmental monitoring and contribute to the sustainable management of ecosystems worldwide.

The developed models have the potential to assist in drought and fire risk management in the study area. The GWL model can provide useful information for water resource management, while the FWI model can provide important information for fire prevention and management. The models can be integrated into decision support systems to help stakeholders make informed decisions regarding drought and fire risk management. However, further studies are needed to validate the models in other regions with different climatic conditions.

Moreover, The proposed work exhibits certain limitations that should be acknowledged. The deployment of a limited number of sensor nodes may restrict the geographical coverage, potentially limiting the generalizability of the findings. Additionally, the reliance on meteorological data collected within a specific timeframe (January 17, 2020, to March 31, 2020) might not capture the full spectrum of climatic variability throughout the year. Human factors, such as the need for regular maintenance and the vulnerability of sensor nodes to external interference, could introduce uncertainties into the dataset.

To address these limitations and pave the way for future research, future work should focus on mitigating the identified limitations by increasing the number of sensor nodes, extending data collection periods, and addressing human-related factors. These enhancements will contribute to a more robust and universally applicable predictive model for wildfire risk assessment based on IoT and machine learning.

CHAPTER 5

CONCLUSION AND FUTURE RESEARCH

Peatland forests provide various forestry products and by-products, such as timber and pulpwood, and play a crucial role in protecting the environment, regulating ecological climate, and preventing floods. They hold significant environmental significance. However, with the continuous development of infrastructure and advances in science and technology, the demand for peatland resources has increased rapidly. This has led to excessive and often unsustainable exploitation, resulting in the depletion of peatland resources. Natural disasters, particularly forest fires, pose a significant threat to peatland resources, causing irreversible damage. The impact on the ecological environment is immeasurable, putting many endangered species at risk of extinction. The severity of forest fire risks in peatland areas cannot be underestimated. Therefore, the research on peatland forest fire risk prediction and forecasting models holds paramount importance in scientifically preventing and mitigating fires and improving disaster prevention and reduction systems. This chapter provides a comprehensive summary of the thesis and offers new research directions and recommendations for future development.

5.1 Conclusion

This thesis focuses on the prediction system for peatland forest fires in the Raja Musa Forest Reserve in Selangor, Malaysia, with an emphasis on tropical peatland areas. The study begins by validating the data collected by the Internet of Things (IoT) system deployed in the peatland forest against METMalaysia data, confirming the authenticity and scientific validity of the IoT system's measurements. Building upon this validation, the integration of groundwater levels into the existing fire weather index system is successfully achieved, allowing for the direct calculation of drought code based on groundwater levels.

Furthermore, an efficient and low-complexity model for computing the Duff moisture code is proposed, which eliminates the need for previous day's data by directly utilizing groundwater levels and air humidity. Subsequently, a 6-input, 3-layer neural network algorithm based on machine learning is employed to accurately predict groundwater levels using weather data measured by the IoT system, which are then integrated into the fire weather index system. Finally, in combination with the weather data collected by the IoT system, machine learning techniques employing neural networks with varying input parameters and layer configurations are utilized to forecast the fire weather index with high accuracy. These advancements are highlighted in the following four key aspects.

- a. By incorporating groundwater levels into the Fire Weather Index (FWI) system, the method of calculating moisture codes using temperature and rainfall was replaced with the use of groundwater levels, successfully integrating them into the system. Initially, a curve fitting analysis was performed, comparing the groundwater levels measured by the IoT system between January 17 and March 31, 2020, with the corresponding drought codes published by the METMalaysia. Two model algorithms were derived from the fitting analysis, demonstrating that groundwater levels alone can be used to calculate drought codes without relying on temperature, rainfall, or the previous day's drought codes. Subsequently, the proposed linear and power algorithms were applied to compute the drought codes, and the correlation between the computed drought codes and the fire weather index was compared to the correlation between the published drought codes and the fire weather index by METMalaysia during the same period (which was 0.505382615) to evaluate their accuracy. The results revealed that the linear algorithm yielded higher accuracy, achieving a correlation of 0.412702, whereas the power fitting algorithm only achieved 0.348317.
- b. The algorithm proposed in this thesis introduces the use of groundwater levels and air humidity to directly compute the Duff Moisture Code (DMC), replacing the need for temperature, rainfall, air humidity, and the previous day's code. Through curve fitting analysis, utilizing the groundwater levels and air humidity data measured by the IoT system and comparing it with the published Duff moisture codes by METMalaysia during the corresponding period, two model algorithms were derived: a linear model and a linear model combined with trigonometric functions. These algorithms allow for the direct calculation of the Duff moisture code using groundwater levels and air humidity without relying on temperature, rainfall, air humidity, or the previous day's code. Subsequently, the performance of the proposed models was evaluated by comparing them with the real Duff moisture codes published by METMalaysia, utilizing the corresponding air humidity, temperature, and rainfall parameters measured by both METMalaysia and the IoT system. The results demonstrated that the proposed linear model combined with trigonometric functions closely approximated the actual Duff moisture codes, achieving a correlation of 0.9071 and a mean square error of 2.5633. In contrast, the linear model showed slightly inferior performance, with a correlation of only 0.6846 and a mean square error of 4.5846. Furthermore, the algorithm used in the Canadian fire weather index system achieved a correlation of 0.7824 but had a significantly higher mean square error of 7.2021. These findings validate the applicability and contribution of the proposed algorithm to tropical peatland areas.
- c. Using a 6-input, 3-layer neural network, this study successfully employed machine learning to predict groundwater levels. The IoT system deployed in the Raja Musa Forest Reserve, Selangor, Malaysia, was utilized to collect minute-by-minute weather data between January 17th and March 31st, 2020. After preprocessing the data by removing outliers and missing

values, a dataset comprising 47,306 samples of soil temperature, soil humidity, rainfall, wind speed, atmospheric pressure, solar radiation, and groundwater levels was obtained. The dataset was divided into 80% training data (37,844 samples) and 20% testing data (9,462 samples). Using a three-layer neural network with six inputs (soil temperature, soil moisture, rainfall, wind speed, atmospheric pressure, and solar radiation), machine learning models were developed to predict the groundwater levels measured by two sensor nodes in the IoT system. The results demonstrated a high correlation of 0.95 between the predicted and actual groundwater levels for both sensor nodes. The mean square error between the predicted and actual values was approximately 13.256 for sensor node 1 and approximately 11.069 for sensor node 2. This discrepancy can be attributed to the proximity of sensor node 1 to an artificial water channel connected to a river, which introduces fluctuations in groundwater levels due to water extraction and the inflow of river water.

- d. By employing different neural network architectures, accurate prediction of the Fire Weather Index (FWI) using machine learning was achieved. Initially, the weather data collected by the IoT system monitoring the peatland was preprocessed, removing outliers and missing values. This resulted in a dataset of 47,306 samples containing various weather parameters. Among these parameters, the ground soil measurements from sensor node 2 were selected due to their stability and accuracy compared to those from sensor node 1. Subsequently, neural networks with different layer configurations (three, four, five, six, and seven layers) and input parameters (four, and nine inputs) were employed to predict the FWI. The input parameters included the traditional inputs of temperature, rainfall, air humidity, and wind speed from the Canadian Fire Weather Index system, as well as additional parameters such as atmospheric pressure, solar radiation, soil temperature, soil humidity, and groundwater level, totaling nine inputs. The results revealed that the neural network with nine inputs consistently outperformed the four-input configuration, and both achieved optimal performance when using a five-layer structure. Specifically, the four-input, five-layer neural network achieved a prediction with a mean square error of 1.537 and a correlation of 0.852 for the FWI, while the nine-input, five-layer structure attained a mean square error of 1.116 and a correlation of 0.890. This finding provides valuable insights for improving the accuracy of decision-making in wildfire prevention efforts in tropical peatland forests.

In conclusion, the study embarked on a journey to address specific objectives, initially focusing on the direct computation of Drought Code (DC) through Groundwater Level (GWL) and subsequently utilizing GWL and humidity for the calculation of Duff Moisture Code (DMC). The methodology seamlessly integrated these objectives, laying the groundwork for a comprehensive approach to wildfire risk assessment.

The initial step involved leveraging GWL to directly derive DC, illuminating the crucial interplay between groundwater levels and fire weather conditions. Following this, the incorporation of GWL alongside humidity data facilitated the computation of DMC, enriching the predictive capabilities of the Fire Weather Index (FWI). These parameters used for calculation then formed the basis for machine learning models, allowing for real-time FWI predictions.

The alignment of objectives, methodology, and results underscored the coherence of our research approach. By intricately linking the direct influence of GWL on DC, the combined impact of GWL and humidity on DMC, and the subsequent utilization of these parameters in machine learning models, the study aimed at providing a nuanced understanding of wildfire risk dynamics. The results, as validated through rigorous analyses and performance evaluations, substantiated the effectiveness of the proposed framework.

In essence, the study's journey traversed the realm of meteorological parameters, establishing a symbiotic relationship between GWL, DC, DMC, and ultimately, the FWI. This comprehensive exploration not only contributed to the refinement of wildfire risk assessment but also laid the groundwork for future endeavors in advancing predictive models and methodologies in this critical field.

5.2 Recommendations for Future Work

This thesis focuses on the prediction of wildfires in tropical peatland forests and presents innovative and successful integration of groundwater level into the existing fire weather index system. By leveraging machine learning in conjunction with data collected by the IoT system deployed in the peatland, accurate predictions of groundwater level and fire weather index were achieved. While some pioneering efforts have been made, there remain numerous areas for further exploration, which are constrained by limitations in time and resources.

- a. While this study focuses on leveraging ground parameters from peatlands along with selected meteorological variables for predictive modeling, it is essential to acknowledge the inherent limitation of this approach. The current model's predictive accuracy is constrained by its exclusive consideration of specific ground and atmospheric factors. To improve the accuracy of the prediction system, it is important to consider the complex factors that contribute to forest fires in peatland areas. While this thesis mainly focuses on naturally occurring forest fires, it is essential to account for anthropogenic factors that can also lead to forest fire incidents, such as smoking, waste burning, and lightning strikes. Future research efforts should aim to incorporate various human-related factors to enhance the accuracy of the prediction models. Additionally, forest fires are influenced

by multiple factors including meteorology, topography, fuel characteristics, and human activities. This study primarily considers meteorological factors and soil factors as input variables, which represents a relatively narrow focus. To further enhance the prediction system, future studies could explore the impact of topographic factors such as slope, aspect, position, and elevation on forest fires. Other factors such as fuel types, human activities, vegetation characteristics, historical fire occurrence, population density, and infrastructure can also be investigated. Therefore, incorporating a broader range of fire risk factors and exploring additional algorithms for comparison can improve the accuracy of forest fire occurrence probability predictions.

- b. It is essential to note that the present study relies exclusively on data sourced from two sensor nodes within a singular Internet of Things (IoT) system. To enhance the IoT system, future efforts should focus on expanding the infrastructure of peatland forest IoT monitoring stations, gradually densifying the network for collecting forest fire risk monitoring information, and improving the accuracy of input factor acquisition and meteorological data. However, there are several challenges in implementing IoT-based monitoring for peatland forests, such as limited automation capabilities of sensors and their restricted functionality, slow wireless transmission speeds, complex data processing algorithms, and incomplete coverage of monitoring locations. To improve the quality of monitoring, it is necessary to enhance the environmental emergency monitoring capabilities, especially in response to significant events and the frequent activity of uncontrollable wildlife in peatland forest areas. This can be achieved by strengthening the automation of operation and maintenance, gradually realizing remote maintenance of precision monitoring instruments, and improving the speed of data transmission. For instance, sensor devices can be upgraded or data processing algorithms optimized to enable qualitative and quantitative monitoring of pollutant indicators. Furthermore, the integration of IoT technology with other information technologies should be pursued to further enhance the monitoring capabilities. The design of the IoT system should also consider the scientific layout of monitoring locations, the precision of monitoring equipment performance, and the accessibility of data transmission, ensuring that the monitoring is real, accurate, and comprehensive.
- c. One potential limitation is the reliance on data from a single IoT system with limited spatial coverage. The development of Geographic Information System (GIS) and remote sensing technology can assist forest fire management agencies in deriving a series of management tools to further improve the accuracy of fire risk and potential fire behavior predictions. This advancement enables the application of these tools to a wider range of combustible materials and terrain conditions, while enhancing the effectiveness and accuracy of fire risk information. The combination of remote sensing and GIS technology holds great potential for applications in agriculture, forestry, marine science, meteorology, hydrology,

environmental protection, and geological environments. As the data in this thesis pertains to a single region with similar forest types and terrain, the predictive models may have certain limitations. In the future, remote sensing and GIS techniques can be utilized to incorporate ground survey data on vegetation type, age, biomass, and litter, in order to obtain maps depicting the spatial distribution and fuel capacity of forest fires. Additionally, vegetation moisture indices can be generated to establish spatial databases of forest fire risk climate indices and their spatiotemporal dynamics through integrated algorithms and systematic models.

- d. Moreover, a potential limitation of the current study is the IoT system, which may be susceptible to environmental disturbances, such as wildlife interference. To mitigate this concern and bolster the reliability of the monitoring infrastructure, there is a prospective avenue for integrating real-time surveillance using high-resolution cameras within the IoT system. The integration of high-resolution cameras into forest fire monitoring systems holds great potential for enhancing fire detection and response capabilities. High-resolution cameras provide detailed and real-time visual information that can complement existing sensor networks and improve situational awareness during fire events. These cameras can capture high-quality images of the fire perimeter, smoke plumes, and fire behavior, enabling accurate and timely assessment of the fire's intensity and spread. Furthermore, advancements in image processing algorithms and computer vision techniques can be leveraged to automatically analyze the captured images, extract relevant features, and provide valuable insights into fire behavior patterns. Additionally, the combination of high-resolution cameras with advanced data transmission technologies, such as satellite or wireless networks, enables the remote monitoring of fire-prone areas, even in remote and inaccessible locations. Future research efforts should focus on optimizing camera placement strategies, developing efficient image analysis algorithms, and integrating camera data with other sensor data to create a comprehensive and integrated forest fire monitoring system. The use of high-resolution cameras has the potential to revolutionize forest fire management and response, offering a valuable tool for early detection, accurate fire behavior prediction, and informed decision-making.
- e. A current limitation is the independent nature of monitoring and predictive information, lacking seamless integration within the study. To overcome this constraint, there is a prospective opportunity to integrate all monitoring and predictive data into a comprehensive, visual interface system. The integration of the forest fire prediction process into a comprehensive and visualized interface system can greatly enhance the application of the developed models. The data collection, preprocessing, fire risk factor extraction, and prediction procedures presented in this thesis are currently independent modules. In future research, these modules can be integrated to form a complete forest fire prediction system, which can provide an intuitive and user-friendly interface. This integrated system will enable the

utilization of meteorological forecasts for different regions and forest types to predict fire risk factors. By combining this information with the spatial distribution of fire fuels, the intensity and spatial patterns of forest fire hazards, and regional characteristics, a database for predicting and forecasting the spatial distribution of forest fire risk can be established. Additionally, an information dissemination system for forecast and decision support can be developed to provide more economically effective services.

- f. An existing limitation in the current research lies in its exclusive focus on wildfire prediction, without the incorporation of suitable response strategies. To enhance the effectiveness of forest fire management, it is crucial to develop a comprehensive fire response classification plan. This plan should establish a systematic framework for categorizing fire incidents based on their severity, size, and potential impact. The classification plan can be formulated by considering various factors such as fire behavior, fuel type, weather conditions, and the proximity of human settlements or critical infrastructure. The plan should include clear criteria and guidelines for each classification level, specifying the appropriate response actions, resource allocation, and evacuation protocols. Additionally, the plan should incorporate real-time monitoring and communication systems to facilitate efficient decision-making and coordination among fire management agencies. By formulating a well-defined fire response classification plan, authorities can effectively allocate resources, prioritize actions, and mitigate the risks associated with forest fires, ultimately minimizing the potential damage to both human lives and the environment.

In conclusion, further exploration and development in the field of forest fire prediction and management are essential to response to these complex natural disasters. The integration of advanced technologies, such as machine learning, IoT systems, remote sensing, and GIS, holds great potential in enhancing the accuracy and effectiveness of forest fire prediction models. By incorporating additional factors, such as human activities, terrain characteristics, and vegetation types, into the existing models, it can better assess fire risks and enhance the precision of fire behavior predictions.

Furthermore, the establishment of a comprehensive fire response classification plan is crucial for organizing and prioritizing firefighting efforts. This plan should consider various factors, including fire severity, size, and potential impact, to determine appropriate response actions and resource allocation. Additionally, the integration of real-time monitoring systems and communication platforms can facilitate timely decision-making and coordination among fire management agencies.

It is also important to emphasize the need for continuous improvement and validation of the developed models and systems. Regular evaluation using historical fire data and field observations can help refine the predictive models,

enhance their accuracy, and provide valuable insights for decision-making. Moreover, the utilization of visual interfaces and integrated platforms can facilitate the efficient dissemination of fire risk information, enabling stakeholders to make informed decisions and take proactive measures to mitigate fire hazards.

By combining these advancements in technology, comprehensive fire response planning, and continuous evaluation, it can enhance our capabilities in predicting and managing forest fires. This will ultimately contribute to the preservation of valuable ecosystems, protection of lives and property, and the sustainable management of our natural resources. Continued research and collaboration among scientists, policymakers, and stakeholders are crucial for the successful implementation and improvement of these strategies to combat forest fires effectively.

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