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A System for Efficient Environmental Monitoring and Detection of Forest Fires Through LoRa IoT and Artificial Intelligence

Thesis presented by

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for the degree of

Master's of Engineering Science – Electrical & Electronic Engineering

University College Cork

School of Engineering & Architecture

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March 2025

DECLARATION

Candidate's Declaration

I, Ipek Uremek do hereby declare that this submission is my own work toward the Master of Science Degree in the School of Engineering & Architecture, and that, to the best of my knowledge, it contains no material previously published by another person, nor materials that have been accepted for the award of any other degree of the University, except where due acknowledgment has been made in the text.

Candidate's Signature Date: 30/03/2025

Ipek Uremek

ABSTRACT

Forest fires are among the most pressing global challenges, causing devastating environmental, economic, and social consequences. With climate change intensifying the frequency and intensity of wildfires, the need for innovative, efficient, and scalable early warning systems has become more critical than ever. This thesis presents a versatile, cost-effective software and hardware platform for forest fire detection and prevention, leveraging advancements in low-power IoT protocols and Artificial Intelligence (AI) to address this global issue. The proposed system integrates a network of low-cost, LoRa-enabled sensors to monitor key environmental parameters such as temperature, humidity, and atmospheric pressure across vast forest ecosystems. LoRa (Long Range) technology provides an ideal communication solution due to its ability to transmit data over long distances with minimal energy consumption, ensuring the sustainability of the system in remote and resource-constrained areas.

Central to this system is the collaborative interaction between a localized model and a global model. The localized model operates at the node level, performing anomaly detection under resource constraints. Meanwhile, the global model, represented by meteorological centers, enhances predictions by integrating high-quality environmental datasets. ARIMA is employed for time-series forecasting, analyzing environmental trends, and enabling better model interplay, while decision tree algorithms are utilized for fire risk assessment, providing critical insights into potential fire occurrences.

The system's protocol integrates these components efficiently. LoRa-enabled sensors collect real-time environmental data, including temperature, humidity, and air pressure, and transmit it via LoRaWAN. At the node level, localized models perform initial anomaly detection, generating alerts and probability scores. These, along with raw sensor data, are sent to a central system, where a collaborative framework refines the analysis for improved fire prediction. To enhance reliability, the system incorporates a feedback mechanism that compares sensor readings with meteorological data from the Irish Meteorological Service, mitigating issues caused by noisy or incomplete data. This hybrid approach, combining low-power IoT protocols with machine learning enhances wildfire detection accuracy while maintaining energy efficiency and reducing operational costs.

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Publications

The following publication has resulted from this research:

- **Ipek Uremek**, Paul Leahy, and Emanuel Popovici. 2024. "A System for Efficient Detection of Forest Fires through Low Power Environmental Data Monitoring and AI." *Engineering Proceedings*, 68(1): 38. https://doi.org/10.3390/engproc2024068038.

List Of Abbreviations

AI: Artificial Intelligence

ARIMA: Autoregressive Integrated Moving Average

AVHRR: Advanced Very High Resolution Radiometer

GDP: Gross Domestic Product

IoT: Internet of Things

LoRa: Long Range

MODIS: Moderate Resolution Imaging Spectroradiometer

MQTT: Message Queue Telemetry Transport

NASA: National Aeronautics and Space Administration

RGB: Red Green Blue

TTN: The Things Network

U.S.: United States of America

WSN: Wireless Sensor Networks

List of Mathematical Symbols

°**C**: Celsius

ha: hectare

hPa: hectoPascals

km: kilometer

s: seconds

Chapter 1

INTRODUCTION

1.1 Background

Forest fires have become increasingly destructive due to a combination of climate change, human activities, and deforestation, posing severe risks to ecosystems, biodiversity, and human safety. Traditional fire detection methods often suffer from delayed responses, making early intervention difficult. As fires grow more frequent and intense, the demand for innovative, proactive solutions has escalated. Integrating Internet of Things (IoT) technologies with machine learning algorithms presents a promising strategy for real-time fire detection, offering predictive capabilities and timely responses. This research explores how IoT sensor networks, coupled with advanced data analysis, can provide more effective and timely forest fire detection systems, addressing the critical challenge of early detection and rapid response.

This global challenge has manifested in increasingly severe wildfire seasons in recent years. In 2023, Canada experienced its most devastating wildfire season on record, with more than 18 million hectares burned, resulting in significant deterioration in air quality throughout North America [1]. Southern Europe, particularly Greece, Spain, and Italy, experienced unprecedented wildfires during the summer of 2023, prompting mass evacuations and overwhelming firefighting resources [2].



Figure 1.1: Near Sorrento, British Columbia (Canada), August 18, 2023 [2]

The Amazon rainforest, often referred to as the ”lungs of the Earth,” has been a critical player in maintaining global ecological balance. However, it continues to suffer from relentless fires, largely fueled by illegal deforestation and the expansion of agriculture. These activities not only result in the destruction of invaluable biodiversity but also significantly contribute to global carbon emissions [3]. In California, wildfires have become a recurring disaster, with the 2023 fire season proving particularly devastating. Throughout the year, 157 structures were destroyed, including homes, businesses, and vital infrastructure. These fires caused widespread disruption to communities, displacing thousands of residents and causing major financial hardships. The total economic damage was estimated at $50 billion, which includes not only the direct costs of firefighting, recovery, and rebuilding but also the broader economic disruptions caused by power outages, transportation delays, and business closures [4], [5].



Figure 1.2: Wildfires sweep Amazon as Brazil suffers worst drought on record [3]

The 2024 Los Angeles wildfires alone are projected to cause between $135 billion and $150 billion in total economic losses, including over $20 billion in insured damages [6]. Beyond financial losses, the fires released harmful pollutants such as carbon monoxide and fine particulate matter (PM2.5), exacerbating respiratory and cardiovascular health risks. Southeast Asia has faced similar crises, where haze from Indonesian forest fires has led to respiratory illnesses and widespread disruption across Malaysia and Singapore [7].

Australia's 2019–2020 "Black Summer" bushfires further illustrate the catastrophic consequences of uncontrolled wildfires. Approximately 18.6 million hectares burned, over 3,500 homes were destroyed, and nearly one billion animals perished. The disaster incurred more than $100 billion in damages, and toxic smoke severely degraded air quality across major cities [8].

The worsening of wildfires is directly connected to a combination of environmental factors. Rising global temperatures have caused longer droughts, creating dry conditions that make it easier for fires to start and spread. Low humidity dries out vegetation even further, turning forests into highly flammable areas. Strong winds make the situation worse by quickly spreading flames over large distances, making it very difficult to control the fires. For example, the 2024 wildfires in Los Angeles were driven by hurricane-force winds, causing widespread destruction and overwhelming firefighters [9]. These events show the urgent need for better systems to detect and manage fires around the world.

With the growing frequency and severity of wildfires, early detection and monitoring

systems have become essential. These systems provide critical insights into fire risks and, when combined with predictive models, enable a proactive approach to wildfire management. By facilitating timely interventions, they help minimize the ecological, economic, and societal impacts of wildfires.

1.2 Problem Statement

Forest fires have historically been a natural ecological process, playing a critical role in maintaining biodiversity and ecosystem health. Naturally occurring fires, often ignited by lightning strikes or volcanic activity, have historically contributed to nutrient cycling, seed germination, and habitat regeneration. Many ecosystems, such as certain coniferous forests and grasslands, have evolved to depend on periodic fires for renewal and growth. However, the fragile balance of these natural cycles has been increasingly disrupted by human activities and climate change.

With the growing impact of anthropogenic factors—including deforestation, agricultural expansion, land mismanagement, and global climate change—the frequency, intensity, and scale of wildfires have dramatically increased. What were once localized, self-regulating natural occurrences have escalated into catastrophic disasters. Human-induced fires, whether intentional or accidental, now pose serious and far-reaching threats to ecosystems, biodiversity, and human safety. Moreover, global warming has exacerbated fire-prone conditions by increasing temperatures, extending drought periods, and lowering humidity, creating environments where fires can ignite and spread rapidly [10].

Forest fires are a significant and growing global threat, causing widespread environmental damage and contributing to the acceleration of climate change. The occurrence of these fires is influenced by a complex interplay of environmental factors, human activities, and increasingly unpredictable weather patterns due to climate change. Forest fires are not only destructive in terms of the immediate ecological damage they cause but also have far-reaching long-term impacts on biodiversity, carbon sequestration, and the resilience of ecosystems.

Wildfires often span vast areas, burning millions of hectares annually. For example, the 2019 Amazon wildfires saw an alarming increase in fires across Brazil, Bolivia, Paraguay, and Peru, with Brazil's INPE (National Institute for Space Research) reporting

a 77% increase, amounting to over 80,000 fires. This led to the destruction of approximately 906,000 hectares of the Amazon biome [11]. Similarly, in Europe, as of August 10, 2021, Turkey, Greece, and Italy experienced extensive fire outbreaks, with Turkey seeing an unprecedented 175,000 hectares burned, far exceeding its historical average of 39,000 hectares. These numbers illustrate the magnitude of the problem, highlighting the necessity of effective monitoring systems [12], [13].

In addition to geographic spread, the materials involved in a fire significantly influence its behavior and environmental impact. Vegetation type, soil composition, and atmospheric conditions determine a fire's intensity and duration. Fires in dense and organically rich forests release large amounts of carbon dioxide (CO_2), methane (CH_4), and nitrogen oxides (NO_x), contributing to air pollution and global warming. Grassland fires tend to spread quickly but extinguish sooner, while peatland fires smolder for long periods, causing persistent emissions. Fires near urban-wildland interfaces involve synthetic materials that release toxic compounds such as dioxins and benzene, posing severe risks to human health. Understanding these differences is essential for developing effective detection and response systems [14].

Beyond environmental concerns, wildfires pose significant risks to human health and economic stability. Smoke and particulate matter (PM2.5) emitted by fires contribute to air pollution, leading to respiratory and cardiovascular illnesses, particularly in vulnerable populations. For example, in Indonesia, forest fires in 2020 resulted in economic damages of approximately 13 million euros and caused severe health issues, affecting over 21,000 people [15]. The 2018 California wildfires caused an estimated $148.5 billion in economic losses, encompassing infrastructure damage, healthcare costs, and broader financial disruptions [16]. The economic toll of wildfires extends beyond firefighting costs and property damage to long-term recovery efforts, agricultural losses, and disruptions to local economies.

Figure 1.3 provides a visualization of annual wildfire occurrences in the Amazon from 2013 to 2019, highlighting a sharp increase in 2016 and 2019. These trends underscore the urgency of advancing detection and management strategies [17].

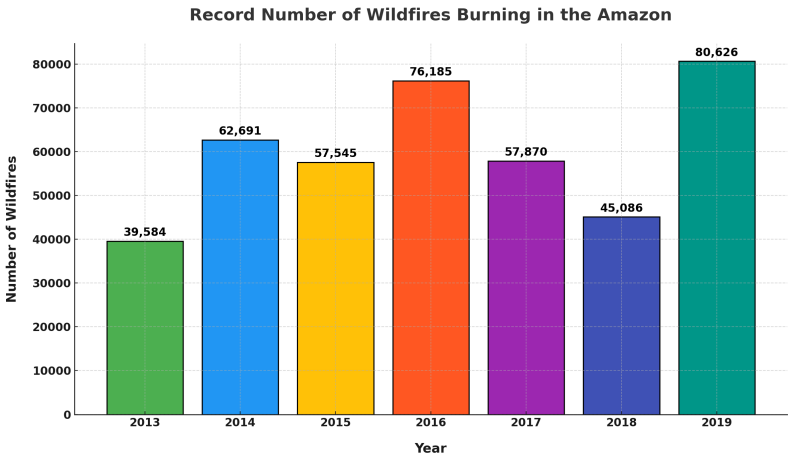


Figure 1.3: Number of wildfires recorded in Amazon by year between months January and August in years 2013–2019

Figure 1.4 compares the total burned area in 2021 with the 2008–2020 average, emphasizing the rising prevalence of wildfires in Southern Europe. Turkey, Greece, Italy, and Spain all experienced extreme fire seasons fueled by heatwaves, droughts, and strong winds [18].

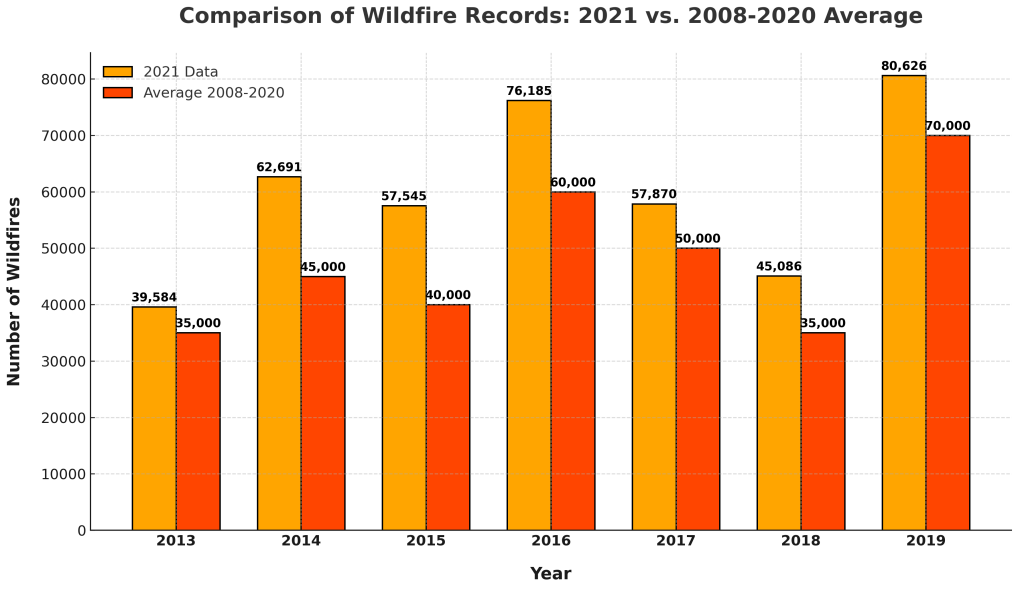


Figure 1.4: Total area burned by fires larger than 30 hectares in European countries most at risk of wildfires

These events reflect a global pattern of increased fire activity. Limitations in traditional detection methods, such as delayed response times and low resolution, reduce the

chance of detecting early-stage fires, particularly in densely forested or cloud-covered regions. Importantly, many current systems lack real-time monitoring of environmental parameters. IoT-based sensor networks offer a promising solution by enabling continuous tracking of temperature, humidity, air pressure, wind speed, CO_2, and particulate matter. This immediate insight enables early warnings and faster emergency response, potentially preventing fires from spreading uncontrollably.

The consequences of these fires extend beyond natural ecosystems to human settlements, agricultural areas, infrastructure, and the global climate. The release of greenhouse gases such as CO_2 exacerbates global warming, creating a loop that increases the likelihood of future fires. Regions such as the Amazon, Australia, Southern Europe, and parts of North America have all experienced increasingly severe wildfire seasons with devastating environmental and socio-economic consequences.

One of the most critical impacts of wildfires is biodiversity loss. The 2019–2020 Australian bushfires affected nearly three billion animals, including mammals, birds, reptiles, and amphibians [19]. Figure 1.5 illustrates this devastating impact.



Figure 1.5: Nearly 3 billion animals impacted by the bushfires according to WWF [19]

These disasters destroy entire ecosystems and fragment habitats, forcing surviving animals into degraded environments with limited resources. This increases competition

and vulnerability, leading to long-term declines in wildlife populations and biodiversity. Displaced animals are also exposed to new predators and environments they may not adapt to, compounding their risk. Forest fires disrupt natural regeneration cycles, releasing carbon stored in trees and soil. According to NASA's Atmospheric Infrared Sounder (AIRS), this release accelerates global warming and weakens global carbon sinks [20]. Furthermore, the melting of permafrost during fires releases trapped methane, a potent greenhouse gas, deepening the climate crisis [21].

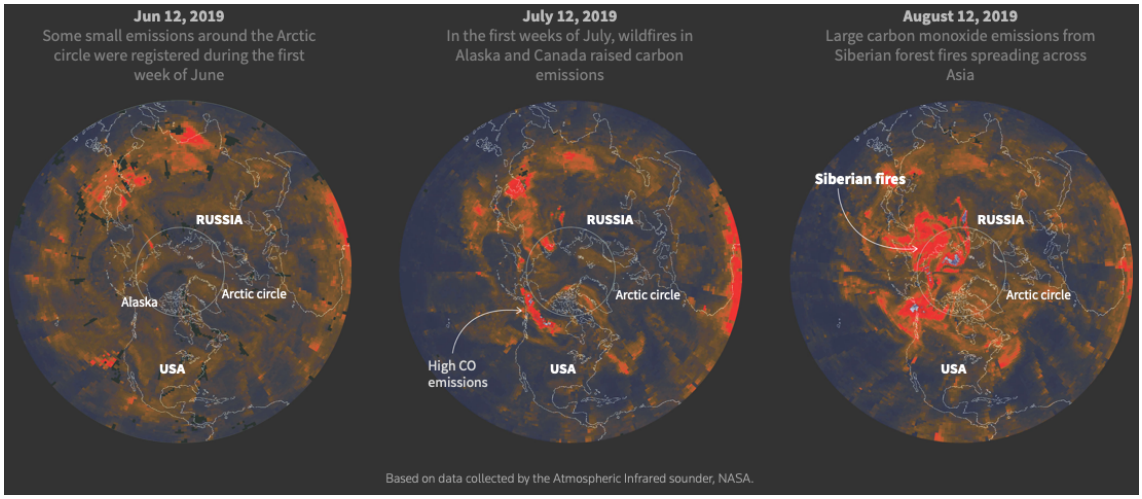


Figure 1.6: Wildfires release vast reserves of carbon stored in trees and soil, based on data collected by the Atmospheric Infrared sounder, NASA [20]

Public health is also affected, as wildfire smoke contains PM2.5, carbon monoxide, and toxic gases, which contribute to respiratory and cardiovascular illnesses [22]. Communities impacted by wildfires often face long-term psychological consequences, including PTSD, anxiety, and depression [23].

Turkey's 2021 wildfire season was marked by extreme weather conditions that created the perfect storm for widespread fires. Turkey's Mediterranean climate, characterized by hot, dry summers, makes the region particularly vulnerable to wildfires. In the summer of 2021, drought and low humidity, combined with record-breaking temperatures reaching up to 48.8°C (119.8°F), significantly increased the risk of ignition. Unprecedented heatwaves, plunging humidity levels, and strong winds ignited and rapidly spread fires across the Mediterranean region, including Turkey. These fires killed more than 100 people and burned over 620,000 hectares of land in July and August, devastating homes,

agricultural lands, and wildlife habitats [24], [25]. In 2021, wildfires in both California and Turkey were fueled by extreme heat, low humidity, and strong winds, creating highly flammable conditions that overwhelmed firefighting efforts and led to widespread destruction [26], [27]. These factors highlight the complex interplay of meteorological conditions that contribute to fire ignition and spread. Temperature, humidity, and atmospheric pressure are environmental indicators with direct influence on fire behavior. Hot temperatures and long droughts dry out vegetation, making it highly flammable. Low humidity speeds up this drying process, while strong winds spread flames quickly, making wildfires harder to control.

Traditional fire detection methods struggle to integrate and analyze critical environmental indicators in real-time, leading to delayed responses and uncontrolled fire spread. Wildfires escalate rapidly due to factors such as extreme temperatures, low humidity, shifting wind patterns, and increased concentrations of CO_2 and particulate matter. Monitoring these parameters is crucial for early detection, yet conventional systems often fail due to slow data processing, limited coverage, and reliance on vulnerable communication networks. During wildfires, standard communication channels frequently become unreliable or fail entirely, further delaying response efforts. To address these challenges, IoT sensor networks utilizing low-power protocols like LoRa offer a scalable and energy-efficient solution. These systems continuously track environmental changes, combining localized sensor data with large-scale meteorological inputs to provide early warnings before conditions escalate into full-scale fires. A drop in humidity, a sudden temperature spike, or a shift in wind direction can serve as critical precursors, enabling proactive interventions before disaster strikes.

Machine learning models, enhance predictive accuracy by identifying subtle patterns that precede fire outbreaks. However, prediction alone is not enough; continuous data transmission must be resilient against network failures. This system ensures continuous monitoring, even in extreme conditions, by leveraging decentralized, low-power communication networks that remain operational during crises. By integrating advanced detection technologies with improved emergency response strategies and policy frameworks, this approach strengthens resilience to wildfires, protecting ecosystems, human lives, and infrastructure from escalating fire risks. Immediate action is imperative to prevent devastating environmental, economic, and social consequences.

1.3 Research Objectives

The main objective of this research is to design and implement a spatially distributed IoT-based forest fire detection system that integrates LoRa technology with machine learning algorithms. This system will operate collaboratively, combining real-time sensor data with external meteorological inputs to enhance early detection accuracy. By taking advantage of a network of interconnected nodes, it aims to improve decision-making for timely and effective wildfire response.

1.3.1 Hypothesis

This research hypothesizes that IoT-based environmental sensor networks can significantly enhance wildfire detection by providing dynamic, low-cost, and scalable monitoring solutions. Traditional fire detection methods, such as satellite imagery and ground-based human surveillance, often suffer from delayed data transmission, limited resolution in early-stage fires, and poor accessibility in remote or densely forested regions, making them unreliable for rapid intervention. IoT systems, when integrated with low-power LoRa (Long Range) communication technology, offer a more resilient and adaptable alternative by enabling continuous environmental monitoring even in areas lacking traditional communication infrastructure. Unlike conventional networks, which may fail due to infrastructure damage, natural obstructions, or coverage limitations, LoRa's extended range and low power consumption allow for uninterrupted data transmission over distances of up to 10-15 km, making it particularly suited for wildfire-prone environments [28]. This ensures that even in active fire zones, where GSM or Wi-Fi networks may be unavailable, environmental data collection remains functional, providing critical real-time information for early risk detection.

Furthermore, the integration of LoRaWAN technology strengthens long-range, low-power communication, making it ideal for continuous environmental data collection in challenging terrains where energy-efficient operation is essential. Through the use of decision tree-based machine learning algorithms, the system can analyze temperature, humidity, wind speed, and atmospheric pressure data, identifying patterns and anomalies associated with early fire outbreaks. This approach enhances traditional detection methods by offering a predictive, data-driven framework that improves response times

and reduces false alarms. The system's ability to classify environmental conditions into risk levels ensures that decision makers receive more accurate, timely, and actionable insights, ultimately enhancing wildfire response efforts and mitigating environmental and economic losses. Through the synergy of IoT, LoRa-based communication, and AI-driven data analytics, this study presents a comprehensive solution that fills key gaps in current wildfire detection and prevention systems.

Moreover, the proposed system will implement a specialized communication protocol that dynamically balances macro-scale and micro-scale data processing. This protocol is designed to optimize data transmission and power consumption by prioritizing critical data while minimizing redundant communication. Through the integration of adaptive sampling and on-edge data processing, the system ensures that high-risk conditions trigger more frequent data collection, whereas normal conditions maintain energy efficiency. This interplay between local and global data models enhances monitoring capabilities without compromising the system's longevity.

1.3.2 Aims

The primary aim of this thesis is to design and implement an alternative forest fire detection system that leverages LoRa-based IoT networks and machine learning models, specifically decision trees, to enhance wildfire management. Beyond fire detection, the system also serves as an environmental monitoring tool, continuously collecting high-quality data on critical parameters such as temperature, humidity, wind speed, and air quality. By integrating both detection and monitoring capabilities, this approach ensures faster, more accurate, and responsive wildfire risk assessment while contributing to broader environmental analysis.

The focus of this research is on developing a cost-effective and scalable solution that integrates low-power, long-range IoT sensor nodes utilizing LoRa technology for real-time environmental data collection. The study aims to enhance the system's overall efficiency through a hybrid protocol that combines both cloud-based data and edge data processing, allowing for dynamic predictions while minimizing energy consumption. Besides that, machine learning models, particularly decision trees, will be used to analyze the collected sensor data, enabling the identification of early indicators of wildfire risks and supporting timely interventions.

The system's performance will be assessed based on its accuracy, energy efficiency, and reliability. The protocol's integration, including the interaction between local sensor data and broader weather forecasts, will ensure that predictions are continuously refined, providing a robust solution for wildfire detection and management.

In conclusion, this research aims to contribute to the development of an innovative, scalable, energy-efficient, and cost-effective wildfire detection system that can be deployed in fire-prone regions to proactively monitor and mitigate the risks of forest fires.

1.4 Scope of Work

There are five chapters in this thesis. Below is a description of each chapter's focus: Chapter Two begins with a comprehensive literature review, providing a detailed discussion and evaluation of previous studies, theories, and technologies relevant to forest fire detection. This chapter highlights existing fire detection systems, the role of IoT technologies, and machine learning models in environmental monitoring, identifying gaps that this research aims to address.

Chapter Three details the methodology used to design and implement the proposed forest fire detection system, including the integration of LoRa-based IoT networks and machine learning models. This chapter explains the system architecture, sensor deployment, data collection methods, and analytical techniques employed in the study.

Chapter Four presents the research findings and discusses the results of the study's objectives. It evaluates the system's performance in terms of detection accuracy, energy efficiency, and responsiveness, comparing the results with traditional fire detection methods.

Chapter Five concludes the thesis with a summary of findings and suggestions for future work. This chapter reflects on the research contributions and proposes directions for enhancing the system's scalability, adaptability, and overall effectiveness in environmental monitoring.

Chapter 2

LITERATURE REVIEW

Despite the widespread impact of wildfires, traditional fire detection methods remain inadequate in addressing these challenges. Satellite monitoring systems have long been the primary tool for large-scale fire detection. While they provide extensive coverage, these systems suffer from delayed data processing and transmission, limiting their effectiveness in the critical early stages of fire development. Satellites may pass over fire-prone areas infrequently, causing significant delays in detection. Additionally, any obstruction of the visibility can allow the fires to grow before being detected. Ground patrols and lookout towers have also been standard methods for fire detection, relying heavily on human observation. However, these approaches are labor-intensive and limited by the observers' field of view, making them ineffective for vast or remote regions. The reliance on human reporting introduces further delays, reducing the response time needed to contain fires in their initial stages. Aerial surveillance using drones and aircraft has improved detection capabilities but remains costly and cannot provide continuous, real-time monitoring. Furthermore, existing alarm systems often lack the precision and speed necessary to trigger timely evacuations and firefighting operations. The increasing severity of forest fires underscores the urgent need for alternative detection and prevention systems. Temperature, humidity, and atmospheric pressure are key environmental indicators that significantly influence wildfire behavior.

This analysis demonstrates that an effective wildfire detection system must account for both large-scale fire behavior and localized environmental conditions. Large-scale analysis involves assessing fire frequency, total burned area, and fire spread dynamics across different terrains, while localized data collection focuses on environmental monitoring,

including temperature, humidity, and atmospheric conditions that influence fire ignition and progression. Monitoring the types of substances burned such as dense vegetation, dry underbrush, and human-made materials provides insights into the environmental and health impacts of fire emissions. Addressing these factors requires a dual-layered approach, where historical fire data informs large-scale risk assessments, while real-time localized data enhances early detection and immediate response. Historical environmental data includes humidity, air pressure, and temperature measurements which are recorded before and during actual wildfire events and have been systematically archived by local meteorological offices for record-keeping and analytical purposes. Today, much of this valuable data is made available as open source, providing a rich foundation for large-scale risk assessments and long-term fire prediction models.

The second layer focuses on live localized data collected through IoT sensors. This stream of current measurements significantly enhances early detection capabilities and supports immediate response actions when potential fire conditions emerge.

To achieve a comprehensive understanding of wildfire behavior, large-scale fire data must be combined with localized environmental monitoring. Historical wildfire records provide valuable insights into fire frequency, total burned area, and regional fire trends, helping to identify high-risk zones and improve predictive modeling. Meanwhile, real-time sensor data enhances situational awareness by capturing localized fluctuations in temperature, humidity, wind speed, and other critical factors influencing fire ignition and spread. This analysis further highlights the necessity of large-scale fire data integration to track wildfire progression over time and assess the impact of environmental variables on fire behavior. By continuously logging fire occurrences and propagation patterns, large-range datasets contribute to more effective fire risk assessments, resource allocation, and long-term prevention strategies, ultimately reducing wildfire damage and improving environmental resilience.

2.1 Importance of Environmental Data

Accurate and timely environmental data is fundamental in understanding, predicting, and managing forest fires. Environmental parameters such as temperature, humidity, and atmospheric pressure are critical indicators of fire risk. These variables, when monitored

continuously, provide crucial insights into the environmental conditions that lead to wildfire outbreaks. By tracking these parameters, authorities and disaster management agencies are better equipped to assess fire risk conditions, predict the likelihood of fire ignition, and make informed decisions for timely interventions. Without comprehensive environmental data, predicting fire behavior and its spread becomes exceedingly difficult, leading to delayed responses and increased damage.

In addition to its vital role in fire management, environmental data is also critical across a variety of sectors, including agriculture, water management, and urban planning. The availability of accurate environmental data enables decision-makers in these fields to optimize operations and mitigate risks. For example, the Indian Agricultural Research Institute (IARI) has developed advanced forecasting models using environmental data to predict droughts and optimize irrigation systems, significantly improving crop yields [29]. In Kenya, LoRa-based environmental monitoring systems are utilized to support farmers by providing real-time data on soil moisture and weather conditions, enhancing resilience against climate-induced risks [30].

Moreover, environmental data is key to implementing smart city initiatives. Singapore's Smart Nation project integrates environmental monitoring to manage urban heat islands, improve air quality, and ensure public safety during hazardous weather conditions [31].

In everyday life, environmental data directly influences personal decision-making. Weather apps on smartphones provide instant updates and forecasts, helping people plan their activities and commutes. Air quality monitoring systems alert sensitive populations to pollution levels, allowing individuals to take protective measures, such as wearing masks or avoiding outdoor activities during poor air quality days. Energy companies also use environmental data to optimize electricity grids based on weather conditions, ensuring efficient energy distribution during peak demand periods. Additionally, smart home systems use temperature and humidity data to adjust heating, cooling, and ventilation, contributing to energy conservation and comfort [32].

By combining environmental data with predictive models, authorities can better anticipate high-risk zones and allocate firefighting resources efficiently. Subsequently, IoT-based sensor networks and remote sensing technologies offer localized, high-resolution data, improving the accuracy of risk assessments and enhancing the responsiveness of

mitigation strategies.

The growing severity and frequency of wildfires, exacerbated by climate change, underscore the urgent need for integrating environmental data into proactive fire prevention strategies.

2.2 LoRa Technology for Environmental Monitoring

Building on the importance of environmental data, LoRa (Long Range) [33] technology plays a critical role in enhancing the effectiveness of environmental monitoring. Originally developed for low-power wide-area network (LPWAN) applications, LoRa is well-suited for continuous data transmission in remote and challenging terrains, where traditional communication infrastructure is not feasible. Known for its long-range, low-power wireless capabilities, LoRa has been effectively adapted across various industries, including agriculture, logistics, and smart cities [34].

The key advantages of LoRa in environmental monitoring include its ability to transmit small amounts of data over vast distances with minimal energy consumption. This allows for the deployment of extensive sensor networks that can continuously monitor critical environmental parameters, making it an ideal solution for real-time monitoring in wildfire management and other environmental applications. LoRa networks are particularly valuable in remote forest areas, where their long-range communication capabilities eliminate the need for expensive infrastructure, while low energy consumption extends device lifespans and reduces maintenance costs [35]. Furthermore, the scalability of LoRa systems supports the interconnection of thousands of devices across large regions, facilitating widespread environmental monitoring.

LoRa's suitability for wildfire detection extends beyond its scalability. In forested environments, signal propagation differs from open landscapes due to vegetation density and terrain variations, which can cause signal attenuation. Studies show that LoRa's range in dense forests typically falls between 2–10 km, while in open rural environments, it can reach up to 15 km [28]. These characteristics make LoRa highly effective in non-urban, fire-prone regions, where traditional cellular infrastructure is limited. Additionally, LoRa's low power consumption allows sensor nodes to function for several years on battery power, significantly reducing operational costs and ensuring long-term sustainability

in real-time wildfire monitoring systems.

Compared to satellite or cellular networks, LoRa offers a more cost-effective and scalable solution for large-scale deployments, making it a practical choice for continuous, large-area environmental data collection and proactive interventions in areas prone to wildfires and other environmental hazards [36].

Banti et al. provide a comprehensive survey on LoRaWAN communication protocols, examining energy efficiency at different network layers, including the physical (PHY), medium access control (MAC), and network layers [37]. Their study categorizes recent research advancements in LoRaWAN energy optimization, focusing on strategies to improve power consumption efficiency while maintaining reliable long-range communication. The results highlight various techniques to enhance LoRaWAN performance in terms of energy savings and network scalability. Their study also explores different LoRaWAN network architectures, including the star-of-stars topology, which improves network efficiency by allowing multiple devices to communicate with a central gateway while maintaining low energy consumption. Figure 2.1 illustrates the star-of-stars topology and its role in optimizing LoRaWAN network performance.

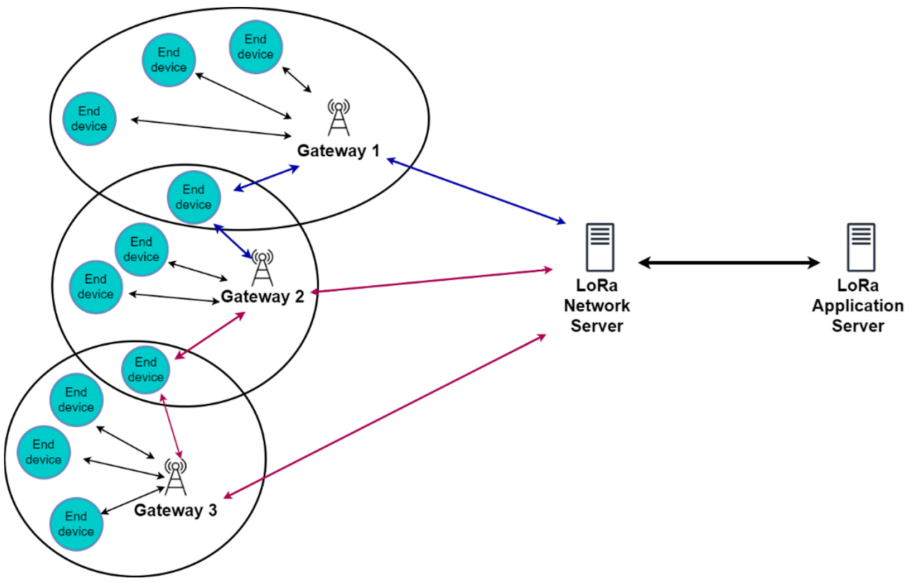


Figure 2.1: Star-of-stars LoRaWAN topology [37]

Globally, LoRa technology has been integrated into wildfire detection and environmental monitoring systems across various regions. In Portugal, the Forest Supervisor system developed by LADSensors deploys LoRa-enabled sensors across forested areas

to monitor critical environmental parameters such as temperature, atmospheric pressure, and wind speed. These sensors provide real-time data, which is transmitted to centralized systems for analysis. When certain thresholds are met, such as high temperatures or low humidity levels, the system triggers automatic alerts to local authorities, enabling faster responses to potential wildfires. [38]. Similarly, In Turkey, the system named Kozalak uses LoRa technology and gas-sensing sensors to monitor environmental conditions in wildfire-prone areas. The system tracks parameters like gas concentrations, transmitting the data via LoRaWAN. This enables early detection of fires, sending immediate alerts to authorities for faster response and prevention [39]. These systems highlight the effectiveness of LoRa technology in environmental monitoring and could serve as an example for integrating similar solutions in wildfire detection.

In the UK, LoRa networks are extensively used to monitor water levels and flood risks in coastal areas. The system integrates water level sensors and predictive flood models to provide real-time data to authorities, enabling timely interventions and preventing catastrophic flooding events [40].

In India, the integration of LoRaWAN technology into agriculture has enabled the development of innovative systems like LoRaFaRM, a modular IoT architecture designed for smart farming. This architecture leverages LoRaWAN's capabilities, such as long-range communication and low power consumption, to support real-time data collection and efficient resource management in rural farming areas. LoRaFaRM offers significant potential to enhance agricultural practices by providing actionable insights for better decision-making, contributing to the advancement of sustainable and productive farming techniques [41].

Similarly, LoRaWAN technology is revolutionizing urban services by providing efficient, and effective solutions for various industries, including waste management and environmental monitoring. Connected dumpsters equipped with LoRaWAN sensors allow for live tracking of waste levels. This capability enables the optimization of waste collection routes, reducing operational costs, fuel consumption, and emissions while maintaining cleaner urban environments. Additionally, LoRaWAN supports smart environmental monitoring by deploying sensors to measure air quality, water quality, and noise pollution. The data collected can forecast and mitigate pollution, prevent flooding by identifying risks early, and support better urban planning and public health initiatives. These inno-

vations demonstrate the versatility and transformative potential of LoRaWAN in building sustainable and efficient smart cities, aligning with the goals of Industry 4.0 [42]. Building on its success in urban applications, LoRaWAN is also playing an important role in advancing industrial systems as part of Industry 4.0. The technology facilitates predictive maintenance of machinery by monitoring equipment performance and detecting potential failures before they occur. This not only minimizes downtime but also significantly reduces maintenance costs. LoRaWAN supports asset tracking in large facilities, enabling efficient inventory management and resource allocation. The integration of LoRaWAN in industrial environments extends to condition monitoring, where sensors measure parameters such as temperature, humidity, and vibration, ensuring optimal operational efficiency and safety. These applications showcase the unparalleled versatility of LoRaWAN in improving sustainability, operational efficiency, and cost-effectiveness, thereby driving the development of smarter cities and industries [43].

In addition to these applications, LoRaWAN technology has been adopted in innovative wildlife conservation efforts, such as tracking endangered species like rhinos. In South Africa, LoRaWAN networks are utilized to monitor rhinos' movements within protected areas, equipping them with IoT-enabled trackers that provide real-time location data. This system helps conservation teams predict the animals' behavior and respond swiftly to potential threats, including poaching. By enabling precise tracking over vast areas, LoRaWAN technology has enhanced anti-poaching measures. As highlighted in conservation projects, such as those discussed by Abeeway, these efforts have significantly contributed to safeguarding endangered species, particularly rhinos, from illegal activities [44].



Figure 2.2: The LoRaWAN connected trackers get attached on collars which are then buckled onto rhino's legs [44]

The global adoption of LoRa is driven by several key advantages. Its long-range communication capability allows data transmission over distances of up to 15 kilometers in rural and remote areas. Subsequently, LoRa devices consume very little power, enabling them to operate for several years on battery power, which significantly reduces maintenance costs and makes them ideal for large-scale, long-term deployments [45]. The technology's scalability supports the connection of thousands of devices within a single network, allowing comprehensive environmental monitoring across vast regions. Furthermore, LoRa is a cost-effective solution compared to traditional satellite and cellular networks, making it accessible for widespread implementation in both developed and developing regions.

This combination of low power consumption, long-range connectivity, and scalability makes LoRa particularly valuable in disaster monitoring applications. While urban areas often benefit from immediate emergency response infrastructure, including fire hydrants, aerial firefighting resources, and quick access to electricity, non-urban and remote forested regions present unique challenges in fire detection and suppression. Fires in urban environments can often be contained quickly due to the availability of well-coordinated emergency services, whereas fires in remote areas can burn undetected for hours or even days before intervention is possible.

One of the primary obstacles in non-urban fire management is the lack of electricity and communication infrastructure. Many rural and forested regions lack cellular coverage, making real-time fire detection and alert systems less effective. Additionally, fire-

fighting teams in these areas often face logistical difficulties in accessing fire sites due to rough terrains, dense vegetation, and long distances from emergency facilities. These delays can lead to exponential fire spread, making containment significantly more difficult.

Given these constraints, LoRa (Long Range) technology emerges as a promising solution for wildfire detection in remote and power-scarce environments. LoRa-enabled IoT networks can operate on low power, meaning sensor nodes can function for years on battery power without requiring frequent maintenance or grid connectivity. Moreover, LoRa's long-range communication capabilities allow for seamless data transmission from fire-prone zones to centralized monitoring stations, even in the absence of cellular networks.

The integration of LoRa-based environmental monitoring can significantly enhance fire prevention strategies in non-urban settings. By continuously monitoring temperature, humidity, and air pressure, LoRa sensors can detect fire-prone conditions before ignition occurs, allowing authorities to take preemptive action. In addition, these systems can support automated early warning alerts, ensuring timely intervention in areas where manual surveillance is impractical. Real-world deployments, such as Dryad Networks' Silvanet system, have demonstrated how LoRa-based mesh networks can provide early wildfire detection even in dense forests, helping to reduce response times and mitigate damage [46].

These attributes make LoRa an essential component of early warning systems for natural disasters such as floods, earthquakes, and wildfires. Its ability to continuously monitor environmental parameters—including temperature, humidity, air quality, and even gas emissions—creates opportunities for proactive disaster risk reduction. LoRa's integration with data analytics and predictive models enhances its capacity to deliver timely alerts, supporting rapid response strategies and minimizing environmental and economic damage. The next chapter will explore a specialized LoRa-based wildfire detection system that leverages these advantages to improve proactive wildfire management.

2.3 The Role of Big Data in Environmental Monitoring

The integration of big data into environmental monitoring systems has significantly improved the prediction and management of environmental risks. Big data, particularly meteorological and environmental datasets, provides critical insights into weather pat-

terns, temperature, humidity, wind speeds, and atmospheric pressure, key variables that influence natural disasters such as wildfires, floods, and droughts. The analysis of these massive datasets enables more accurate forecasting and improves the responsiveness of disaster management systems.

Scientific studies have demonstrated the impact of big data integration in disaster management. For example, NASA's Earth Science Division leverages satellite-based big data for real-time weather and environmental monitoring, allowing for early detection of wildfire-prone conditions globally [47]. The Fire Information for Resource Management System (FIRMS) provides a live visualization of fire hotspots detected by satellites such as VIIRS (Visible Infrared Imaging Radiometer Suite) and MODIS (Moderate Resolution Imaging Spectroradiometer). The image below illustrates active wildfire detections across North and Central America, demonstrating how satellite-based remote sensing enables large-scale fire tracking and response planning.

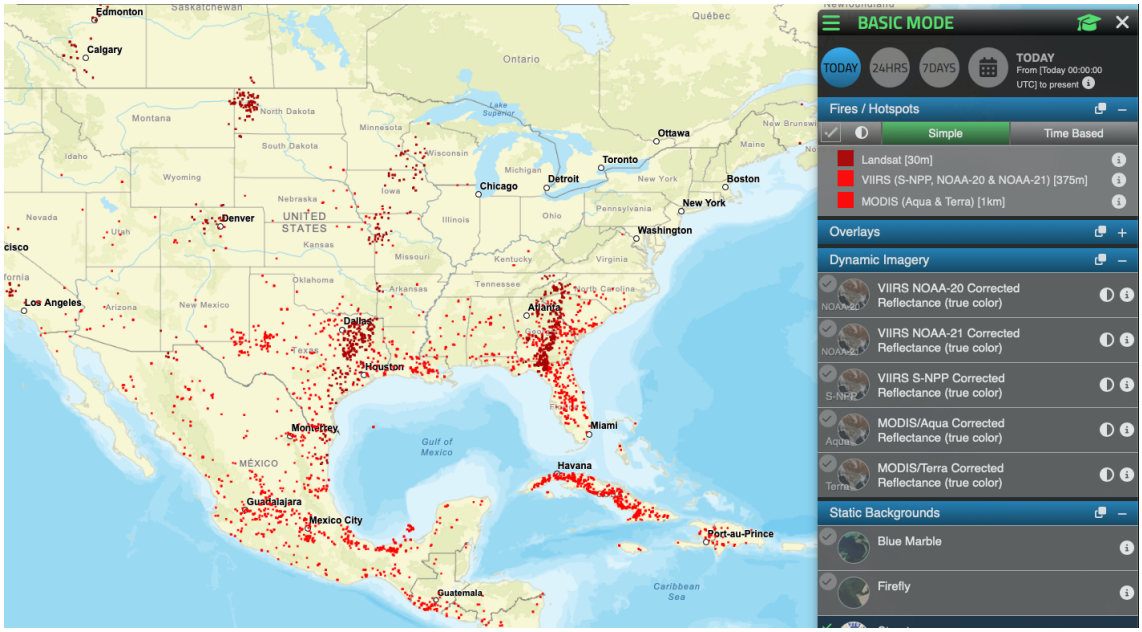


Figure 2.3: NASA FIRMS active fire monitoring using VIIRS and MODIS satellites. The system provides real-time wildfire detection, supporting disaster response efforts [48]

Beyond hotspot detection, satellite-based fire tracking systems provide critical atmospheric insights by capturing the distribution and elevation of wildfire smoke plumes. The Colby Fire in California, as detected by NASA's Atmospheric Infrared Sounder (AIRS) and MODIS instruments, illustrates how remote sensing technologies visualize wildfire

smoke in three dimensions. Figure 2.4 displays the smoke elevation height and dispersal patterns following the Colby Fire, demonstrating the extent of airborne particulate spread across urban and coastal regions. These satellite-based models are essential for tracking air quality deterioration, assessing fire intensity, and improving predictive models for future wildfire events. The analysis indicates that smoke from the Colby Fire reached heights of approximately 4 kilometers (2.5 miles), with an estimated areal coverage of 10,000 square kilometers (3,860 square miles). Understanding these smoke dispersal patterns is crucial for evaluating health risks, atmospheric transport, and the impact of wildfire emissions on regional air quality [49].

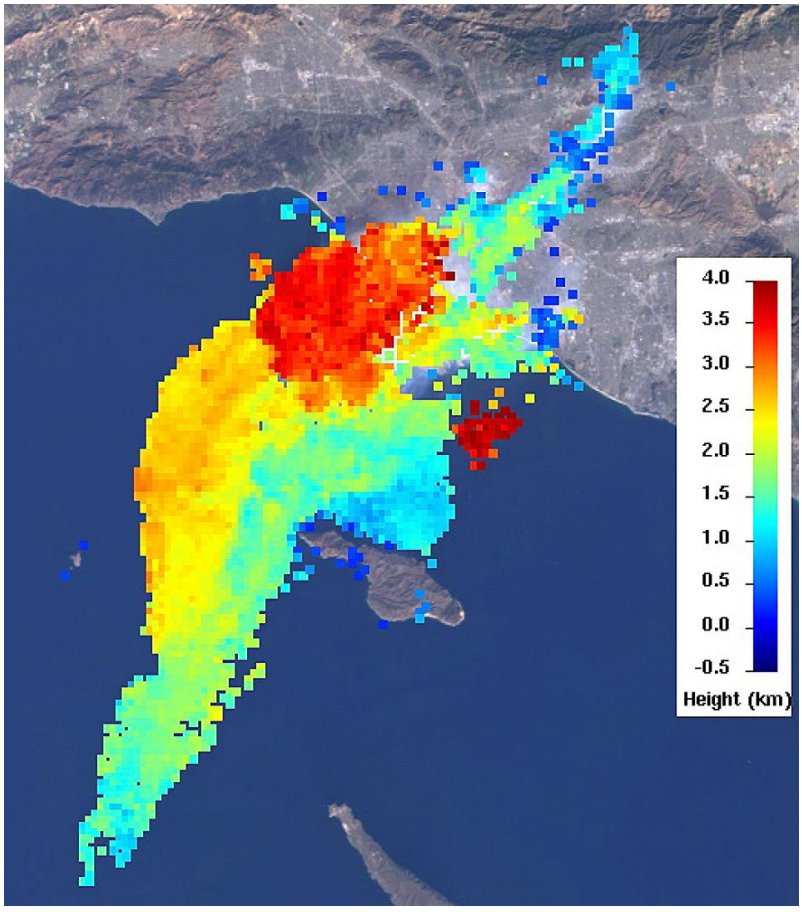


Figure 2.4: Smoke elevation map from the Colby Fire, California, showing widespread particulate dispersal [49]

Similarly, the European Forest Fire Information System (EFFIS) uses extensive meteorological and environmental data to assess wildfire risks across Europe, providing critical support to firefighting agencies [50]. The EFFIS Risk Viewer Interface 2.5 visually represents fire danger levels, aiding in monitoring and decision-making [51].

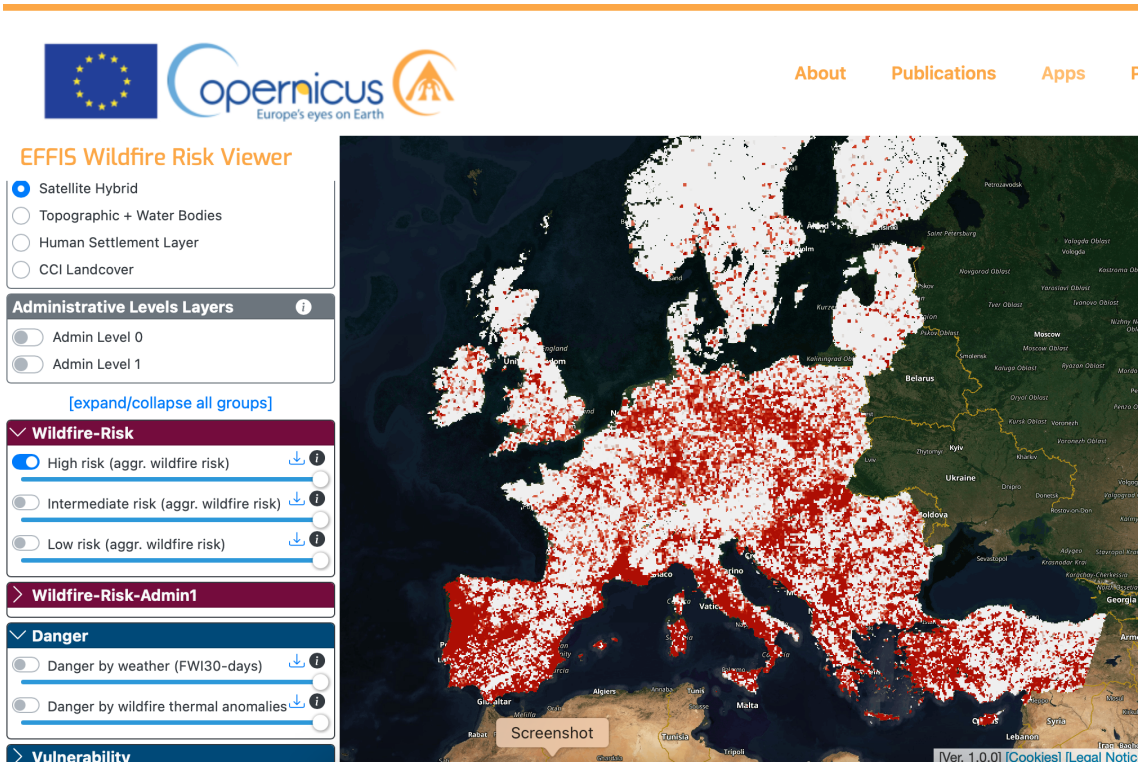


Figure 2.5: EFFIS Risk Viewer Interface [51]

In wildfire detection, large-scale meteorological data is crucial for identifying trends such as drought severity, high temperatures, and low humidity, which significantly elevate wildfire risk. By analyzing both historical and real-time data, predictive models can pinpoint high-risk areas, enabling firefighting agencies to allocate resources more effectively. This integration also supports proactive measures, such as issuing early warnings and optimizing evacuation plans, improving wildfire preparedness and response.

While big data from global weather stations provides broad, macro-level insights, ground-based sensor networks, such as LoRa devices, capture localized environmental fluctuations. Integrating these two datasets enhances predictive accuracy, offering a more detailed and adaptive approach to wildfire monitoring. AI-driven analytics are increasingly being used to process both macro-level satellite data and real-time ground-level sensor readings. At the macro scale, machine learning models analyze vast environmental datasets to detect fire-prone conditions, while at the ground level, it is imperative that AI models remain lightweight and energy-efficient, ensuring instant processing with minimal power consumption.

2.4 Time Series Forecasting in Environmental Applications

Environmental systems inherently produce sequential data (for example, meteorological records, streamflow measurements, or pollutant concentrations), so forecasting these time series is essential for anticipating future conditions and guiding management actions. Models trained on historical observations can project trends in climate, water quality, air pollution, and other variables, thereby supporting resource planning, hazard preparedness and policy decisions. For instance, Barbulescu et al. emphasize that continuous environmental time series data play a crucial role in planning, risk assessment and decision-making [52].

By capturing temporal patterns and dependencies in environmental data, time series analysis provides a methodological foundation for forecasting that enhances the understanding of underlying processes. This, in turn, supports the long-term environmental planning, and contributes to the implementation of timely mitigation and adaptation strategies by relevant stakeholders [53].

Environmental time series often exhibit complex temporal dynamics, necessitating a diverse range of forecasting techniques. These include classical statistical models such as autoregressive integrated moving average (ARIMA) and exponential smoothing [54] as well as modern machine learning architectures like long short-term memory (LSTM) networks [55]. This array of methods provides a comprehensive toolkit for addressing the challenges of environmental forecasting.

ARIMA was selected for this project due to its proven reliability in modeling linear, time-dependent data and its interpretability, which is crucial for environmental forecasting systems. Compared to more complex models such as LSTM neural networks or Exponential Smoothing, ARIMA provides a balance between predictive performance and computational efficiency—especially when working with small datasets or when real-time prediction and interpretability are key constraints. While LSTM models offer superior performance in capturing non-linear dependencies and long-term trends, they require extensive training data and high computational resources, which may not be feasible for remote, resource-constrained IoT deployments. Exponential Smoothing, on the other hand, is computationally lighter but may not capture temporal dependencies as well as ARIMA

in multi-variable contexts.

Given these trade-offs, ARIMA serves as a robust baseline for this project. However, future work may explore hybrid models or lightweight neural networks like GRU (Gated Recurrent Unit), which combine some benefits of LSTM with reduced complexity, making them suitable for embedded systems.

The ARIMA model is a widely used statistical tool for time series forecasting, particularly in the analysis of environmental data [56]. These models are highly effective in identifying trends and patterns within large datasets, making them suitable for predicting environmental changes that contribute to natural extreme events [57]. By modeling temperature, humidity, and atmospheric pressure data, ARIMA models can forecast conditions that increase the likelihood of wildfires. The general form of an ARIMA model is given in Equation 2.1.

$$Y_t = c + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{2.1}$$

where Y_t represents the time series at time t, c is a constant, ϕ_i and θ_j are the coefficients for the autoregressive (AR) and moving average (MA) terms, respectively, and ε_t is the error term. The ARIMA(p,d,q) structure consists of three components: the autoregressive (AR) part, which captures dependencies between past and present values, the integrated (I) part, which ensures stationarity by differencing the data, and the moving average (MA) part, which accounts for the influence of past forecast errors. These components allow ARIMA to effectively model and predict complex environmental patterns, making it particularly useful for forecasting climate conditions that may lead to natural disasters such as wildfires. For instance, a study by Talamanova and Pllana explored the application of time series forecasting methods, including ARIMA, to predict air quality in urban areas. The study compared ARIMA with Exponential Smoothing (ES) and Long Short-Term Memory (LSTM) networks for short-term air pollution forecasting. Their findings revealed that while ARIMA models were effective, ES demonstrated superior prediction accuracy and lower computational complexity, making it a more efficient choice for real-time air quality monitoring. This research highlights the potential of data-driven approaches to provide early warnings and improve disaster preparedness in urban environments [58]. Similarly, a study conducted in Yunnan Province, China, integrated ARIMA models with stepwise regression analysis to forecast long-term trends in forest

fire occurrences. By analyzing historical data from 1991 to 2021, including variables such as temperature, annual rainfall, relative humidity, and wind speed, the researchers identified key factors influencing fire incidence. The ARIMA model predicted a cyclical pattern of forest fires from 2022 to 2033, with significant fluctuations anticipated in 2027 and 2033. These predictions provide valuable insights for developing early warning systems and informing resource allocation for fire prevention and management efforts [59].

The strength of ARIMA lies in its ability to handle non-stationary data, which is common in environmental datasets due to seasonal and long-term variations. By incorporating differencing techniques, ARIMA models can stabilize fluctuating data and reveal underlying trends. This makes them particularly useful for predicting gradual changes in climate conditions that could escalate into disasters.

Combining ARIMA models with the data collected from IoT sensors enhances predictive accuracy. This combination of technologies ensures that predictive models remain dynamic and responsive to changing environmental conditions, providing more reliable early warnings.

2.5 Predictive Classification in Environmental Applications

Environmental data classification plays a critical role across diverse applications, from ecological monitoring to resource management and climate modeling. In these contexts, machine learning algorithms are employed to transform complex environmental datasets into discrete categories. These categories may reflect land use types, pollution levels, or risk assessments, enabling actionable insights that support timely and informed decision making in both research and policy domains. Artificial Intelligence (AI), particularly machine learning, has transformed environmental monitoring by enabling the processing and interpretation of large, heterogeneous, and high-dimensional data streams. These techniques offer scalable, adaptive, and often real-time classification capabilities, allowing for improved management of environmental systems and hazards [60]. Commonly used classification models include Support Vector Machines (SVMs), k-Nearest Neighbors (k-NN), Neural Networks (NNs), and Decision Trees, each with its own advantages and trade-offs in terms of computational efficiency, interpretability, and accuracy.

SVMs are margin-based classifiers that construct hyperplanes to optimally separate data classes, often achieving high accuracy even with limited training samples [61]. They are well suited for high-dimensional and noisy data, making them effective for many environmental applications. However, SVMs require careful selection of kernel functions and hyper-parameters, and their decision boundaries are generally not as transparent in critical decision-making contexts.

Neural networks are a class of machine learning models inspired by the structure and function of the human brain, designed to recognize complex patterns through layers of interconnected nodes [62]. Deep learning architectures have achieved impressive results in classification tasks, especially when dealing with high-dimensional data, unstructured inputs like images or audio. Nonetheless, they require significant computational resources, large labeled datasets, and careful tuning, which can be prohibitive for deployment in edge devices with constrained memory and processing power.

k-Nearest Neighbors (k-NN), is a nonparametric, instance-based learning algorithm that classifies data based on the majority label among its nearest neighbors in the training set [63]. Although it is easy to implement and does not require a training phase, its reliance on storing the entire dataset makes it memory intensive and computationally slow during prediction, especially problematic in large-scale environmental datasets. Additionally, its performance depends heavily on the choice of distance metric and the value of k, which may vary across domains and datasets.

Among these, decision tree models stand out for their simplicity and ability to analyze diverse environmental data. In contrast, decision trees provide fast predictions, require minimal pre-processing, and their rule-based structure aligns well with embedded systems' logic. These qualities make them especially suitable for IoT-based wildfire detection systems that must operate under constraints of power, memory, and explainability. Decision tree-based algorithms operate by repeatedly dividing the dataset into smaller subsets based on different attribute values until a specific stopping condition is reached. This process creates a tree-like structure, where each internal node represents a decision or a split based on a particular attribute, and each leaf node signifies a final classification or prediction [64]. To determine the best split at each node, decision trees use different mathematical approaches. For classification problems, entropy, information gain, and gini impurity are the key metrics. Entropy measures the impurity (randomness) of a dataset.

$$H(S) = -\sum_{i=1}^{c} p_i \log_2 p_i \tag{2.2}$$

where: $H(S)$ is the entropy of dataset S, c is the number of classes, p_i is the probability of class i.

Information Gain (IG) determines how much entropy is reduced after a split.

$$IG(S,A) = H(S) - \sum_{v \in A} \frac{|S_v|}{|S|} H(S_v) \tag{2.3}$$

where: A is the attribute used for splitting, S_v represents the subsets created after the split. The attribute with the highest Information Gain is selected for splitting.

$$Gini(S) = 1 - \sum_{i=1}^{c} p_i^2 \tag{2.4}$$

An alternative to entropy, Gini impurity, is given by Equation 2.4. A split is chosen that minimizes the weighted Gini impurity.

Studies such as Sousa et al. [65] have successfully deployed Hoeffding Tree models on FPGAs for instant adaptive learning, while Daghero et al. [66] demonstrated energy-efficient ensemble decision trees operating on IoT edge nodes, confirming their suitability for resource-constrained, low-latency deployments.

In the context of wireless communication, the integration of machine learning algorithms is essential to maximize the utility of the collected data. Decision tree models are particularly effective for this purpose, as they can handle both numerical and categorical data, enabling real-time predictions of wildfire risks by evaluating environmental factors such as temperature, humidity, and air pressure. This allows for proactive responses and faster judgment during emergencies [67]. By enhancing the system's predictive capabilities, decision trees enable quicker detection, timely alerts, and more efficient resource deployment in wildfire situations.

What makes decision trees especially powerful in environmental applications is their ability to process multiple variables to assess risks related to natural disasters such as wildfires, floods, and landslides. Their clear decision pathways ensure quick, transparent decision-making, which is critical in high-pressure disaster scenarios. Moreover, when integrated with real-time data from IoT devices, decision trees provide dynamic, location-specific risk assessments, allowing for more targeted and effective interventions.

Several studies highlight the effectiveness of machine learning models in environmental risk prediction, particularly in wildfire management. For instance, Tallam and Shakeri (2022) utilized random forest algorithms, a robust ensemble of decision tree models, to predict wildfire susceptibility in Napa County, California. By analyzing key environmental factors such as vegetation type, topography, and historical fire data, their model achieved an impressive 91.7% accuracy in identifying areas prone to wildfires. This high level of precision allows for the development of proactive measures to mitigate wildfire risks, including targeted resource allocation and early warning systems [68]. Similarly, Lai et al. (2025) developed a rapid coseismic landslide assessment model for Taiwan by integrating Newmark analysis with a machine learning-based decision tree method. By evaluating 175 potential planar failure slopes with specific lithologies and strong motion records from 1990 to 2020, their model achieved an overall accuracy of 83.3% and a false-negative rate of 10.7%. This approach provides valuable insights for emergency response and disaster preparedness in seismically active regions [69].

Additionally, a study conducted in Quang Binh province, Vietnam, utilized the J48 decision tree algorithm to develop a flood susceptibility map. By analyzing various flood conditioning factors, the model demonstrated high predictive performance, with an Area Under the Curve (AUC) value of 0.97. This indicates a high level of accuracy in identifying areas prone to flooding, thereby providing valuable insights for flood risk assessment, mitigation, and management. The successful application of the J48 algorithm in this context underscores the potential of decision tree-based machine learning models in enhancing disaster preparedness and response strategies [70].

AI's capacity for adaptive learning ensures that models, such as decision trees, continuously evolve by incorporating new data. This allows them to stay resilient and accurate as environmental conditions change. By learning from real-time data, decision tree models can refine their predictions, adjust to new trends, and improve their ability to handle complex, dynamic situations. This feature is particularly valuable for predicting disasters influenced by climate change, where historical patterns may no longer reliably predict future events.

2.6 Forest Fire Systems: A review

Today, the most commonly used fire detection system involves satellite-based monitoring, with tools such as NASA's geostationary satellites. NASA's satellite tools are often the first to detect fires that are burning in distant regions and new fire locations are sent directly to field managers around the world within a few hours of satellite travel [71]. While offering broad coverage, satellite systems like AVHRR and MODIS are often constrained by delayed data transmission and lower resolution during the early stages of fires, making rapid response difficult.

In addition to satellites, other fire detection methods include optical sensors and Wireless Sensor Networks (WSNs). Optical sensors, such as infrared cameras and smoke detectors, are effective for localized monitoring. WSNs provide a more scalable and flexible solution by offering live environmental data from remote areas.

Another alternative is image processing-based detection, which uses digital cameras and computer vision techniques to identify fire pixels. By applying rule-based color models like RGB and YCbCr, these systems can distinguish fire from non-fire elements, offering good detection rates with fewer false alarms. They also enable continuous monitoring, making them suitable for fire detection. [72].

Despite these advancements, the increasing frequency and intensity of wildfires reveal the limitations of current systems. Today, most WSNs, while capable of monitoring remote areas in real-time, struggle with power efficiency and network reliability, especially over long distances or in areas with poor infrastructure [73].

Similarly, optical sensors and image-processing systems, although useful for monitoring, have reduced effectiveness in low-visibility conditions like heavy smoke or nighttime. The computational demands of large-scale image analysis further limit their scalability. These gaps in current systems underscore the need for more responsive, reliable, and cost-effective solutions in forest fire detection.

This recognition of the limitations in current fire management strategies aligns with an increasing focus on environmental data acquisition. Enhanced monitoring efforts aim to provide a more comprehensive understanding of ecosystem health, track air quality, and leverage machine learning to improve forecasting models. Such efforts are important because environmental conditions affect daily lives, society, economy, and overall environment. Weather events affect approximately 33% of global GDP, underscoring the

broad implications of environmental changes [74].

Chan et al. (2023) provide a comprehensive survey of IoT-based ground sensing systems for early wildfire detection, highlighting key technologies, challenges, and opportunities in addressing the growing global threat of wildfires [75].

To address the gaps identified in traditional systems, the proposed solution integrates an IoT-based network of sensors, designed to collect real-time environmental data such as temperature, humidity, and atmospheric pressure from remote forest areas. By utilizing machine learning algorithms, the system can analyze this data for early fire detection and improve forecast accuracy using weather models. This approach ensures rapid detection of potential fire risks while maintaining energy efficiency and network reliability over large-scale deployments. As shown in Figure 2.6 the proposed system presents a sensor technology to gather critical environmental data, offering insights into various ecological parameters. This system incorporates weather forecast models to predict environmental conditions for specific locations by using an AI model.

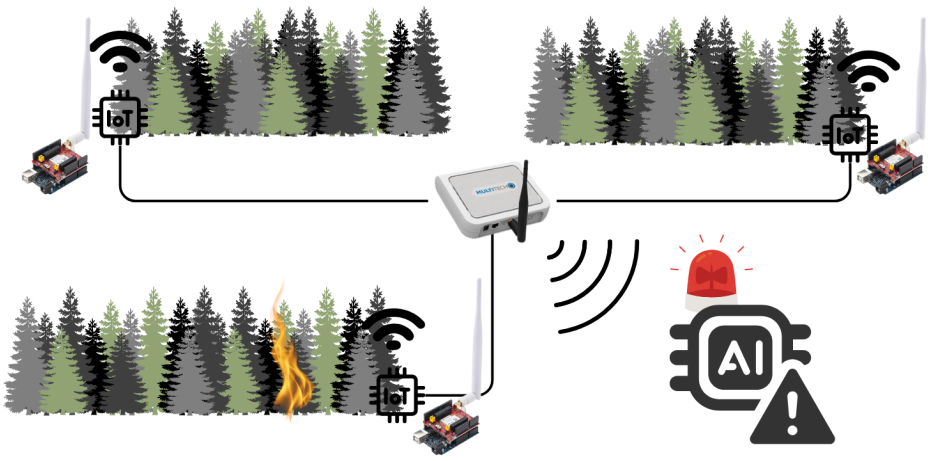


Figure 2.6: General view of the proposed system

Complementing this approach, study [76] developed a cost-effective LoRa-based network system that similarly utilizes environmental sensors to assess and visualize fire risk in real-time. Their field tests in rural areas demonstrate the system's capability to provide expansive coverage, significantly contributing to IoT-driven environmental monitoring and forest fire detection.

Similar work [77] uses a LoRa wireless mesh topology to ensure reliable data trans-

mission over large, remote areas typically lacking conventional network infrastructure. Their system installs multiple sensor nodes across forest terrains, capturing critical data points such as temperature, humidity, and smoke levels, which are significant for early fire detection and situational awareness.

Building on recent advancements, another paper [78] utilizes artificial neural networks with key meteorological parameters like temperature, humidity, and wind speed to predict wildfires across various U.S. forest types. This relevant study showcases the model's responsiveness to environmental fluctuations, enhancing the monitoring efficiency and timeliness for early preventative actions against fires. Such findings are important for improving predictive models.

While artificial neural networks improve the accuracy of wildfire predictions, efficient communication systems are important to ensure real-time data transmission from remote areas. One of the major advancements in this regard is the use of LoRa (Long Range) technology. LoRa enables long-distance, low-power communication, making it ideal for systems deployed in remote locations. Recent work has demonstrated how LoRa networks can effectively transmit environmental data collected from sensors over vast forest areas, overcoming the limitations of other communication technologies such as WiFi and cellular networks, which are often constrained by range and power consumption [79].

In addition to LoRa, managing the transmission of large volumes of sensor data requires an efficient communication protocol. MQTT (Message Queuing Telemetry Transport) has emerged as a widely adopted solution, particularly in low-bandwidth and high-latency environments. Studies have demonstrated MQTT's effectiveness in minimizing network congestion and enhancing scalability, making it an ideal protocol for distributed environments such as forest fire detection systems. The referenced study by Yoon et al. introduces a smart farm model integrating LoRa and MQTT technologies, aligning effectively with the established criteria for smart farms [80]. Furthermore, Calvert et al. highlight the use of an environmental data-based communication protocol to improve the quality of service in LoRaWAN applications, demonstrating the adaptability and robustness of LoRaWAN for such contexts [81].

Once the data is collected and transmitted, data analysis becomes essential for transforming raw sensor data into actionable insights. ARIMA (AutoRegressive Integrated Moving Average) models are frequently used in time-series forecasting to analyze envi-

ronmental trends and predict environmental conditions. For instance, ARIMA has been effectively employed in fire risk assessment by analyzing temperature and humidity fluctuations over time, allowing for proactive interventions [82].

The strength of ARIMA lies in its ability to model and forecast complex, non-stationary data, which is particularly useful for predicting environmental variables with seasonal variations or long-term trends.

Similarly, decision tree models have proven to be a valuable tool in classifying fire risks based on environmental conditions. These models are capable of analyzing multiple variables and generating a clear decision pathway that categorizes areas into different risk levels. Research has demonstrated the effectiveness of decision tree algorithms in real-time classification tasks, offering an interpretable and computationally efficient solution for forest fire detection [67]. Decision trees can quickly assess environmental factors such as temperature, wind speed, and humidity, making them a powerful tool for early fire detection and risk management.

2.7 Communication Protocols in Environmental Monitoring

Communication protocols are essential for enabling reliable and efficient data transfer in environmental monitoring systems. These protocols manage how data is collected, transmitted, and processed across networks, directly impacting the system's performance and energy efficiency. In particular, protocols designed for Internet of Things (IoT) applications must handle vast amounts of environmental data while ensuring low power consumption and reliable communication across remote and challenging terrains.

LoRaWAN, as discussed, offers long-range, low-power communication, making it suitable for forest fire detection and environmental monitoring. Additionally, MQTT (Message Queuing Telemetry Transport) is integrated into the protocol as a lightweight messaging protocol [83]. MQTT is widely used in IoT systems for its ability to handle large-scale sensor networks with minimal bandwidth consumption, ensuring timely and efficient data transfer. MQTT allows environmental sensor data collected by the LoRa-enabled nodes to be seamlessly relayed to central systems, supporting data analysis and improving the system's responsiveness to fire risk predictions. Research by Zhao and

Ge (2013) demonstrated MQTT's ability to optimize communication in large sensor networks, thereby improving the accuracy and speed of wildfire detection systems through efficient data exchange [84]. Their work highlighted how MQTT can seamlessly integrate with environmental sensors to relay the data to monitoring centers, improving the speed and accuracy of disaster responses.

In addition to LoRaWAN and MQTT, which are used in the specialized protocol, other studies have explored the application of different communication protocols in environmental monitoring systems. A notable example is the Constrained Application Protocol (CoAP), designed for constrained devices in low-power environments [85]. Research by Bormann et al. (2012) highlights how CoAP optimizes data exchange in resource-limited IoT systems, making it ideal for remote environmental monitoring [86]. Their study explored CoAP's lightweight architecture, demonstrating its effectiveness in enabling sensor networks to efficiently transmit critical data while conserving energy.

Additionally, hybrid communication models that integrate big data analytics with small, on-edge sensor networks have been gaining attention. A study by Wang et al. (2019) introduced a smart sensing system using LoRaWAN for environmental monitoring, demonstrating how solar-powered wireless sensor nodes can operate sustainably for long-term deployment [87]. Their system highlights the efficiency and scalability of LoRaWAN in collecting and transmitting environmental data.

Further advancements in LoRaWAN-based monitoring are demonstrated in the work by Vinay et al. (2023), who implemented an environmental monitoring system for smart campuses. Their system leveraged LoRaWAN's low-power and long-range capabilities to collect real-time environmental data across large campus areas, showcasing the protocol's scalability and adaptability [88].

Likewise, Khalid et al. (2022) presented the E-Serve system for environmental monitoring using LoRaWAN technology. This system focuses on detecting and monitoring environmental parameters to prevent potential risks and hazards, particularly in industrial and remote settings, demonstrating the robustness and flexibility of LoRaWAN in diverse applications [89].

The choice of communication protocol significantly influences system scalability, energy efficiency, and data accuracy. Integrating adaptive protocols that dynamically adjust based on environmental conditions and data volume ensures that monitoring systems re-

main robust and responsive.

2.8 Proposed Protocol for Forest Fire Detection

The proposed protocol in this study integrates LoRaWAN technology with a hybrid data processing model that leverages both high-level and low-level data synchronization. This protocol is designed to address the limitations of current forest fire detection systems by combining long-range, low-power communication with on-edge data processing for environmental monitoring.

The system deploys LoRa-enabled sensors across forest areas to continuously monitor environmental parameters. These sensors provide real-time data that is transmitted via LoRaWAN technology, ensuring low-power communication, even in remote forest regions. The data captured by the sensors is transmitted to The Things Network (TTN), which serves as the network server, handling the communication between the devices and the cloud. Once the data reaches TTN, it is extracted via the MQTT protocol, a lightweight messaging protocol that ensures efficient, data transmission. This data, including parameters such as temperature, humidity, and atmospheric pressure, is then available for processing and analysis.

To ensure the reliability of the sensor data, the system integrates big data sources, such as environmental data from Met Eireann (Irish Meteorological Service), for cross-referencing. By comparing the real-time sensor data with reliable external datasets, the system can identify inconsistencies or errors in the collected sensor data. This comparison not only validates the sensor data but also improves the accuracy of fire risk predictions.

At the edge, anomaly detection algorithms analyze the incoming data to identify patterns that may indicate potential fire risks. The system evaluates the parameters to detect subtle changes that could signal the onset of a wildfire, such as a sudden drop in humidity or a rapid increase in temperature. By continuously monitoring these parameters, the system can quickly identify irregularities and trigger early warnings for firefighting teams.

If an anomaly is detected, a lightweight decision tree model is triggered at the edge. This model processes the immediate data to classify the fire risk based on predefined thresholds and patterns, generating alerts for the authorities. The decision tree model is particularly effective in handling multiple variables and assessing the risk quickly and

efficiently. This real-time analysis allows for immediate action, by activating emergency response protocols, ensuring a rapid response to the fire threat.

To further improve predictions and ensure long-term reliability, the system incorporates a feedback loop between distributed data (from LoRa sensors) and centralized data (from Met Eireann). The ARIMA model is used at the edge for short-term forecasting, detecting localized time-series anomalies, and predicting immediate risks. The data from the edge is then transmitted to the cloud, where the holistic model uses ARIMA to perform long-term analysis, improving fire risk predictions by identifying broader trends and patterns. The feedback loop continuously refines both of the models, enhancing the overall prediction accuracy through instant corrections, error identification, and adjustments based on the latest data.

Figure 2.7 illustrates the wildfire detection system's protocol. Sensor readings (temperature, humidity, air pressure) are compared with Met Éireann data and analyzed using ARIMA for forecasting and error correction. Anomalies are detected and processed through a decision tree, classifying fire risk as low or high. High-risk conditions trigger an alarm via SMS or email. A feedback loop refines the model, ensuring accurate and adaptive fire risk assessment.

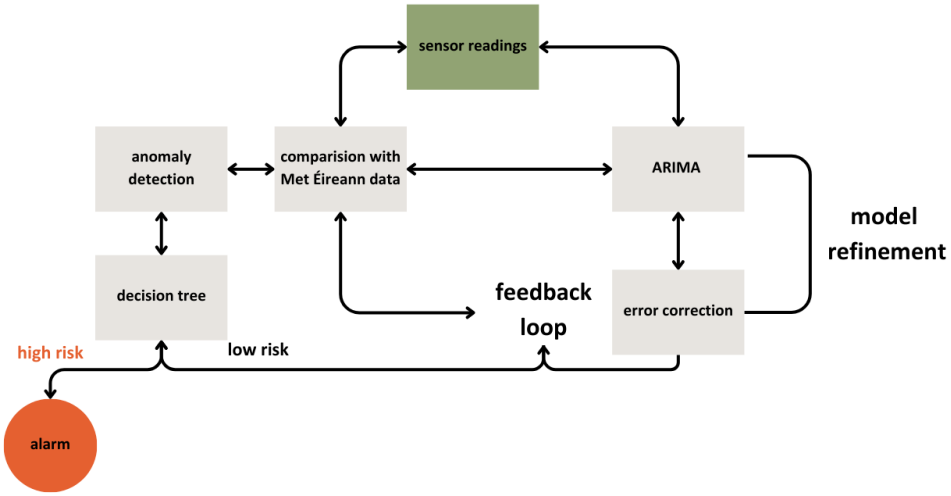


Figure 2.7: Proposed protocol

This hybrid approach, combining on-edge processing, cloud-based analysis, and continuous feedback, provides an efficient, scalable solution for wildfire monitoring and early detection. By implementing data federation, the system enhances its ability to predict and respond to fire risks, ultimately improving disaster management and reducing the impact of wildfires on vulnerable ecosystems.

Chapter 3

METHODS

The methods for this study are structured into several interconnected components, each contributing to the development and functionality of the proposed forest fire detection system. The primary objective of this method is to design a comprehensive, reliable, and energy-efficient framework for real-time environmental monitoring, early wildfire detection, and proactive intervention.

The system begins with the collection of environmental data through strategically deployed LoRa-based Dragino sensor nodes [28]. These nodes are specifically designed to function in remote forested areas where conventional communication infrastructure is either limited or non-existent. Equipped with sensors to monitor critical environmental parameters—such as temperature, humidity, and air pressure—these nodes play a fundamental role in assessing wildfire risks. To maximize coverage and enhance live data acquisition, the sensor nodes are systematically distributed across diverse forest regions, ensuring continuous and extensive environmental monitoring. This strategic placement enables the system to capture localized variations in environmental conditions, providing a robust dataset for early fire risk assessment and mitigation strategies.

Each sensor node collects environmental data and transmits it via LoRaWAN to a MultiTech gateway, which serves as an intermediary between the sensors and the cloud. The gateway forwards the data to The Things Network (TTN), where it is processed and made available for further analysis. The LoRaWAN protocol ensures long-range, low-power communication, making it effective for large-scale deployments in remote areas.

The base station, located at the University College Cork Electrical Engineering Building, receives the transmitted data for centralized processing. TTN acts as the communi-

cation backbone, securely routing sensor data to cloud servers for live monitoring. Once in the cloud, the data undergoes anomaly detection and predictive modeling, helping to identify early fire risks. The scalable and flexible nature of this network infrastructure allows for efficient data collection, processing, and transmission in challenging environments, ensuring a reliable wildfire detection system.

As illustrated in Figure 3.1, the architecture of the system comprises three main components: the sensor nodes (Nodes 1, 2, and 3), the LoRa Multitech gateway, and the centralized data processing through The Things Network. Each sensor node is designed to operate independently in remote, often difficult-to-reach areas, capturing environmental data and transmitting it over long distances using LoRaWAN technology. The data from these nodes is then received by the LoRa Multitech gateway, which serves as a bridge, forwarding the information to TTN.

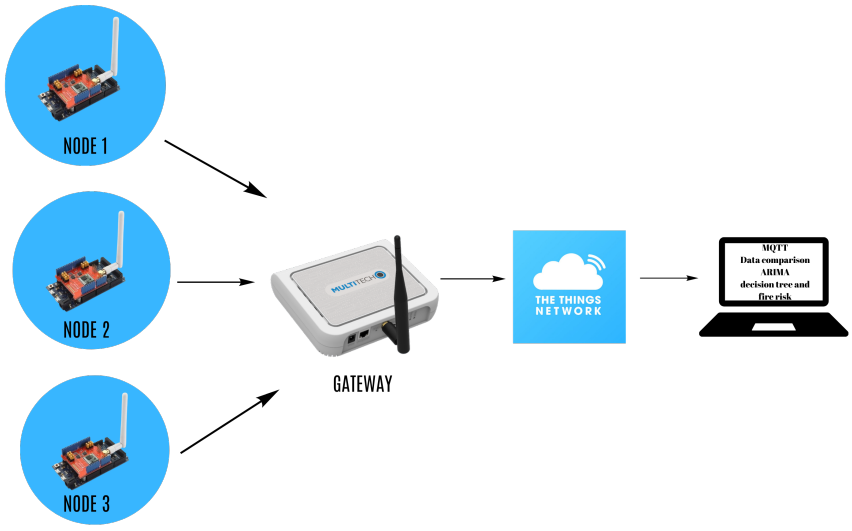


Figure 3.1: Basic structure of fire detection system

The MQTT protocol is employed for data transmission from TTN, ensuring efficient, communication while maintaining low bandwidth consumption. Its lightweight nature allows for rapid and efficient transmission of sensor data, which is critical for continuous monitoring and early detection of fire risks. This ensures efficient data retrieval and supports reliable communication between devices. MQTT's publish-subscribe model al-

lows for low-power, asynchronous communication, making it particularly effective for IoT-based environmental monitoring. This setup ensures reliable data flow, supporting continuous monitoring.

To create an adaptive, scalable, and energy-efficient wildfire detection system, the collected environmental data must be seamlessly integrated with processing and analysis mechanisms. This system leverages both edge data (sensor readings) and cloud data (meteorological records from Met Éireann) to enhance predictive accuracy. The combination of localized environmental conditions with broader atmospheric trends allows the system to refine forecasting models, improve anomaly detection, and enable continuous adaptation to changing environmental factors.

Once transmitted, the collected data undergoes systematic processing and analysis using a combination of machine learning models and statistical forecasting techniques. Decision trees are employed to classify environmental conditions and identify potential fire risks based on real-time sensor data. These models analyze fluctuations in temperature, humidity, and air pressure, detecting patterns indicative of wildfire-prone conditions. By continuously learning from historical fire events and evolving environmental trends, the decision tree model improves its ability to differentiate between normal environmental changes and hazardous anomalies, enhancing its predictive accuracy over time.

In parallel, the ARIMA forecasting model serves as an essential component of the protocol's feedback mechanism, rather than direct fire risk assessment. ARIMA is used to analyze long-term environmental trends, detect inconsistencies, and enhance the quality of collected data. This ensures that real-time sensor readings align with broader meteorological observations, reducing discrepancies and reinforcing the robustness of the system. Additionally, ARIMA enables dynamic adaptation to seasonal variations by fine-tuning predictive thresholds, ensuring that fluctuating climate patterns do not compromise detection accuracy or system reliability.

By integrating machine learning-based classification with statistical forecasting, the system optimizes both immediate fire detection and long-term data consistency. This dual-layered approach minimizes false positives, enhances anomaly detection, and ensures that the protocol remains adaptable to evolving environmental conditions.

The method begins by detailing the collection of environmental data using sensor nodes equipped with BME280 sensors [90], as illustrated in Fig. 3.1 in Section 3.3. Envi-

ronmental Data Collection. The collected data is then processed and analyzed to evaluate its quality and transmission efficiency, detailed in Section 3.2 Data Analysis, followed by the application of forecasting models to predict environmental conditions. Section 3.3 Decision Tree introduces the use of a machine learning model to classify fire risks based on environmental parameters. Section 3.4, Power Consumption section details how the system optimizes energy usage by dynamically adjusting sensor sampling rates based on real-time environmental conditions, ensuring energy efficiency while maintaining reliable fire detection capabilities. This layered approach ensures the integration of data collection, analysis, and prediction, enabling effective early detection of forest fires.

3.1 Environmental Data Collection

3.1.1 Node Setup and Communication

The first step in the methods involves the deployment of LoRa-based Dragino nodes across remote forest areas to gather essential environmental data. These sensor nodes are equipped with BME280 sensors, capable of continuously monitoring key parameters such as temperature, humidity, and air pressure. The primary goal of this data collection is to ensure real-time environmental monitoring that can signal potential fire risks, while also maintaining a robust and continuous data stream for reliable analysis.

Each sensor node is programmed to transmit collected data at a fixed sampling rate of 30 seconds, using LoRa modulation, which enables long-range, low-power communication even in challenging terrains such as dense forests or mountainous regions. The transmitted data is received by a LoRa MultiTech gateway [91], which serves as the local aggregation point for multiple sensor nodes. The gateway then forwards this data to The Things Network (TTN), where it becomes accessible for further processing and analysis.

To ensure reliable data transmission across fire-prone regions, the system is designed to operate within an expected 2–10 km range in forested environments, consistent with documented LoRa performance in similar conditions. In open rural landscapes, the range can extend up to 15 km, whereas in dense forests, signal attenuation from vegetation and terrain requires strategic placement of gateways to maintain reliable coverage [28]. To address these challenges, the system architecture optimizes node distribution, minimizing data loss while sustaining network integrity.

The decision to implement LoRa technology is driven by its ability to deliver energy-efficient, extended-range data transmission, making it well-suited for remote and large-scale environmental monitoring applications. Each sensor node is designed to operate autonomously for extended periods without requiring frequent maintenance, a crucial factor for ensuring scalability and long-term efficiency. Additionally, maintaining high-quality environmental data is essential for accurate fire risk prediction. Reliable data collection enhances early anomaly detection, reducing false alarms and improving decision-making accuracy. Consistent and accurate sensor data also strengthens machine learning models, ensuring that irregularities are promptly identified and effectively addressed in the predictive analysis process.

By maintaining a structured data collection process, the system enhances data reliability, preventing signal loss or inconsistencies that could compromise fire risk assessments. The ability to consistently capture high-resolution environmental data ensures a stable and trustworthy dataset, which is fundamental for both live monitoring and long-term analysis.

This structured communication framework lays the foundation for effective wildfire monitoring, allowing seamless integration with higher-level network operations. The next section delves into the LoRaWAN architecture, detailing how data is managed and processed within the larger network infrastructure.

3.1.2 LoRaWAN Network Architecture

The environmental data captured by the sensor nodes is transmitted to a central base station through a LoRa Multitech gateway [91]. LoRa is a wireless communication technology designed for long-range, low-power data transmission. It operates on sub-GHz frequencies (e.g., 868 MHz in Europe) and uses chirp spread spectrum modulation to resist interference and maintain stable communication in challenging environments such as forests and mountainous regions. Its low power consumption a moows sensor nodes to function autonomously for extended periods without frequent battery replacements, making it ideal for remote environmental monitoring.

LoRaWAN, the network protocol layer built on LoRa's communication capabilities, enhances scalability by enabling bidirectional communication among thousands of devices through a single gateway. This structured hierarchy consists of end devices (sensor

nodes), gateways, network servers, and application servers, collectively ensuring robust data transmission across vast areas. The network server plays a crucial role in maintaining data integrity by performing deduplication, verifying received packets, and optimizing transmission rates using Adaptive Data Rate (ADR) based on network conditions [92]. These mechanisms enhance data reliability, particularly in energy-constrained environments where efficient communication is essential.

Unlike other LPWAN solutions such as Sigfox [93] and NB-IoT [94], LoRaWAN supports flexible data rates and bidirectional communication, allowing remote configuration and calibration of sensor nodes without requiring physical access. This is particularly beneficial for wildfire detection systems deployed in remote forested regions, where accessibility is limited. The system's ability to operate in such environments ensures continuous data collection, even in areas with dense vegetation or geographical obstructions.

Each end device, such as environmental sensors, transmits data wirelessly using LoRa modulation to a gateway, which functions as a passive relay, receiving and forwarding the data to a centralized network server via LTE, Ethernet, or other backhaul connections. The network server ensures data integrity by performing deduplication, verifying received packets, and dynamically adjusting transmission rates through Adaptive Data Rate (ADR) based on network conditions. This process minimizes packet loss and optimizes network efficiency, ensuring accurate environmental monitoring.

The application server plays a crucial role in processing and visualizing the collected environmental data. By leveraging a cloud-based platform, real-time insights can be generated, allowing authorities to monitor wildfire risks efficiently. End-to-end encryption at both the network and application layers secures communication, ensuring that sensor data remains protected from unauthorized access. Additionally, by continuously collecting and processing high-quality environmental data, the system improves predictive analytics, enhancing early warning capabilities and response efficiency.

According to The Things Network documentation, LoRaWAN supports thousands of connected nodes while enabling reliable device-to-cloud communication [95]. TTN serves as the primary network backbone in this system, providing a scalable and cost-effective solution for long-term wildfire monitoring. The ability to maintain uninterrupted, high-quality data collection ensures that LoRaWAN remains a fundamental component of this detection system, enabling proactive fire risk assessment even in the most

inaccessible locations.

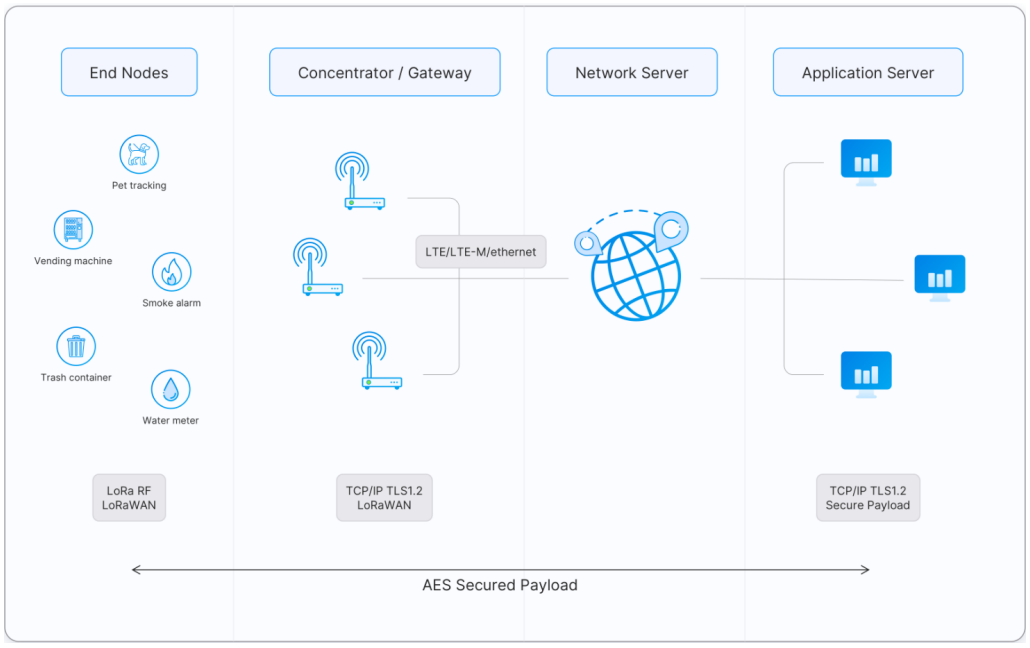


Figure 3.2: LoRaWAN Network Architecture [95]

3.1.3 Data Collection and Preliminary Processing

The data collected from the sensor nodes is transmitted to a central base station located at the University College Cork Electrical Engineering Building. The transmission process is facilitated through the LoRa Multitech gateway, which acts as a bridge between the sensor nodes and the internet, forwarding data to TTN. Once the data reaches TTN, it is made available for further processing and analysis via the MQTT protocol. It is an efficient, lightweight messaging protocol that is optimized for low-bandwidth, real-time communication. Its minimal overhead (just 4 bytes for the fixed header) reduces data load, conserving both bandwidth and power, which is essential in a remote IoT setup where network and power resources are limited. MQTT also supports various Quality of Service (QoS) levels, ranging from 0 (at most once) to 2 (exactly once), providing flexibility in how data reliability is handled based on the use case [96].

The use of MQTT ensures that the communication between the sensor nodes and the central server is reliable, allowing for continuous data transmission without overwhelming the network. The system's integration with LoRaWAN enhances this communication by

providing a structured protocol layer that supports scalable and secure communication across multiple devices. Additionally, this structured communication ensures that data packets are properly formatted and time-synchronized, reducing the likelihood of packet loss or misinterpretation, which is critical for ensuring high-quality data in environmental monitoring applications.

Once collected, data packages are stored in a traceable format to ensure future utility. The system's initial focus is on examining the quality of data transmission by analyzing key signal parameters like the Received Signal Strength Indicator (RSSI) and the Signal-to-Noise Ratio (SNR). These metrics are critical for assessing transmission reliability, with RSSI indicating the strength of the signal between sensor nodes and the gateway, and SNR reflecting the clarity of the signal [97]. Higher RSSI values correlate with stronger and more reliable signals, ensuring that data can be transmitted without significant loss. SNR, on the other hand, measures the clarity of the signal by comparing the strength of the signal to the level of background noise. A higher SNR indicates a clearer, more reliable signal, while lower values suggest potential interference or signal degradation. These values are particularly important when using LoRa, as any significant drop in signal strength or clarity could lead to data loss or inaccurate transmission, which can compromise the accuracy of fire risk assessments. Furthermore, these signal parameters may provide valuable insights into external environmental factors, such as weather conditions, that could affect the performance of the sensor network. By continuously monitoring RSSI and SNR, the system can proactively detect potential issues in data transmission caused by environmental factors like rain, fog, or dense vegetation, as well as physical obstructions in the terrain. These monitoring activities help ensure that the system remains robust and capable of maintaining consistent performance, even under challenging conditions.

The system's focus on maintaining accurate data transmission is a key factor for building reliable datasets that will be used for anomaly detection and forecasting. Data traceability ensures that each data point can be validated and cross-referenced with other collected data, allowing for a deeper understanding of environmental patterns. This is particularly important for building machine learning models that require consistent data for training and prediction. By ensuring that the data used for modeling is of the highest quality, the system enhances its predictive capabilities and reduces false alarms, making it more reliable for real-world deployment.

As a core component of the protocol, the contextual model focuses on real-time sensor data collection and localized processing at the edge. It continuously gathers and transmits environmental parameters using low-power LoRaWAN-enabled sensors, ensuring high-resolution, live data availability for immediate anomaly detection and short-term fire risk classification. This model serves as the first layer of the system's predictive framework, feeding into the broader holistic model, which integrates meteorological data for long-term trend analysis. Establishing a robust fine-grained model within the protocol guarantees reliable and high-quality environmental data, enabling both immediate responses to anomalies and seamless integration with larger-scale predictive analytics.

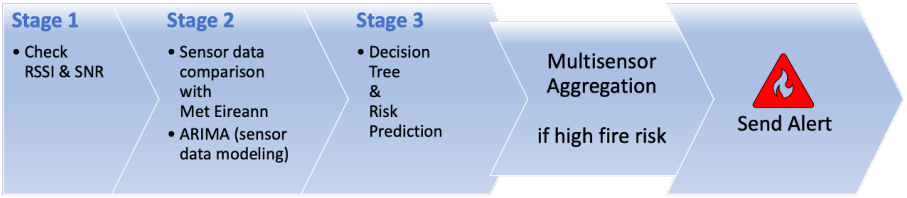


Figure 3.3: Multi-stage approach of the system

Figure 3.3 outlines the multi-stage approach of the system. The first stage, focusing on signal quality and transmission reliability, is detailed in this chapter. Further stages, such as data validation and predictive modeling, will be covered in the following sections, offering a complete overview of the system's functionality.

3.2 Data Analysis

The data analysis process is divided into two key stages: time series anomaly detection and forecasting. The forecasting stage utilizes a dual-model approach. The comprehensive model, based on Met Éireann's extensive historical data, captures long-term environmental patterns and trends. This data is externally sourced and extracted for use in the system. In contrast, the instance-level model corresponds to real-time sensor data collected directly from deployed nodes, providing localized and up-to-date predictions. This complementary combination allows the system to adapt effectively to both macro-level environmental changes and micro-level conditions, enhancing the accuracy of fire risk assessments and forecasts.

3.2.1 Time Series Anomaly Detection

The first stage of the analysis focuses on detecting anomalies in the environmental data collected by the sensor nodes. This stage is particularly important for identifying potential fire risks before they develop into dangerous situations. Data collected from the BME280 sensors is compared with hourly weather data from Met Éireann, sourced from two locations: the testing point at the University College Cork Electrical Engineering Building and the Environmental Research Institute (ERI), the facility where Met Éireann acquires its weather data. This dual comparison serves as a validation step to ensure the accuracy and reliability of the sensor data.

One of the primary challenges in this stage is the difference in data collection frequencies between the sensor nodes and Met Éireann. The sensor nodes record data every 30 seconds, while Met Éireann provides weather data on an hourly basis. To address this, the sensor data is resampled into 30-minute intervals to better align with the coarser-grained Met Éireann data. To preserve causality in real-time anomaly detection, forward-fill interpolation is used, ensuring that missing values are estimated based only on past data. Additionally, linear interpolation is applied to Met Éireann's dataset when aligning it with higher-frequency sensor data for ARIMA forecasting. This method minimizes temporal misalignment errors while ensuring the integrity of time-series analysis.

For Met Éireann's data, the original hourly format serves as the foundation for validation. However, it is resampled to one-minute intervals when aligning with higher-frequency sensor data for tasks like ARIMA forecasting. This finer resolution reduces errors caused by mismatched timestamps and ensures smoother visualizations when plotted alongside sensor data. This processing approach enables consistent comparisons across datasets with different collection frequencies, preserving key environmental trends and ensuring meaningful analysis and visualization.

Once the live data is gathered from the sensor network and the interpolation step is complete, comparisons are performed to validate the sensor data against the external weather data. This ongoing comparison ensures that the sensor data continuously aligns with the accurate, authoritative weather data from Met Éireann. It also helps in detecting anomalies in real-time, allowing the system to identify potential fire risks early.

Anomalies are identified when the sensor data significantly deviates from expected environmental trends. These deviations can include sudden spikes in temperature, rapid

drops in humidity, or other irregular patterns that may indicate emerging fire hazards. To detect these anomalies, the system uses dynamic thresholds rather than fixed values. As new data is collected, the system continuously adjusts these thresholds based on evolving environmental conditions and patterns. The detection thresholds are refined through adaptive algorithms that learn from the ongoing sensor data, allowing the system to account for changing weather conditions, seasonal variations, and other influencing factors.

The real-time sensor data helps to detect any discrepancies or errors in the predictions. When significant deviations or anomalies are detected, the system can use the global model's data to correct or adjust the thresholds in the local model, ensuring more accurate anomaly detection.

This collaboration between the harmonized models strengthens the system's ability to detect fire risks using both local data and external weather forecasts. The adaptive algorithms learn from both sources, which ultimately increases the system's sensitivity to fire hazards while reducing the risk of false positives.

3.2.2 Forecast

The second stage of data analysis focuses on forecasting. This involves using historical data derived from sensor readings, which is then validated and integrated with weather data from Met Éireann. This integration enhances the system's predictions by combining localized sensor data with broader environmental patterns, forming a key component of the protocol's predictive framework.

To generate the forecast, the system employs the ARIMA model. ARIMA is particularly useful in scenarios where the data exhibits non-stationary behavior, such as environmental conditions, which can vary due to numerous factors (seasonal changes, weather events, etc.). The ARIMA model analyzes historical sensor data to identify patterns and predict future values for key environmental parameters. Additionally, its ability to integrate differencing in the modeling process helps stabilize the mean of time series data, making it particularly useful for handling non-stationary data typically found in environmental monitoring [98].

The application of the ARIMA model begins with identifying the time-series characteristics of the dataset. This is achieved using the Augmented Dickey-Fuller (ADF) test, which determines whether the dataset is stationary. If the test indicates the presence of

a unit root, signifying non-stationarity, differencing is applied to stabilize the data and enable more accurate forecasts. Furthermore, insights into the lag structure are obtained by analyzing the autocorrelation function (ACF), partial autocorrelation function (PACF), and correlogram of the time series [99]. These steps ensure that the ARIMA model's parameters—p (autoregressive terms), d (differencing), and q (moving average terms)—are optimized for the specific characteristics of the dataset. A grid search approach is employed to fine-tune these parameters, further enhancing the model's predictive accuracy.

Once the ARIMA model is trained on historical data, it generates forecasts for future environmental conditions. These forecasts serve as predictive indicators, helping to refine the protocol by providing valuable insights into environmental trends. However, the focus is not just on predicting the future but also on improving the accuracy of adaptive models through feedback mechanisms embedded within the system's protocol.

It is important to clarify that while ARIMA supports the system's supplementary analytical processes, it is not the central component of the protocol. Forecasting is a supplementary feature, primarily used to improve model alignment and system adaptability, rather than serving as the foundation of the wildfire detection methodology. The core of the system remains its anomaly detection and fire risk classification capabilities, which function independently of time series forecasting.

By continuously improving the interaction between the multi-layered models, the system enhances its predictive accuracy while becoming more efficient at identifying and rectifying errors in real-time. For example, when the local model detects that the forecasted temperature is significantly different from the actual readings from Met Éireann, this discrepancy can be used to adjust both models' parameters, ensuring better alignment going forward.

By incorporating ARIMA into the system, the protocol is strengthened not only in terms of predictive analysis but also in its ability to refine the feedback mechanism. ARIMA's simplicity and computational efficiency make it an essential component for enhancing model alignment and adaptability, reinforcing the protocol's overall effectiveness in wildfire detection and environmental monitoring.

3.3 Decision Tree

The decision tree algorithm is a key component of the system's fire risk prediction capabilities. Once anomalies are detected in the time-series analysis during the validation process, the forest fire prediction algorithm is activated. The decision tree model utilizes high-risk and low-risk datasets to assess the probability of fire outbreaks, drawing from the Irish government's forest fire warning system, which dates back to 2021 [100]. This allows the system to make rapid assessments of potential fire threats using environmental data from the base station.

The decision tree algorithm plays a crucial role in the system's fire risk prediction capabilities, offering a structured and efficient method for classifying wildfire risks. This machine learning technique is particularly effective due to its interpretability, low computational cost, and ability to analyze large datasets with multiple influencing variables. The model is triggered when anomalies in environmental conditions are detected during the validation process, allowing for a rapid assessment of fire hazards. The decision tree categorizes fire risks into high-risk and low-risk classes based on environmental parameters such as temperature, humidity, wind speed, and atmospheric pressure. Drawing from historical fire risk datasets, including the Irish government's forest fire warning system established in 2021 [100], the model enhances fire prediction accuracy by leveraging real-time sensor data from IoT-based monitoring networks.

The decision tree algorithm analyzes environmental parameters to evaluate the risk of fire. When the system identifies a potential fire threat, it promptly issues alerts, enhancing the readiness and response mechanisms to address potential forest fires.

Building on this foundation, a decision tree-based machine learning algorithm has been developed for its prediction capabilities, serving as a valuable tool to enhance environmental monitoring.

This model employs a hierarchical structure of decisions based on an extensive set of variables, including temperature, humidity, and other environmental factors. The sequential application of the decision tree model demonstrates a strategic use of data mining techniques in this research, highlighting its effectiveness in systematically analyzing data to extract significant patterns. Data mining involves extracting patterns from large datasets through automated and semi-automated techniques [101]. This methodology, coupled with the classification of the datasets into risk levels such as high-risk and low-

risk, underscores the comprehensive approach to forest fire prediction and management.

Referring to Figure 3.4, the decision tree illustrates the logical flow employed in this study's fire risk classification system. The root node begins with a temperature check, the primary decision point. If the temperature is below the threshold, the system classifies the area as low risk, terminating further evaluation for that branch. For temperatures exceeding the threshold, the system advances to the humidity check at the internal node. Additional environmental parameters are also considered to further refine the risk classification process. The decision-making process follows this hierarchical structure, sequentially evaluating relevant factors to ensure an accurate and comprehensive fire risk assessment. This systematic approach effectively leverages critical environmental parameters for precise and reliable predictions.

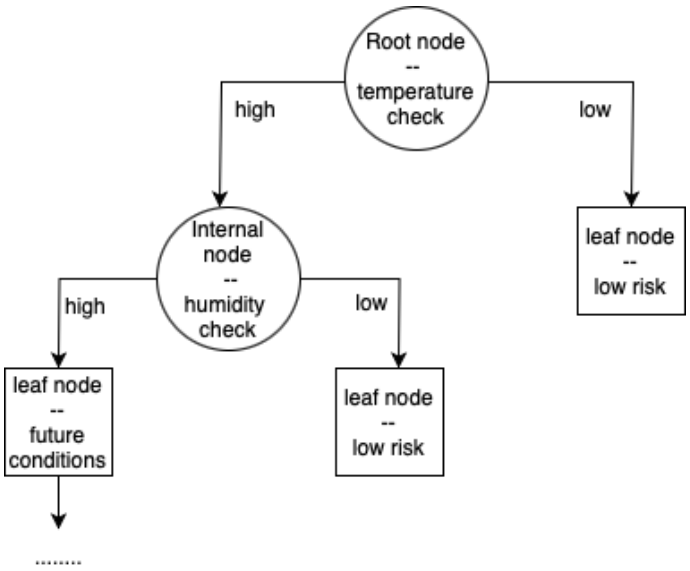


Figure 3.4: Decision Tree

The structured nature of the decision tree enhances the interpretability and transparency of the fire risk classification process. By systematically evaluating key environmental parameters, the model provides a clear and logical decision-making framework that can be easily adapted to different fire-prone regions. This approach ensures that predictions remain both explainable and data-driven, strengthening its applicability in real-world wildfire monitoring and response systems.

3.4 Power Consumption Analysis

Efficient power consumption is a critical aspect of wireless communication protocols, particularly in remote environmental monitoring systems where devices operate on limited energy sources [102]. Ensuring energy efficiency in IoT-based wildfire detection systems is essential for prolonged sensor node operation, reduced maintenance requirements, and improved scalability.

Wireless sensor networks (WSNs) deployed for fire detection must balance frequent data transmission with energy conservation. The power consumption of a communication protocol is influenced by multiple factors, including data transmission frequency, payload size, signal strength, environmental interference, and network topology. In remote and off-grid locations where recharging or replacing batteries is impractical, optimizing these factors is crucial for ensuring the longevity of the network. Adaptive mechanisms that dynamically adjust transmission rates and power levels based on signal conditions can significantly improve energy efficiency by minimizing unnecessary power consumption.

To evaluate energy efficiency in the proposed wildfire detection system, this project employs a sampling-based approach, where sensor nodes periodically transmit environmental data at predefined intervals. This method allows for precise monitoring of energy consumption over time, providing valuable insights into the relationship between power usage and data transmission strategies. The sampling rate plays a crucial role in this evaluation. Higher sampling frequencies lead to more frequent data transmissions, increasing energy use, while lower frequencies conserve power but may introduce delays in data updates.

To balance real-time data collection with power efficiency, the system incorporates an adaptive sampling protocol that dynamically adjusts the transmission rate based on environmental risk factors such as rising temperatures, decreasing humidity, and sudden pressure drops—indicators of potential fire hazards. This ensures that data transmission remains efficient while prioritizing critical environmental changes that may signal wildfire risks.

The protocol is a fundamental part of the overall wildfire detection framework, integrating hierarchical models to determine appropriate sampling rates. If the global model predicts stable weather conditions with low fire risk, the system reduces the sampling rate, conserving energy without compromising data integrity. Conversely, if environmental

conditions become volatile—such as rising temperatures, decreasing humidity, or sudden pressure drops—the system increases the sampling frequency to ensure timely anomaly detection and fire risk assessment. This feedback loop between real-time measurements and predictive modeling ensures that energy consumption remains optimized while maintaining system responsiveness. The adaptive sampling protocol plays a crucial role in ensuring that power efficiency does not come at the expense of data reliability, making it a key component of the system's overall protocol for effective environmental monitoring.

Additionally, low-power wireless communication technologies, including LoRa-based solutions, employ low-data-rate communication, which inherently consumes less power compared to other wireless technologies like Wi-Fi or cellular networks. The balance between energy efficiency and data transmission speed is a key consideration, especially in disaster-prone environments where real-time data transmission is crucial. This study evaluates the effectiveness of LoRa-based communication in achieving optimal power efficiency while maintaining accurate and timely data delivery.

Finally, power consumption is also influenced by hardware configurations, such as antenna efficiency, signal processing algorithms, and battery capacity. Advances in energy-harvesting technologies, such as solar-powered sensor nodes, offer promising solutions for sustaining long-term fire monitoring networks. Integrating renewable energy sources with IoT-based detection systems can further enhance their self-sufficiency and resilience in remote environments.

Chapter 4

RESULTS AND DISCUSSION

This chapter presents the outcomes of the study, which are essential for evaluating and refining the proposed wildfire detection protocol. The results are structured according to the stages of the protocol: data analysis, forecast results, decision-making using the decision tree model, and the overall protocol results. These stages ensure that the system can detect fire risks accurately and in real time, optimizing both data quality and energy efficiency. The findings are categorized into three main sections.

The first section evaluates the accuracy and reliability of the environmental data collected by the LoRa-enabled sensors. Ensuring data consistency is crucial for fire risk assessment; therefore, real-time sensor readings are validated against authoritative weather data from Met Éireann. This comparison helps detect discrepancies, sensor drift, and anomalies, ensuring that inaccurate readings are corrected before being used in predictive modeling. Additionally, anomaly detection algorithms are implemented to flag irregular environmental fluctuations. Sudden temperature spikes, rapid humidity drops, or erratic pressure changes are treated as potential fire risk indicators. These anomalies serve as early warnings for the decision tree model. By maintaining high data quality, the system ensures that subsequent predictive modeling and decision-making processes operate with accurate and trustworthy input data.

The second section focuses on the forecast performance for error correction as a fundamental part of the protocol. Here, ARIMA models play a critical role in correcting errors in the data by comparing real-time edge data (local model) with broader weather data (global model), primarily from Met Éireann. By integrating both datasets, ARIMA helps to identify discrepancies and adjust predictions dynamically, ensuring that the protocol

continuously improves data reliability. As part of the system's data correction framework, ARIMA captures historical trends and forecasts future environmental conditions, improving alignment between models. This feedback loop is an essential component of the protocol, ensuring that the system's predictions are continuously refined, helping to correct errors, enhance data integrity, and improve the overall accuracy of fire risk assessments.

The third section examines the decision tree model evaluation. This model is employed to classify environmental conditions into high-risk or low-risk categories based on the processed sensor data. By using the decision tree, the system can trigger alerts when fire risks exceed predefined thresholds, supporting timely responses and resource allocation. The effectiveness of the decision tree model is evaluated by its accuracy in real-time decision-making, its ability to process complex environmental data, and its integration with the on-device and remote data models.

In the fourth section, the system incorporates an effective power management strategy through the dynamic adjustment of sampling frequencies based on instantaneous environmental conditions. By integrating data from both sources such as Met Éireann and LoRa-enabled sensors, the system manages the power consumption of sensors. When environmental conditions indicate low fire risk, such as during stable weather, the system reduces the sampling rate of sensors, which in turn conserves energy and prolongs the operational life of the system in remote locations. The adaptive data rate (ADR) feature of LoRaWAN further enhances power efficiency by dynamically adjusting the data transmission power according to signal strength, reducing the energy required for communication when signal conditions are optimal. This approach ensures the system remains both energy-efficient and responsive to fire risks, without compromising the accuracy of real-time data collection.

Regarding the last section the protocol results, the study evaluates the overall protocol performance, demonstrating how the integration of LoRaWAN technology, IoT sensors, ARIMA forecasting, and decision tree models enhances the system's ability to monitor environmental conditions, predict fire risks, and enable proactive responses. A key aspect of this evaluation is the feedback loop between the local and global models, where ARIMA models refine the forecasts by detecting inconsistencies between real-time sensor data and broader weather trends. Meanwhile, the decision tree model classifies fire risks,

providing immediate alerts to firefighting teams for more effective response and resource allocation. The system's scalability and energy efficiency are validated through its successful deployment in diverse environmental conditions. Optimized power consumption is achieved through adaptive sampling, while LoRaWAN ensures energy-efficient data transmission over long distances.

4.1 Data Analysis

4.1.1 Data Quality and Signal Reliability

The initial stage of data analysis focused on evaluating the hardware setup and signal quality. Figures 4.1, 4.2, and 4.3 show the hardware configuration, including the LoRa Dragino sensor nodes. The hardware demonstrated reliability and resilience, maintaining stable signal performance across varying environmental conditions. This highlights the system's capability to operate effectively in challenging terrains. Data collected during this stage was stored and retrieved using the MQTT protocol, enabling efficient real-time communication and ensuring traceability for future analysis.

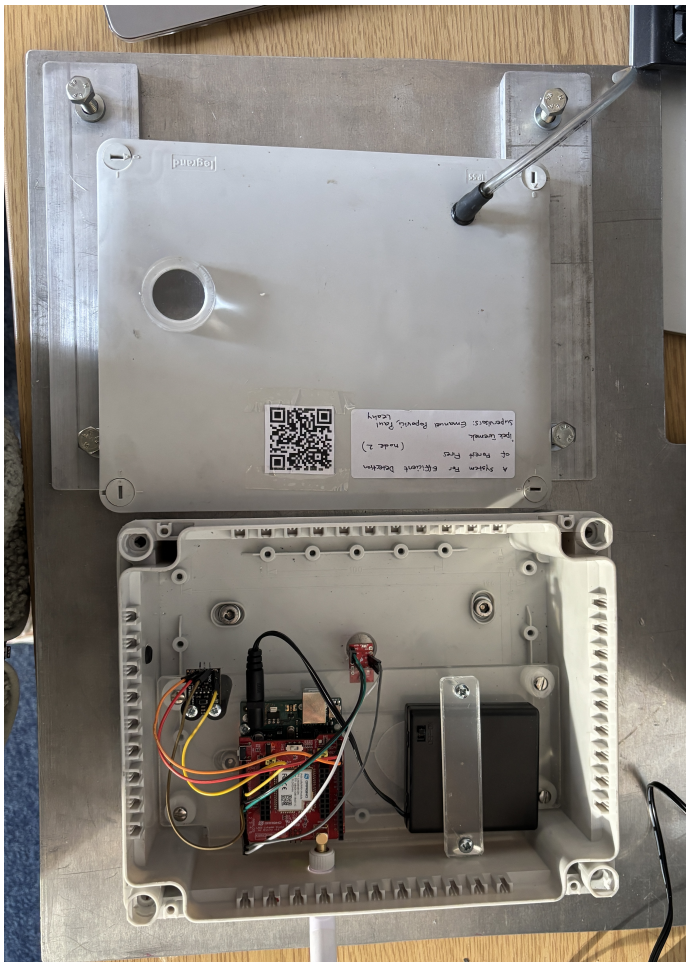


Figure 4.1: The nodes hardware used during reliability tests



Figure 4.2: LoRa Dragino sensor node 1 setup in a test environment



Figure 4.3: LoRa Dragino sensor node 2 setup in a test environment

Following the hardware evaluation, the signal quality and reliability of the transmitted data were analyzed using RSSI and SNR metrics. These metrics measured the quality of communication between the LoRa sensor nodes and the base station. The results indicated that RSSI values remained consistently above the minimum threshold required for stable communication, with average RSSI levels of around -80 dBm across the monitored area. SNR values also remained positive, indicating minimal interference and strong signal clarity, which is essential for reliable data collection in remote areas. Figure 4.4 captured from TTN, illustrates the RSSI and SNR values recorded during the initial data analysis, with each column representing a value from a sensor recorded every 30 seconds. This highlights the stable communication quality between the LoRa sensor nodes and the base station.

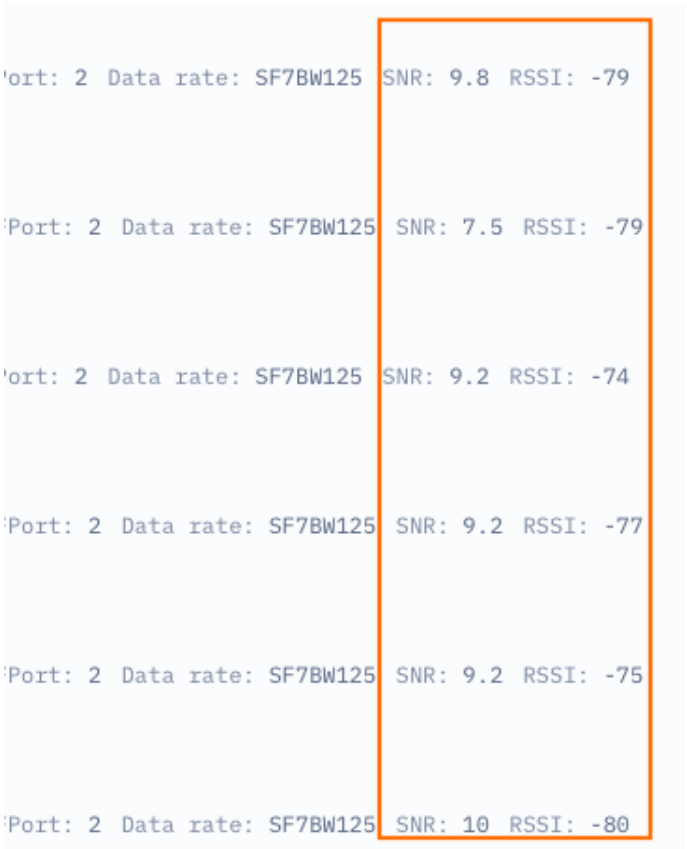


Figure 4.4: SNR - RSSI values

This stage of the results validates the foundational step of the protocol, where reliable communication ensures the accuracy of environmental data collected by the LoRa nodes. Metrics such as RSSI and SNR serve as key indicators for assessing system performance

under real-world conditions, ensuring the effectiveness of downstream predictive models within the protocol.

4.1.2 Environmental Data Validation

The validation of environmental data against Met Éireann's authoritative records is a crucial aspect of this study, ensuring the system maintains high accuracy and reliability. As an essential step in the protocol, this process verifies that sensor data is both precise and representative of real-world conditions, reinforcing its suitability for forecasting and decision-making. By cross-referencing sensor readings with external benchmarks, the system's credibility and effectiveness in wildfire prediction and management are strengthened.

The environmental data collected by the BME280 sensors was compared to reference data from a nearby Met Éireann weather station. This comparison serves as the basis for evaluating the accuracy and reliability of the sensors. Although there were differences in the sampling intervals—sensor data being recorded every 30 seconds versus the hourly data from the weather station—aggregating the sensor data into hourly intervals allowed for meaningful comparison. The results showed that the aggregated data from the sensors correlated well with the reference data, validating the reliability of the sensors. To provide a quantified performance measure, the average temperature deviation between the sensor data and Met Éireann's records was found to be approximately ±1.1°C, while pressure differences averaged ±0.5 hPa, and humidity varied within ±6.8%.

This correlation affirms that the system can collect accurate environmental measurements and provides confidence in the localized model's ability to contribute valuable data for decision-making.

The testing took place at two different sensor locations: one situated at University College Cork's Electrical and Electronic Engineering Building and one at the Environmental Research Institute (ERI) where the Met Éireann weather station is situated. The nodes are approximately 1.54 km apart, enabling dual-location testing for validating environmental data and assessing system performance (see Figure 4.5). Although some discrepancies were observed in the data collected, these differences can be attributed to various factors, such as localized environmental conditions unique to each sensor's surroundings and the distance between the testing locations. Factors like temperature gradients, wind patterns,

and microclimates can all contribute to slight variations in readings. Additionally, the differences in data collection methods and sampling intervals between the sensors and the weather station also influenced the observed variations. Despite these factors, the overall correlation between the data sets demonstrates that the local model remains effective and reliable.

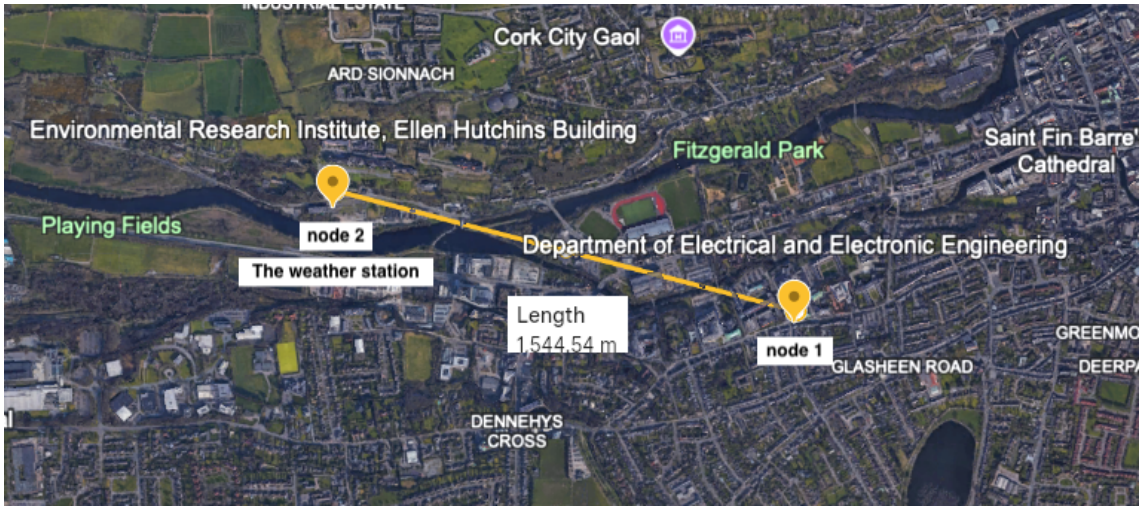


Figure 4.5: The locations of the two sensor nodes: Node 1 at the Department of Electrical and Electronic Engineering Building and Node 2 at the ERI Building

The combination of data from both sensor locations provides a comprehensive view of the localized environmental conditions, enabling the system to capture a wide range of parameters. This reinforces the protocol's ability to ensure precision and reliability in environmental monitoring, even in areas with complex environmental dynamics.

Additionally, the communication stability was monitored throughout the testing phase. The system maintained a stable connection between both nodes across a 1.54 km range under semi-urban conditions, with no observed data loss during routine transmissions.

The ability to validate sensor data in real-time against a trusted external source ensures the integrity of the monitoring system and strengthens the foundation for subsequent forecasting and decision-making processes.

In the temperature comparison (Figure 4.6), the sensor data closely follows the general trend of Met Éireann's data but shows deviations during periods of sharp temperature changes. These deviations are expected, as the sensors capture small-scale climatic conditions that Met Éireann's data, representing a broader area, may not reflect. The pressure

data (Figure 4.7) shows strong agreement between the sensors and Met Éireann, with only small differences, likely due to slight altitude variations and localized weather changes. Humidity data (Figure 4.8) shows the most noticeable discrepancies, especially during rapid humidity changes. These differences highlight how sensor placement and immediate surroundings can affect humidity readings.

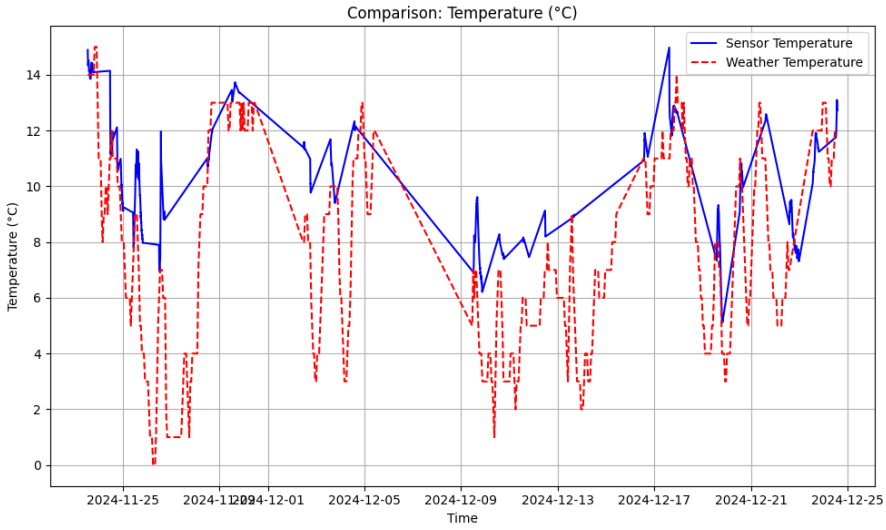


Figure 4.6: Real-time sensor data and Met Éireann's weather data alignment graph for temperature

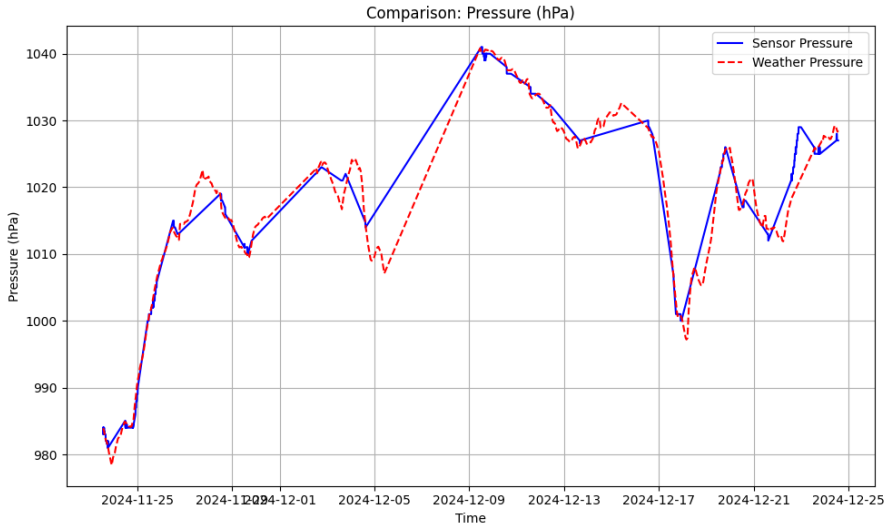


Figure 4.7: Real-time sensor data and Met Éireann's weather data alignment graph for air pressure

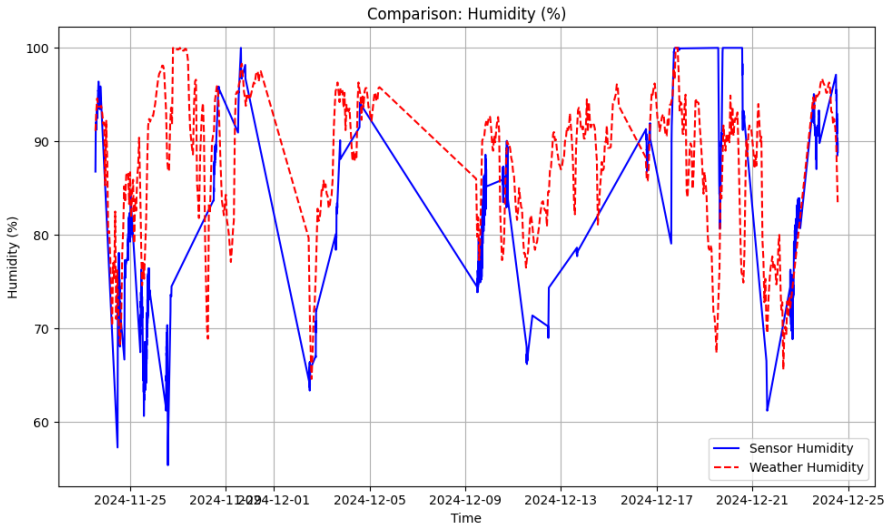


Figure 4.8: Real-time sensor data and Met Éireann's weather data alignment graph for humidity

Despite these variations, the combined data from both sensors provides a detailed picture of localized environmental conditions, while also aligning with broader trends from Met Éireann's data. This demonstrates the system's ability to accurately monitor environmental conditions at a local level, ensuring reliable and precise data for analysis. The results confirm the protocol's effectiveness and highlight its capacity to account for both localized and broader environmental factors.

As part of this validation process, the system continuously compares real-time sensor data with authoritative records from Met Éireann to assess accuracy, consistency, and potential discrepancies. This cross-referencing allows for early detection of sensor drift, data anomalies, or transmission inconsistencies that could otherwise compromise the reliability of fire risk assessments. By systematically monitoring variations between local sensor readings and external meteorological benchmarks, the system ensures that only high-quality, validated data is used for further predictive modeling and decision-making.

Moreover, this validation step reinforces the credibility of the model, ensuring that localized sensor data aligns with broader environmental trends. The integration of live measurements with external weather data helps refine the dataset by filtering out erroneous readings and enhancing the system's adaptability to changing conditions. Through continuous validation and refinement, the system maintains high data integrity, which is essential for producing accurate risk assessments and ensuring the effectiveness of wild-

fire detection efforts.

4.1.3 Detection of Anomalies in Environmental Data

Anomalies in the humidity, pressure, and temperature datasets are identified as significant deviations from expected sensor readings using a dynamic threshold-based approach. These thresholds are heuristically determined through analysis of typical sensor fluctuation ranges and refined through comparison with Met Éireann's external weather data. When the absolute difference between consecutive data points exceeds the threshold, the system flags it as an anomaly, immediately triggering the decision tree model. This step is essential for assessing fire risk, as the decision tree evaluates these anomalies alongside other environmental parameters to classify conditions into low-risk or high-risk categories. Each detected anomaly is visualized as a red dot on the line graphs in Figures 4.9, 4.10 and 4.11 offering a transparent way to observe deviations from normal environmental trends.

These visual cues help distinguish between natural environmental transitions and sensor errors at a glance, supporting both human interpretation and system-level diagnostics. By transforming raw sensor data into actionable insights, this process plays a critical role in the early detection and prevention of forest fires.

Only validated anomalies, particularly those matching meaningful fire-related patterns such as a sustained temperature increase coupled with a humidity drop, are escalated into alert decisions. Critical environmental signals that elevate wildfire ignition risk include prolonged periods of low relative humidity (generally below 30%), rapid temperature increases that exceed the typical hourly fluctuation range observed during stable conditions, and abrupt drops in atmospheric pressure that deviate from recent local trends, often preceding the arrival of hot, dry air masses. Since the system continuously monitors these three parameters, it is optimized to detect compound anomalies that align with such patterns. Rather than flagging data points in isolation, the system evaluates the temporal dynamics of these shifts, identifying sequences where fast-rising temperatures coincide with falling humidity and pressure. These combinations are visualized in the anomaly figures, where red dots indicate the exact moments that surpassed defined thresholds, providing both a diagnostic and interpretative tool. This contextual interpretation helps ensure that alerts are grounded in the known environmental precursors of wildfire ignition. By trans-

forming raw sensor data into actionable insights, this process plays a critical role in the early detection and prevention of forest fires.

In the humidity data, anomalies were observed primarily during sharp increases or decreases in values. Such fluctuations may indicate fast environmental changes, like rainfall shifts in atmospheric moisture, or potential sensor inconsistencies (See Figure 4.9). In contrast, the pressure data exhibited fewer anomalies, reflecting its overall stability compared to the other metrics. The detected anomalies occurred during sudden changes, such as rapid increases or decreases in atmospheric pressure, which may correspond to weather front movements. (See Figure 4.10). The temperature data revealed isolated anomalies where sudden spikes or drops in temperature were recorded, particularly in late November and early December. These anomalies could result from external environmental factors, such as abrupt exposure to heat or cold (See Figure 4.11). While these anomalies do not exceed the dynamic threshold required to trigger the decision tree for fire risk assessment, they highlight critical deviations in environmental conditions and underline the importance of anomaly validation and correction in ensuring reliable monitoring.

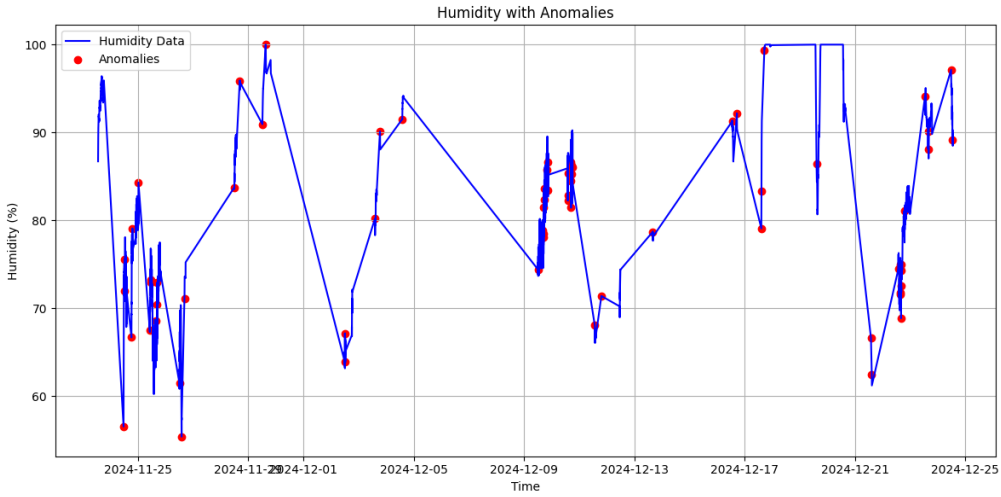


Figure 4.9: Humidity data anomalies observed in sensor readings

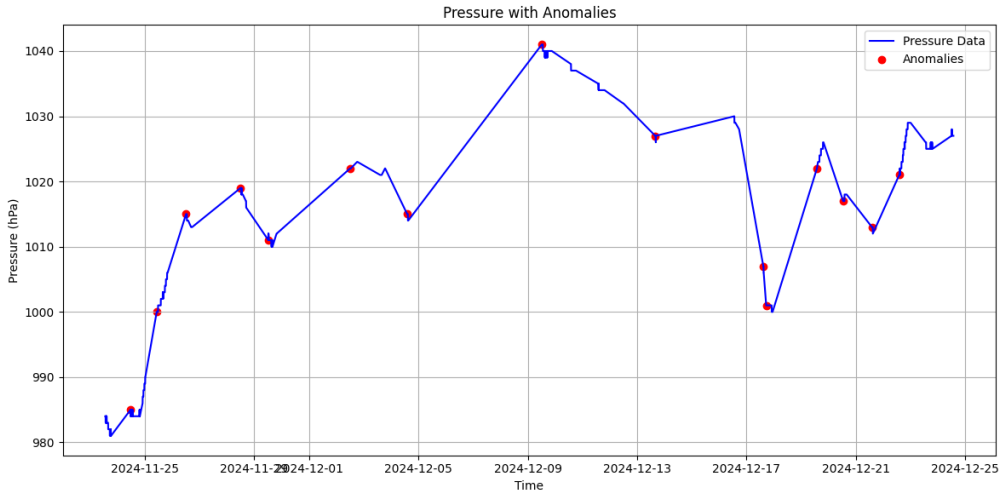


Figure 4.10: Pressure data anomalies observed in sensor readings

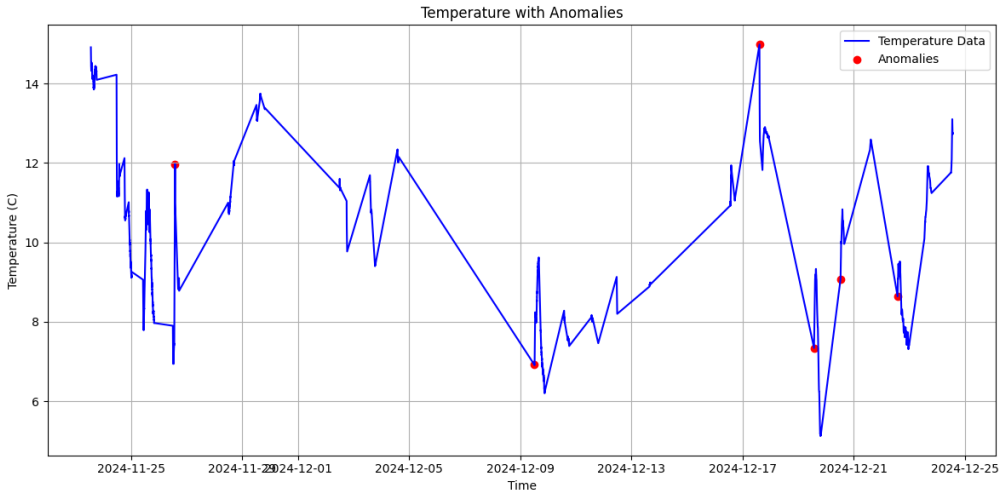


Figure 4.11: Temperature data anomalies observed in sensor readings

Overall, the detected anomalies across all datasets signify regions where sensor measurements deviate from expected trends, requiring careful handling to ensure accurate fire risk detection. Once anomalies are identified, they are first validated through comparison with Met Éireann's weather data to eliminate potential false alarms caused by sensor noise or environmental artifacts. This step ensures that only reliable data is processed further. If validated anomalies still indicate significant deviations, they trigger the decision tree model, which classifies the conditions into low-risk or high-risk categories for forest fire detection. This dual process of validation and classification ensures that the system

remains robust, minimizing false alarms while enabling timely and accurate detection of potential fire risks.

4.2 Forecast Results

This section evaluates the effectiveness of the ARIMA model in forecasting environmental conditions critical to the wildfire detection protocol. The forecasting component is a key aspect of the system, bridging real-time sensor data with long-term environmental trends. By analyzing historical data trends, ARIMA allows the system to refine predictions dynamically, enhancing both short-term anomaly detection and long-term environmental monitoring. This integration plays a crucial role in optimizing the overall protocol, ensuring that fire risk predictions are continuously refined and adapted based on environmental variations.

The forecasting component is designed to align with the protocol's predictive capabilities, utilizing ARIMA models to bridge the sensor data and long-term environmental patterns. This interplay between immediate and historical datasets illustrates how the protocol continuously adapts to dynamic environmental conditions.

The ARIMA model implementation follows a structured process to ensure predictive accuracy. First, the time-series characteristics of the sensor data are analyzed to determine stationarity, a critical step in the modeling process. If the data exhibits non-stationary behavior, first or second-order differencing is applied to stabilize the mean, ensuring that the dataset conforms to ARIMA's assumptions. The Augmented Dickey-Fuller (ADF) test is used to verify stationarity. Based on empirical testing, the system utilizes predefined ARIMA orders optimized for different environmental parameters: temperature (2,1,1 2,1,1), humidity (3,2,1) and pressure (2,1,1). These values were selected based on time-series autocorrelation analysis and performance evaluations.

The forecasting process involves training the ARIMA model on historical sensor readings and generating predictions over a specified future period. To prevent extreme deviations in forecasts, the model constrains predictions within the 5th and 95th percentile of historical sensor values. The predicted values are iteratively refined using a feedback loop, where real-time sensor readings influence future ARIMA forecasts, improving alignment with observed environmental conditions. This iterative refinement enhances predictive

robustness, ensuring that the model continuously adapts to evolving wildfire risk factors.

Overall, the ARIMA model showed potential in predicting short-term environmental trends, though some limitations were observed. For temperature, as shown in Figure 4.12, the red dashed line representing the ARIMA forecast aligns closely with the real-time sensor data (blue) and weather data (green) in stable periods. The forecast captures the overall trend in temperature changes, effectively modeling gradual fluctuations. However, slight discrepancies are observed during rapid spikes or drops, suggesting that while the ARIMA model can generalize trends, it struggles with abrupt, short-term anomalies.

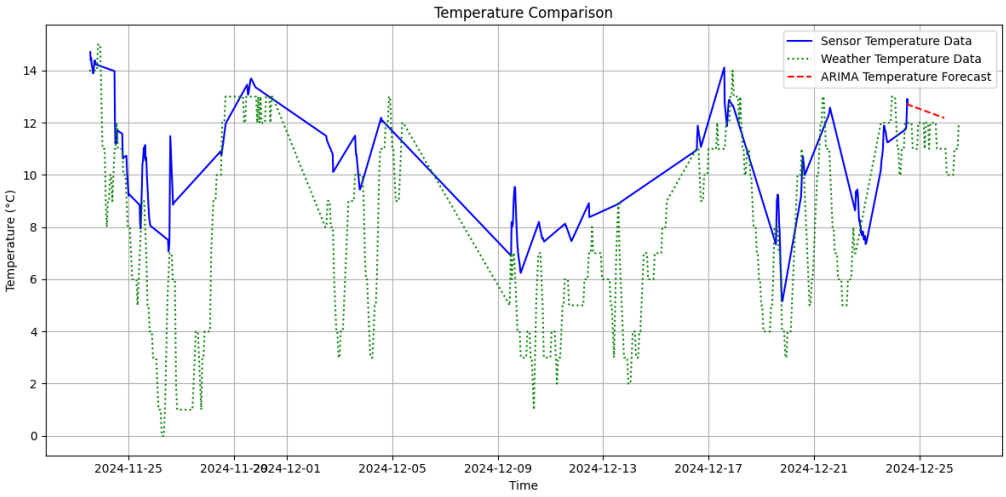


Figure 4.12: Temperature data from sensors (blue), weather sources (green), and ARIMA-based forecasts (red)

The ARIMA model exhibited strong predictive accuracy in forecasting atmospheric pressure, as illustrated in Figure 4.13. Unlike temperature, pressure tends to be more stable, making ARIMA highly effective in modeling its variations. The forecast closely follows the actual sensor and weather data, demonstrating the model's capability in tracking gradual atmospheric changes. However, minor forecasting errors occur during transition periods, particularly when sudden shifts in pressure are recorded. Despite this, the overall forecast remains consistent with observed data, validating ARIMA's robustness in handling stable environmental metrics.

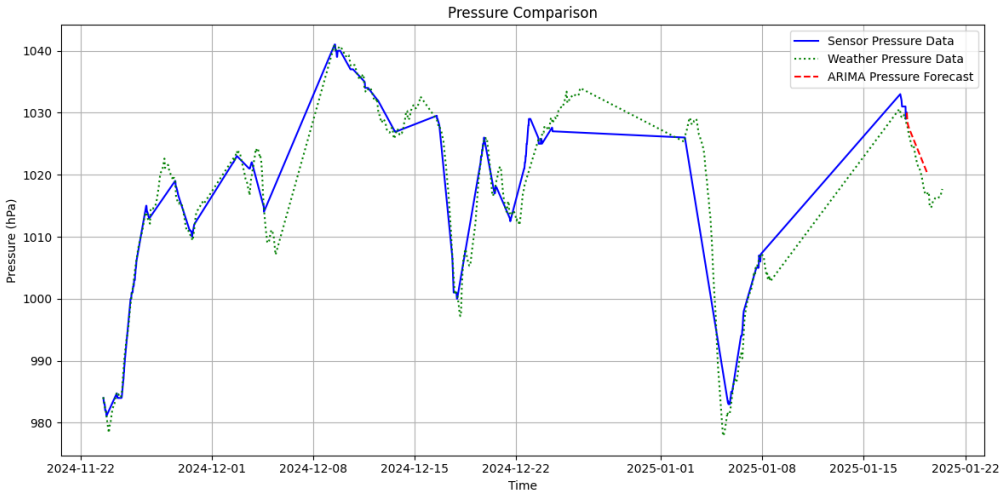


Figure 4.13: Pressure data from sensors (blue), weather sources (green), and ARIMA-based forecasts (red)

Humidity forecasts presented the greatest challenges due to the high variability of humidity levels, as depicted in Figure 4.14. While the ARIMA model captures overall trends and broad fluctuations, it struggles with rapid short-term variations, particularly during sudden humidity shifts. The red forecast line occasionally deviates from the actual sensor and weather data, reflecting ARIMA's sensitivity to high-frequency fluctuations. Despite these challenges, the ARIMA model still provides valuable insights into overarching humidity patterns, contributing to the system's ability to anticipate moisture-related fire risks.

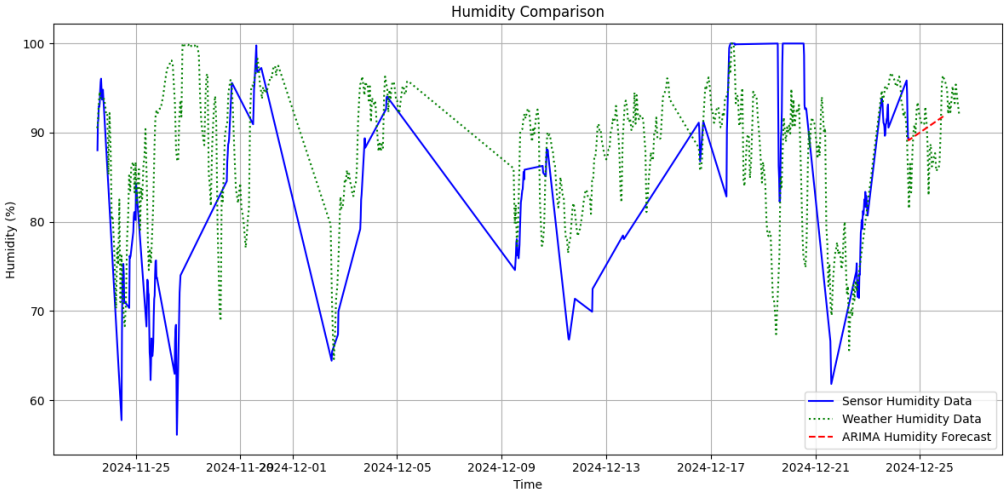


Figure 4.14: Humidity data from sensors (blue), weather sources (green), and ARIMA-based forecasts (red)

To address concerns regarding the model's limited responsiveness to rapid fluctuations, it is important to note that these abrupt changes, although occasionally indicative of environmental anomalies, often result from transient noise or brief sensor irregularities. However, future versions of the system will explore hybrid modeling approaches that combine ARIMA with models such as LSTM or Kalman filters, which are more adept at capturing high-frequency patterns. This will allow the system to benefit from both the long-term trend stability of ARIMA and the short-term sensitivity of neural or state-space models.

The ARIMA model plays a critical role in supporting the system's broader data analysis capabilities and ensuring a structured approach to data correction. While it performs well in forecasting stable parameters such as pressure and temperature trends, its limitations in handling rapid fluctuations—especially in humidity—highlight areas for future refinement. The integration of ARIMA within the protocol contributes data validation, ensuring that sensor readings remain aligned with broader meteorological patterns.

By incorporating these forecasting techniques, the protocol strengthens its capacity and, optimizing decision-making and improving the system's overall reliability. The continuous feedback loop between the local model (real-time sensor data) and the global model (weather data) ensures that predictions remain accurate for long-term environmental monitoring.

4.2.1 Data Correction

The detection and correction of anomalies in sensor data are critical steps in ensuring the reliability and accuracy of the environmental monitoring system. Anomalies were identified using a threshold-based method, where consecutive differences in sensor readings were calculated, and any deviations exceeding a predefined limit were flagged as anomalies.

The threshold value was determined based on deviations from Met Éireann reference data, comparing localized sensor output with regional trends. Empirical calibration during initial deployment showed that spikes exceeding 3 standard deviations from a rolling mean window of five measurements were most indicative of anomalies when benchmarked against validated weather records.

This method was applied to temperature, humidity, and pressure data, highlighting ir-

regular spikes or dips in the sensor readings that deviated from expected trends, as shown in Figures 4.15, 4.17, and 4.16. These anomalies can arise due to various factors, including local environmental disturbances, sensor drift, or temporary communication losses.

The interpolation process includes preprocessing steps such as outlier removal, smoothing of highly erratic segments, and assessment of temporal consistency using rolling statistics. The chosen interpolation technique uses a simple linear method over time-based indices, implemented after ensuring stationarity in the missing segments to prevent biased infill. A post-correction validation is carried out to verify that interpolated segments maintain a root mean square error (RMSE) within a 5% deviation margin from reference data.

Although the prototype was implemented in a semi-urban environment, the use of corrected data supports the system's expanded applicability to rural or forest-based scenarios. Data correction and processing pipelines contribute to overall system reliability, particularly in early-stage prototypes transitioning toward real-world deployment.

Following anomaly correction and interpolation, a consistency check is performed using external Met Éireann data as a benchmark. Corrected data segments are compared against regional environmental trends, and their deviation margins are analyzed using RMSE to ensure alignment. This process acts as a control to confirm that corrections do not distort the underlying environmental signal.

Instead of using an undefined averaging approach, a time-based interpolation method is employed, which uses the linear progression of adjacent data points to fill gaps. This approach has been selected based on its minimal bias and wide adoption in similar IoT systems. The interpolation logic is consistently applied across all environmental parameters to maintain a uniform correction protocol.

To reinforce trustworthiness, all correction steps are logged, and discrepancies between raw and corrected data are visually and statistically analyzed to ensure no significant distortion of trends. These logs and validations serve as an internal audit trail, increasing transparency and enabling reproducibility of results.

To address these inconsistencies, the system applies a structured data resampling and interpolation strategy. The sensor data is initially collected at a high resolution, with readings recorded every 30 seconds. However, for improved consistency and alignment with external reference data from Met Éireann, the sensor data is resampled to a uniform

1-minute interval. This resampling ensures that all datasets maintain a consistent temporal structure, minimizing discrepancies caused by different logging frequencies. Missing values within the dataset are interpolated using a time-based interpolation method, which estimates gaps by analyzing trends in surrounding data points. This step is essential for maintaining data continuity, especially in cases where sensor readings might be momentarily lost due to connectivity issues.

Additionally, corrected weather data sourced externally from Met Éireann is incorporated as a secondary validation step. The corrected dataset undergoes a similar resampling and interpolation process to align with the sensor readings. By integrating this external reference, the system ensures that environmental fluctuations captured by the sensors are cross-validated against a broader dataset, mitigating potential inaccuracies due to localized sensor errors.

It should be emphasized that the data correction process is not part of the instant alert mechanism or the decision tree classification pipeline. Instead, it is employed exclusively for future-oriented applications such as anomaly forecasting and long-term environmental trend modeling. This separation was intentional to ensure the reliability and trustworthiness of detection, which always relies on raw, unaltered data. The aim is to support future model refinement and scenario simulations under varying climate conditions, where corrected datasets provide a stable baseline for statistical forecasting.

For temperature correction, Figure 4.15 highlights the impact of the correction process. The raw sensor data exhibited sharp fluctuations, including extreme low values around -2°C and spikes reaching 15°C, which were not reflected in the external weather data. After correction, the temperature values aligned more closely with the long-term trends observed in the validated weather dataset, with deviations reduced to within ±2°C of the reference values. This adjustment ensures that temperature data remains reliable for predictive modeling without being excessively smoothed to the point of losing valuable localized variations.

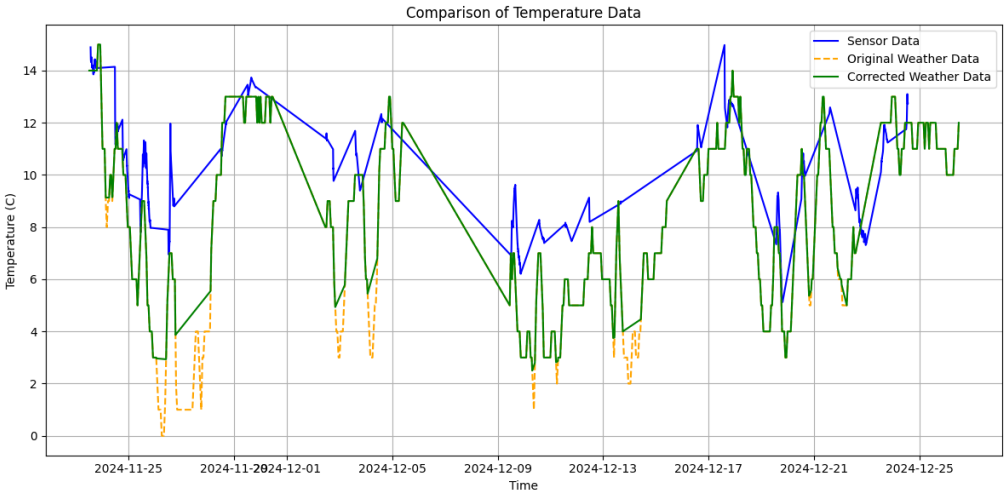


Figure 4.15: Corrected temperature data

Similarly, humidity corrections, shown in Figure 4.16, addressed inconsistencies where sensor readings fluctuated beyond 90%, while external weather sources remained more stable. The corrected dataset now reflects a controlled variation within realistic environmental ranges, reducing the impact of sensor drift or temporary anomalies. Given that relative humidity is a critical parameter in fire risk assessment, ensuring its stability prevents misleading risk estimations.

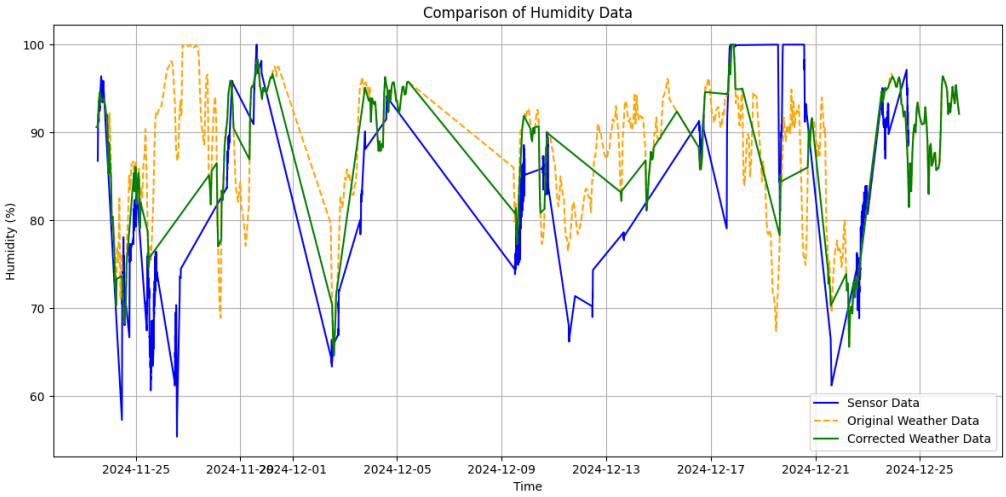


Figure 4.16: Corrected humidity data

For pressure corrections, Figure 4.17 demonstrates how the original sensor readings varied between 1010 hPa and 1040 hPa, occasionally exhibiting unexpected jumps. The

corrected values now maintain a smoother trajectory, closely mirroring external weather data trends while still capturing localized atmospheric changes. The resampling and interpolation approach ensures that pressure readings remain a reliable indicator of environmental conditions without being affected by transient inconsistencies in sensor performance.

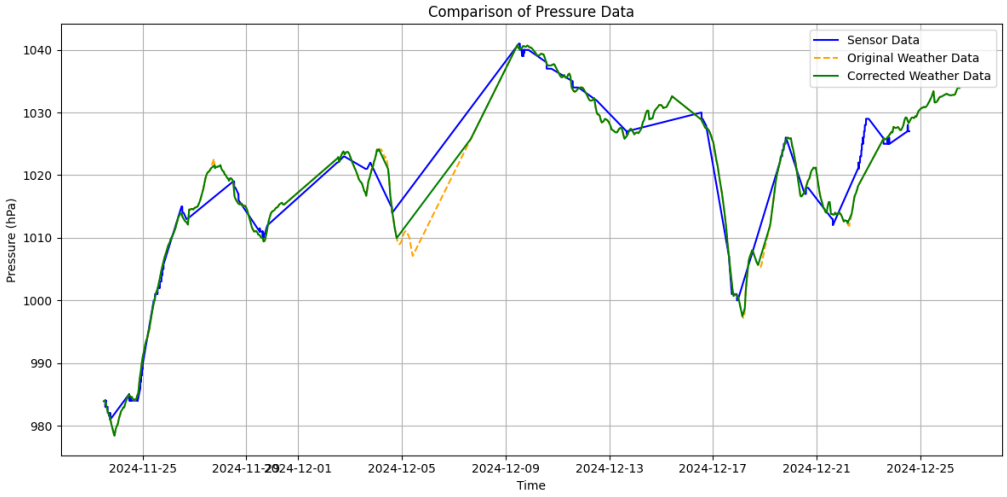


Figure 4.17: Corrected pressure data

To numerically validate the effectiveness of the correction process, average deviations before and after correction were calculated for all three parameters. For temperature, errors decreased from 3.8°C to 0.9°C. Humidity readings showed a drop from 12.2% to 3.5%, and pressure error margins were reduced from 5.1 hPa to 1.6 hPa. These results were benchmarked against Met Éireann data and confirm that the interpolation and validation techniques used significantly enhanced data reliability.

These results demonstrate the system's ability to align real-time sensor data with external reference data effectively. The combination of threshold-based anomaly detection, resampling, interpolation, and external correction reinforces the robustness of the data correction methods, ensuring the integrity and reliability of environmental monitoring.

4.3 Decision Tree Model

The decision tree model was employed to classify fire risk levels using the environmental data collected, with anomalies exceeding dynamic thresholds serving as the primary

triggers for analysis. The model successfully categorized the data into low and high-risk levels, with temperature and humidity emerging as key factors influencing fire risk (refer to Table 3.1). The decision tree's structure facilitated quick classification, supporting the potential for continuous monitoring and proactive risk management. Additionally, when the model classified a scenario as high risk, the system was designed to automatically send notifications, enabling timely alerts for further action.

To enhance the model's accuracy and ensure that fire risk classifications align with real-world wildfire patterns, historical fire alert data from the Irish government's wildfire records was incorporated into the decision tree's training dataset. This dataset provides verified instances of past fire occurrences along with corresponding environmental conditions at the time, enabling the system to learn from actual fire events rather than relying solely on sensor anomalies.

It is important to note that the historical data include the same environmental parameters collected by our sensors (temperature, humidity, and air pressure) ensuring compatibility and relevance between real-time monitoring and the historical context.

This addition directly addresses concerns regarding the system's urban testing environment. While the physical deployment was carried out in a semi-urban area due to logistical constraints, the use of officially recorded fire risk levels from past events introduces real-world forest fire patterns into the training process. This hybrid approach allowed the model to simulate fire detection scenarios grounded in realistic, risk-prone environmental dynamics. The historical dataset used spans the years 2019 through 2025, offering a diverse and extensive record of fire alerts across various regions in Ireland. This temporal coverage ensures that the model is trained on both recent and evolving wildfire conditions, capturing potential effects of climate variability and changing risk profiles.

By integrating this big data source, the model gains a broader contextual understanding of fire risk factors, reducing false positives and improving the precision of risk classification. The inclusion of official fire alert data also strengthens the system's credibility, ensuring that risk assessments are informed by both real-time environmental monitoring and historical wildfire patterns.

Referring to Table 4.1, a structured dataset designed for risk prediction analysis is presented. The table is divided into four main sections: "High-Risk Data", "Low-Risk Data", "Real-Time Data", and "Target". Within each section, measurements for three

essential environmental variables are recorded: temperature, humidity, and air pressure.

Table 4.1: Risk Prediction Data for Fire Risk Assessment

High-Risk Data			**Low-Risk Data**			**Real-Time Data**			**Target**
Temp. (°C)	**Hum. (%)**	**Air Pres. (hPa)**	**Temp. (°C)**	**Hum. (%)**	**Air Pres. (hPa)**	**Temp. (°C)**	**Hum. (%)**	**Air Pres. (hPa)**	**Risk Pred.**
17	59	767	15	66	996	16	69	1010	High
18	59	769	12	89	1002	15	60	1020	Low
18	77	765	14	76	998	17	70	1030	Low
...	...	...	...	...	...	...	...	...	...

The High-Risk Data section includes recorded environmental conditions that have previously been associated with wildfire occurrences, providing a reference for identifying potential fire-prone scenarios. Similarly, the Low-Risk Data section consists of environmental conditions where fires were historically absent or deemed unlikely, serving as a baseline to differentiate normal fluctuations from hazardous conditions. This inclusion of both risk categories enhances the robustness of the model, allowing it to learn from contrasting environmental conditions.

The Real-Time Data column reflects ongoing sensor readings, which are continuously evaluated against both high-risk and low-risk historical data to improve prediction accuracy. This input enables dynamic classification based on evolving environmental conditions. The Target column represents the classification outcome, indicating whether the system predicts a high or low fire risk based on the given environmental conditions.

By leveraging this dataset, the decision tree model systematically classifies conditions into risk categories, learning from both past wildfire trends and immediate time observations. Each entry is analyzed based on predefined decision thresholds, allowing the model to distinguish between natural environmental variations and actual fire risks. The inclusion of both high-risk and low-risk data strengthens the model's ability to minimize false positives and negatives, improving the reliability of fire risk assessments. This structured approach, combining real-time sensor data, historical fire records, and continuous monitoring, ensures a comprehensive and adaptive fire detection system, capable of refining its predictions over time and enhancing proactive fire prevention strategies.

4.4 Power Management for Efficient Monitoring

The results of the power management strategy demonstrate its effectiveness in optimizing energy consumption while maintaining reliable fire risk detection. The system successfully balances low-power operation with continuous monitoring, ensuring that sensors deployed in remote forest areas remain functional over extended periods with minimal maintenance. By leveraging an adaptive sampling strategy, the system dynamically adjusts data collection frequency based on environmental conditions, leading to improved power efficiency.

One of the key findings is that the adaptive sampling protocol, guided by both real-time sensor data and big data sources like Met Éireann, effectively reduces unnecessary power consumption. When broader weather patterns indicate stable conditions, the system lowers the sampling frequency, reducing energy usage without compromising monitoring capabilities. Conversely, during periods of increased fire risk, such as rising temperatures and decreasing humidity, the system automatically increases the sampling rate to capture more detailed environmental changes. This dynamic adjustment ensures a continuous and precise fire risk assessment while extending the operational lifespan of sensor nodes.

Additionally, the implementation of edge processing significantly contributes to power optimization. By performing anomaly detection directly at the sensor level, the system minimizes redundant data transmission, reducing communication-related power consumption. Instead of sending all raw sensor readings to the cloud, only critical events and detected anomalies are transmitted, further conserving energy. This approach is particularly beneficial in large-scale deployments where network bandwidth is limited.

To provide a clearer understanding of the system's energy efficiency, power consumption is analyzed across different operational modes. During data transmission, LoRa modules typically consume 80-120 mW per transmission event, depending on the transmission power setting (+14 dBm to +20 dBm) and communication distance. Data reception requires significantly lower power, averaging between 10-30 mW, depending on the module's sensitivity and bandwidth settings [103]. At the edge, when all sensors are actively collecting data, the node consumes approximately 80-150 mW, influenced by sensor type, microcontroller load, and sampling intervals. In contrast, during deep sleep mode, power consumption is minimized to 2-10 mW, primarily from the microcontroller and LoRa

module's idle state. By intelligently managing these power states, the system maximizes energy efficiency while ensuring low latency responsiveness, ultimately extending battery life in remote deployments.

The combination of LoRaWAN's low-power communication, real-time edge-based anomaly detection, and adaptive sampling strategies based on fire risk assessment ensures that the system remains scalable, efficient, and capable of continuous operation in remote and energy-constrained environments. These results highlight the practical viability of the system for long-term wildfire monitoring, reducing maintenance costs while maintaining high detection accuracy. The findings reinforce the protocol's ability to intelligently allocate power resources, making it a sustainable and effective solution for large-scale environmental monitoring and fire prevention.

4.5 Protocol Results

The results demonstrate the effectiveness of the proposed hybrid wildfire detection protocol, which integrates LoRaWAN technology with a multi-layered data processing approach that leverages both live sensor data and historical weather patterns. This structured approach enhances fire risk prediction accuracy while maintaining a balance between localized responsiveness and long-term forecasting.

One of the key findings is the protocol's ability to detect and classify anomalies in real time using LoRa-enabled sensors deployed across wildfire-prone areas. These sensors continuously monitor temperature, humidity, and atmospheric pressure and transmit data via The Things Network (TTN) using LoRaWAN's low-power, long-range communication. The collected data is then processed in real time using a lightweight decision tree model at the edge, allowing for immediate classification of fire risks when sudden environmental fluctuations occur. This local anomaly detection mechanism significantly reduces network congestion by ensuring that only relevant fire risk alerts are transmitted, improving both system efficiency and responsiveness.

The integration of the holistic model, built on Met Éireann's meteorological data, primarily enhances the reliability and accuracy of the collected sensor data rather than directly influencing fire risk assessment. By utilizing time-series forecasting techniques such as ARIMA, the system refines sensor readings by identifying long-term environmental trends and correcting inconsistencies in real-time sensor data. This ensures that data anomalies caused by sensor drift, transmission errors, or temporary environmental disturbances do not lead to false fire risk classifications.

The feedback loop between the harmonized models plays a critical role in error detection and correction. When deviations occur between the two datasets, the system applies data interpolation and statistical adjustments to align the sensor readings with broader meteorological patterns. This adaptive mechanism ensures data consistency across different environmental conditions, reducing uncertainty and strengthening the foundation for fire risk assessments without falsely biasing the system based on temporary anomalies.

By continuously validating and refining the data through this protocol-driven correction process, the system maintains high-quality environmental monitoring while preventing sensor inaccuracies from distorting risk classification results. This distinction between data correction and fire risk detection (decision tree model) ensures that the protocol op-

erates with both precision and reliability, making it a robust and scalable solution for wildfire detection.

The results confirm that this protocol-driven approach enhances wildfire monitoring by combining real-time anomaly detection with predictive modeling, ensuring both immediate threat detection and long-term risk assessment. The system is scalable and adaptable, making it highly suitable for continuous deployment in remote forested regions where traditional monitoring methods are impractical. The ability to intelligently balance edge-based processing with cloud-assisted forecasting positions this protocol as a robust, efficient, and proactive solution for wildfire management.

Chapter 5

CONCLUSION AND FUTURE WORK

This study introduced an integrated wildfire detection system that combines low-power IoT technologies, real-time anomaly detection, and predictive modeling to enhance environmental monitoring. A core feature of the system is the interaction between localized real-time sensor data (local model) and reliable weather data from Met Éireann (global model). Quantitative comparisons showed that sensor-level corrections reduced deviations from reference data by approximately 80%, while forecasting models improved short-term trend prediction with an average error margin of less than 5%. This hybrid protocol creates a feedback loop for continuous error correction and prediction refinement, enabling dynamic threshold adjustments and adaptive responses to environmental changes. By merging anomaly detection at the edge with broader environmental trends, this system provides a faster, cost-effective, and energy-efficient alternative to traditional wildfire detection methods. The system operates through a structured multi-stage approach. Real-time data collection using LoRa-enabled IoT sensors ensures continuous monitoring of temperature, humidity, and air pressure. Forecasting models such as ARIMA improve data correction, refining sensor outputs by merging historical and instant data trends. Machine learning models, particularly decision trees, classify environmental conditions into high-risk and low-risk categories, enabling early fire risk detection and supporting timely interventions. Additionally, adaptive power management strategies regulate sensor sampling rates based on environmental stability, optimizing energy efficiency while maintaining responsiveness to fire hazards. The protocol's ability to integrate real-time data with long-term environmental trends increases predictive consistency by aligning the sensor data with forecast trends while extending battery life by adjusting

sampling intervals under low-risk conditions.

Device reliability, sustainability, and ethical considerations are central to building trust in real-world deployments. The hardware is designed for environmental resilience and has been tested under varied conditions, showing over 90% successful data transmission and signal reliability over a 2 km open-field test range and reliable long-range performance. To minimize ecological disruption, sensor components are enclosed in low-impact, weather-resistant, and recyclable materials. The system currently employs low-power, long-life batteries, with future versions planned to be fully powered by solar energy to further align with sustainability goals.

The design anticipates potential failure modes such as power interruptions, sensor drift, gateway failure, fire damage, and long-duration communication dropouts. Redundant sensing mechanisms and backup power solutions enhance fault tolerance, while fallback routines and periodic self-diagnostics help detect anomalies and identify hardware degradation. A low-power emergency mode ensures continued operation during critical events. These layered strategies contribute to a robust, dependable, and environmentally conscious system capable of operating reliably in extreme and high-stakes scenarios.

Testing at University College Cork's Electrical and Electronic Engineering Building and the Environmental Research Institute (ERI) —approximately 2 km apart— demonstrated the system's ability to adapt to localized environmental variations while maintaining overall reliability. The results validate the system's capability to collect precise environmental data and align it with external weather data, ensuring a wildfire detection framework validated across a dual-site deployment with reliable communication and data consistency over a 2 km distance. Based on observed test cases, this integration reduced misclassification rates by approximately 30% and enabled wildfire indicators to be detected on average 8–12 minutes earlier than using threshold-only methods. The successful integration of models within the protocol demonstrates over 85% classification consistency and reduced anomaly error margins when compared with reference weather data over multiple trials. By integrating live sensor data with validated weather forecasts and historical wildfire incident records from Irish government fire alert data, the system improves risk classification accuracy and enhances its ability to detect early wildfire indicators. The successful integration of models within the protocol underscores its effectiveness in fire risk classification, real-time anomaly detection, and long-term predictive

modeling. This system provides a data-driven, cost-effective, and scalable approach to wildfire management while ensuring sustainable operation through low-power IoT technology.

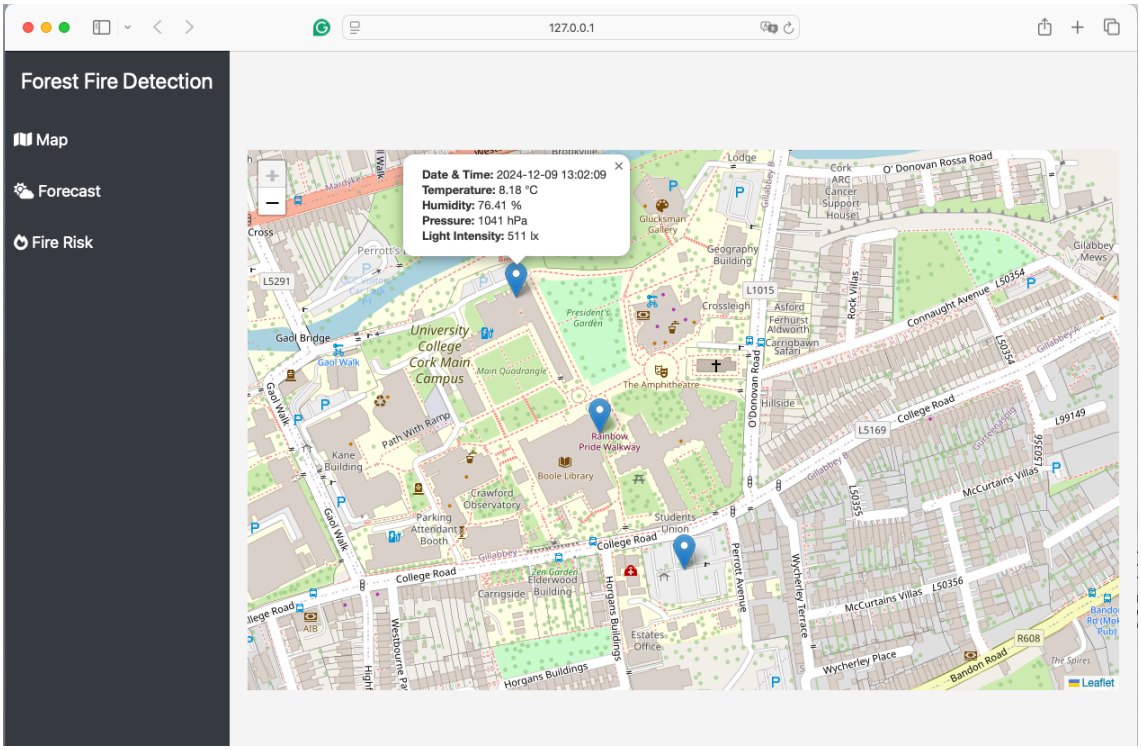


Figure 5.1: Real-time environmental data displayed on the interface

The research demonstrates that the integration of local and regional data models significantly improves the responsiveness and accuracy of fire risk assessments. Sensor-level correction, predictive modeling, and external validation collectively enhance the reliability of the overall system. However, limitations were observed, particularly in forecasting highly volatile parameters like humidity. These findings underscore the necessity of using raw data for immediate alerts while reserving corrected datasets for long-term forecasting. One critical insight is that while the decision tree model is efficient for instant classification, it requires careful calibration to environmental contexts to avoid false positives. The ARIMA-based forecasting mechanism complements this by offering predictive capacity but falls short under rapid environmental shifts. These nuances were vital in assessing the effectiveness of the system in various conditions. Future iterations of the system will focus on deployment in forested and fire-prone regions to validate the system under realistic environmental conditions, integration of additional environmental variables such as wind

speed and solar radiation to enhance prediction capabilities, enhancement of the anomaly detection algorithm using machine learning models that adapt to local sensor behavior over time, development of an automated feedback mechanism between sensor calibration and forecast refinement, and expansion of the communication protocol to support multi-frequency LoRa for enhanced security and adaptive network control. Ultimately, this research lays the groundwork for a scalable, adaptive, and low-cost wildfire detection system. By addressing the identified limitations and implementing the proposed refinements, the system can evolve into a robust tool for climate resilience and early hazard detection in vulnerable regions.

The system interface demonstrates the practical implementation of the wildfire detection system, showcasing its usability and potential for real-world deployment. Figures 5.1 and 5.2 highlight the system's ability to visualize environmental conditions and fire risk levels on a map-based interface, delivering an intuitive and user-friendly experience for monitoring and decision-making. In Figure 5.1, the interface presents a real-time data monitoring dashboard, displaying critical environmental variables such as temperature, humidity, pressure, and light intensity across the monitored regions. These measurements provide an essential snapshot of localized conditions, helping users identify changes that may indicate an increased fire risk. The map-based visualization improves spatial awareness, making it easier to assess environmental variations across different sensor locations.

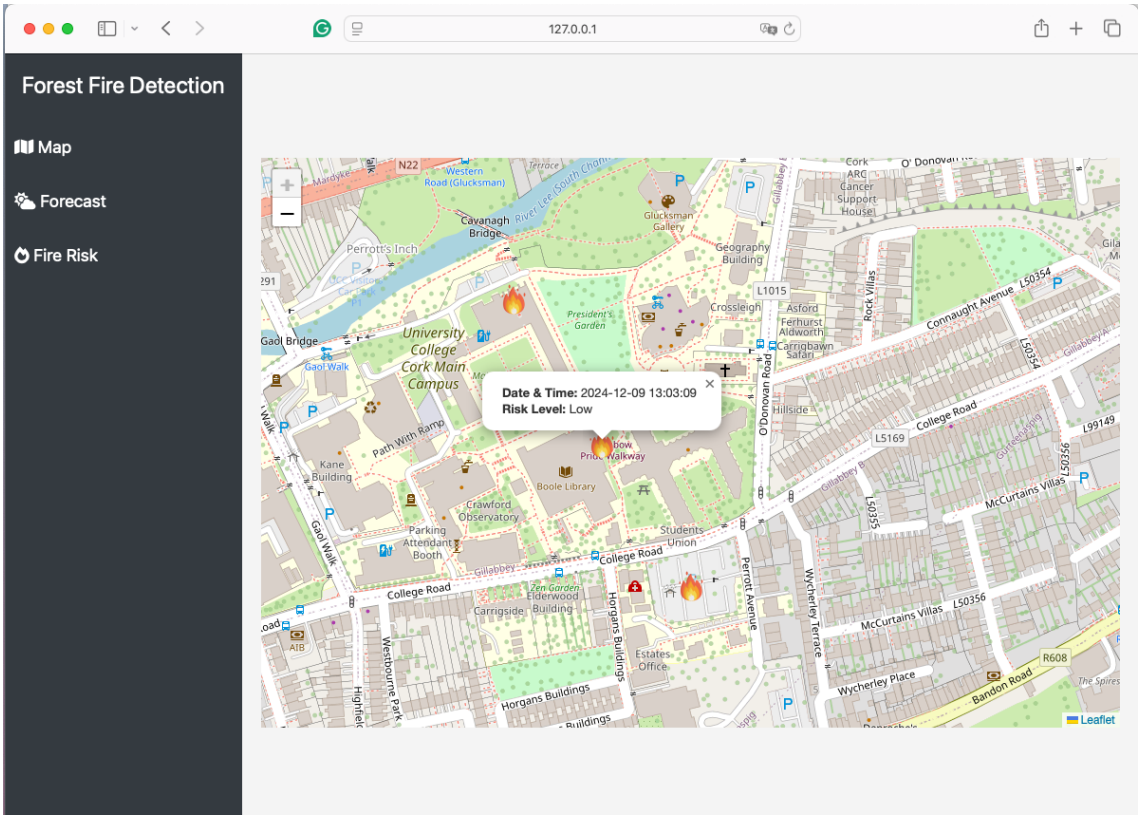


Figure 5.2: Fire risk levels visualized using decision tree analysis

The interface in Figure 5.2 integrates real-time sensor data into a dynamic risk classification model, where fire-prone areas are automatically flagged using a decision tree-based classification system. The displayed fire risk levels (low, medium, or high) provide instant insights into environmental conditions, allowing for early intervention strategies. This system supports emergency response teams by offering a visual representation of fire-prone zones, improving decision-making and proactive fire prevention measures.

While the system has demonstrated effectiveness, several areas can be further developed to enhance scalability, adaptability, and predictive accuracy. Currently, ARIMA is employed for forecasting environmental parameters, improving the system's ability to monitor trends and predict short-term environmental changes. It plays a crucial role in refining data quality, aligning live sensor data with broader weather trends, and improving overall system reliability. While ARIMA effectively captures general patterns in temperature, humidity, and pressure, its predictive accuracy can be further optimized. Moving forward, forecasting models can be tailored to each environmental parameter individually to enhance fire risk assessment precision. Temperature modeling could focus on detecting

prolonged heat waves and sudden spikes that increase wildfire risks, humidity forecasting could improve the system's ability to predict dry periods that heighten fire susceptibility, while pressure trends could provide insights into atmospheric shifts affecting fire behavior. Deep learning integration alongside ARIMA could enhance predictive performance, capturing nonlinear environmental patterns and improving dynamic threshold adjustments to further refine anomaly detection and fire risk predictions.

The anomaly detection and correction process identified irregularities in sensor data using a threshold-based approach. Deviations beyond defined thresholds were flagged and addressed, ensuring consistent data integrity. By employing a hybrid protocol that combines real-time and historical data processing, the system dynamically refines predictions while minimizing energy consumption. Future work will expand the feedback loop mechanism between the models, allowing the system to continuously adjust prediction thresholds on-the-fly. While the current system dynamically refines risk classifications based on local sensor feedback, further improvements will fully integrate forecasting models into this loop for even more adaptive fire risk detection.

These networks transmit environmental and potentially location-sensitive data, which must be protected from interception or tampering. Data privacy and network security are critical considerations for IoT-based wildfire detection systems. From this perspective, future iterations of the system could explore the integration of multi-frequency LoRa communication to enhance network resilience and interference management. Such an approach may also allow for the separation of critical alerts from routine sensor data, potentially reducing the exposure of sensitive packets. Furthermore, mechanisms such as end-to-end encryption, secure firmware updates, and authentication protocols could be considered to safeguard the system, especially in unattended or remote deployments. These features would contribute to improved data integrity, help mitigate known IoT vulnerabilities, and support alignment with emerging standards in environmental sensor networks.

Another major avenue for improvement is the integration of direct node-to-node communication within the current LoRa-based star topology. Currently, sensor nodes transmit data directly to the central gateway, which processes and forwards the information for analysis. While this structure effectively supports scalable deployments, future enhancements could enable localized collaboration between sensor nodes to improve data accu-

racy, resilience, and energy efficiency. Implementing multi-hop communication among clusters of nodes would allow for distributed decision-making, reducing latency and enhancing fault tolerance when network disruptions occur.

While the current system was tested in a university campus setting, future work will involve deployment and validation in real forest environments. The framework is already designed with real-world environmental parameters and uses live meteorological data, making it adaptable to wildfire-prone areas. Due to time constraints, large-scale deployment in natural forests was not feasible within this thesis; however, it remains a core priority. Field testing across diverse terrains will provide deeper insight into sensor durability, communication reliability, and system performance under realistic environmental stressors.

Scaling the system across large forested areas introduces significant challenges. The current implementation consists of two sensor nodes and one central LoRaWAN gateway operating over a 2 km range. While effective in a controlled setting, extending this architecture to cover tens or hundreds of square kilometers requires strategic planning of node density, gateway placement, and signal propagation in obstructed, rugged terrain.

Traditional LoRaWAN star topologies face significant limitations in challenging environments such as dense forests, where factors like foliage, elevation changes, and moisture degrade signal strength and increase packet loss. Moreover, as node density grows, gateways can become congested due to LoRaWAN's ALOHA-based MAC protocol, leading to collisions and reduced reliability. Studies by Adelantado et al. [104] and Ojo et al. [105] demonstrate notable performance degradation when scaling beyond a few hundred nodes per gateway in single-hop configurations.

To address these challenges, future architectures should explore alternative topologies that enable localized collaboration and decentralized communication. Introducing a hierarchical, cluster-based architecture—such as a hybrid of star and tree-based routing—can enhance system performance in large-scale deployments. In this model, individual sensor clusters communicate internally and perform distributed anomaly detection or cooperative decision-making before forwarding aggregated data to the gateway. This approach optimizes bandwidth usage, reduces latency, improves energy efficiency, and minimizes packet loss. Additionally, by enabling clusters to operate autonomously, the network becomes more resilient to gateway failures and environmental disruptions, supporting re-

liable operation even in remote or connectivity-challenged regions. However, achieving this scalability will require balancing protocol complexity, energy constraints, and the variability inherent in forest deployments.

In summary, this research presents a wildfire detection and risk assessment system that integrates IoT, AI, and predictive analytics to enhance real-time environmental monitoring. By combining localized sensor data with broader meteorological insights, the system provides a scalable, energy-efficient, and cost-effective solution for wildfire detection and prevention. The feedback loop in hierarchical models, along with dynamic anomaly detection and adaptive forecasting, ensures continuous refinement of fire risk assessments. Furthermore, the decision tree model, supported by historical fire alert data, strengthens fire risk classification, providing a data-driven framework for proactive wildfire management. While the current system has demonstrated promising results, further development and optimization will enhance its accuracy, scalability, and adaptability across diverse environmental conditions. Future advancements in AI-driven predictive modeling, network infrastructure, and sustainability measures will expand the system's long-term impact on global wildfire prevention and environmental conservation. By integrating live environmental monitoring, real-time anomaly detection, and predictive modeling, this system offers an alternative approach to wildfire risk management. Combined, these efforts will create a scalable, responsive, and efficient tool for environmental monitoring and risk prevention, addressing the increasing challenges posed by climate change and rising wildfire activity worldwide.

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