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FIRE MITIGATION STRATEGIES IN SFERA@UMS BASED ON FIRE RISK CLASSIFICATION USING RANDOM FOREST

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ABSTRACT. *Forest fires pose significant threats to ecosystems, biodiversity, and community. In a forested area in a university area, conducting early predictions and assessing mitigation strategies are essential for reducing the impact. This study evaluates the effectiveness of the Random Forest (RF) algorithm in predicting forest fire risk within the Sustainable Forest Education and Research Area (SFERA@UMS) and proposes targeted mitigation strategies. The approach integrates machine learning with GIS-based spatial analysis using variables such as elevation, slope, land use classification, and proximity to roads. Results show that the RF model achieved an overall prediction accuracy of 91%, with high-risk zones concentrated in low-elevation areas with steep slopes and near roads. These conditions increase fire susceptibility during higher temperatures and increase of human activity near or in the forest area such student's practical and forest camp, which elevate ignition potential. GIS tools were employed to generate a fire risk map, classifying areas into low, moderate, and high-risk categories for better visualization and planning. Furthermore, Unity-based digital twin technology was utilized to simulate fire spread and assess mitigation measures, including firebreaks, hydrant installations, signage, and community-based fire teams. This research demonstrates the potential of fire occurrences and suitable mitigation strategies to increase fire resilience and improve forest fire management.*

INTRODUCTION

Forest fires are among the most destructive natural hazards, causing severe environmental, economic, and social impacts globally. Their occurrence is influenced by multiple factors, including topography, vegetation, ignition sources, and weather conditions. Meanwhile, human activities and climate change have further altered fire regimes, increasing risks to ecosystems and communities (Saha et al., 2023; Trang et al., 2022; Talukdar et al., 2023). In Malaysia, open burning for land preparation and illegal logging exacerbate fire hazards, threatening biodiversity and its ecosystem (Kumalawati et al., 2022). Early prediction and detection are critical for minimizing damage and reducing firefighting costs, which amount to millions annually (Preeti et al., 2021; Alkhatib et al., 2023). Moreover, m achine learning offers a promising approach to improve prediction accuracy and support proactive fire management strategies.

Spatial analyses are widely applied to analyze factors contributing to forest fires, including topography, land use, and human activities, for creating fire risk maps (Sivrikaya & Küçük, 2021). By integrating spatial data layers like slope, elevation, land cover, and satellite imagery, users can identify patterns and predict fire-prone areas (Parajuli et al., 2020). Topography significantly influences fire risk, with low elevations and gentle slopes posing higher risks due to warmer, drier conditions, while steeper slopes and higher elevations are less vulnerable (Daşdemir et al., 2020; Ciesielski et al., 2022; Sivrikaya & Küçük, 2021). Land use also affects fire probability, where natural forests are low-risk, recreation areas moderate-risk, and forest plantations or commercial zones high-risk due to logging and extraction activities (Ascoli et al., 2021; Zhang et al., 2020; Gellman et al., 2021; Wulandari et al., 2022). Human proximity further increases risk, as areas near roads, settlements, and tourism hotspots are more susceptible (Enoh et al., 2021). Fire risk levels were determined by extracting DEM data in ArcGIS and reclassifying them into weights for topography and land use (Zhao et al., 2021).

Universiti Malaysia Sabah (UMS) was blessed to have a Sustainable Forest Research and Education Area known as SFERA@UMS. SFERA@UMS hosts endangered species like the Sunda Pangolin (New Strait Times, 2024; Sompud et al., 2023). Predictive accuracy for forest fires is limited, particularly in localized contexts such as SFERA@UMS, which located inside a university. Recorded fire incidents near UMS indicate an increasing potential for fire spread into this forest research and education area. Currently, there is no forest fire management in the area, highlighting the urgent need for forest fire management research in this domain.". Integrating machine learning models for fire prediction, risk mapping and propose mitigation strategies in this area is essential to create awareness and reduce the forest fire a threat.

This study aims to propose a mitigation strategies using unity based on risk classification using Random Forest in SFERA@UMS area. By leveraging predictive analytics, this research seeks to enhance early warning capabilities, optimize resource allocation, and contribute to sustainable forest management and increase fire resilience in the area.

MATERIALS AND METHODS

Research design

This study integrates GIS-based spatial analysis and Random Forest which was applied to classify fire risk zones using environmental variables, while GIS was employed to generate risk maps based on elevation, slope, and land use classification. In this study, **'tourism hotspots'** are defined as high-traffic locations within SFERA@UMS, specifically the Conservation & Recreation , the Forest Plantation and Non-Timber Forest Product Area, and designated student forest camps. **Proximity** was quantified using the **Euclidean Distance** method, measuring the shortest linear distance in meters (m) from each observation point to the nearest road, urban boundary, or tourism hotspot. A virtual simulation environment was developed in Unity to model fire scenarios and assess the mitigation measures in high-risk areas. The study area of SFERA@UMS is shown in Figure 1. *The research framework is illustrated in Figure 2*.

Figure 1. Study area of SFERA@UMS

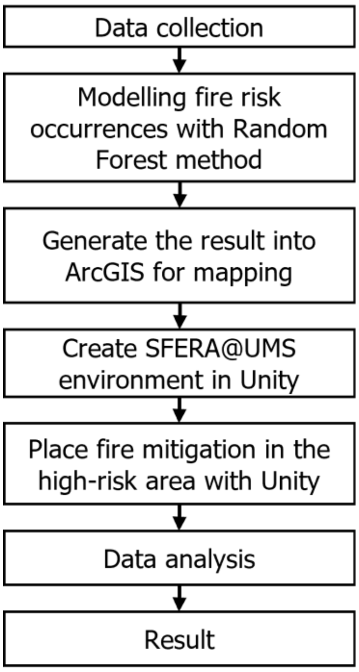


Figure 2. The framework of research design.

Data Collection and validation

Data were collected from multiple sources to capture factors influencing forest fire occurrence, including human activities, topography, and land use. Climate and historical fire data were excluded due to limited accessibility. Key variables such as elevation, slope, proximity to roads and settlements, and land use patterns were derived from publicly available datasets and satellite imagery, processed using GIS tools. These factors are critical for identifying fire-prone areas, as steep slopes accelerate fire spread, while low elevations tend to be drier and more susceptible to ignition in this area due to anthropogenic factors such as drainage system and access road adjacent to the forested area.

Data validation on the location, land-use, slope and elevation, also the anthropogenic factors available near SFERA@UMS, which was performed using GPS and Global Navigation Satellite System (GNSS) technologies to validate spatial data and hotspot locations. Conventional forest inventory methods were supplemented with earth observation technologies for cost-effective and accurate mapping. Fire Information for Resource Management System (FIRMS) and Google Earth Engine (GEE) were utilized to obtain hotspot datasets from multiple sensors, ensuring high-resolution validation of fire risk maps.

Fire Risk Classification

Elevation and slope were reclassified into three fire risk levels: low, moderate and high risk as shown in Table 1. The table is based on topographical and anthropogenic proximity. Values for Elevation and Proximity are expressed in meters (m), while Slope is expressed as a percentage (%) The lower elevations and steeper slopes assigned higher risk due to their influence on fire spread. Land use was categorized based on human activity intensity, where plantation and commercial areas were considered high-risk. These layers were combined using a weighted overlay to produce a composite fire risk map, which served as input for the predictive model and simulation. While steeper slopes generally promote faster fire spread, this study weighted Human Access more heavily than physical fire-dynamics factors. Therefore, lower elevations and flatter slopes were assigned higher ignition risk due to their greater exposure to human activities due to the location of the SFERA@UMS.

The digital twin of SFERA@UMS was constructed in Unity using terrain and vegetation data to replicate the real-world conditions of the area. Fire simulations incorporated GIS outputs and terrain algorithms to visualize the fire spread and behaviour. From here, the mitigation strategies such as firebreaks, hydrants, signage, and community-based response teams were implemented virtually in high-risk zones and tested under different fire scenarios. This integrated approach enabled both predictive analytics and scenario-based validation, supporting proactive forest fire management and preparedness.

Table 1. Fire risk classification

Fire risk classification	Elevation (m)	Slope (%)	Land use classification
Low	135 – 200	48 – 70	Restoration & Natural Forest Management
Moderate	68 – 134	25 – 47	Conservation & Recreation
High	1 – 67	1 – 24	& Non-timber Forest Product, and Commercial

RESULTS AND DISCUSSIONS

Fire risk prediction map using Random Forest

The fire risk prediction map was generated by using Random Forest machine learning, derived from factors as features selection that contribute to the predictive power of the model. The fire risk level of each point was predicted with Random Forest by splitting the dataset into two sets: training set (70%) and testing set (30%). Table 2 shows the predicted fire risk level after going through Random Forest machine learning based on the land uses classification in SFERA@UMS (Figure 3). The area has been classified into three levels: high, moderate and low fire risk based on fire prone analysis. Figure 4 shows the colours are indicated to green (low risk level), orange (moderate risk level) and red (high risk level). The accuracy of prediction with Random Forest reached 91% as shown in the Table 3.

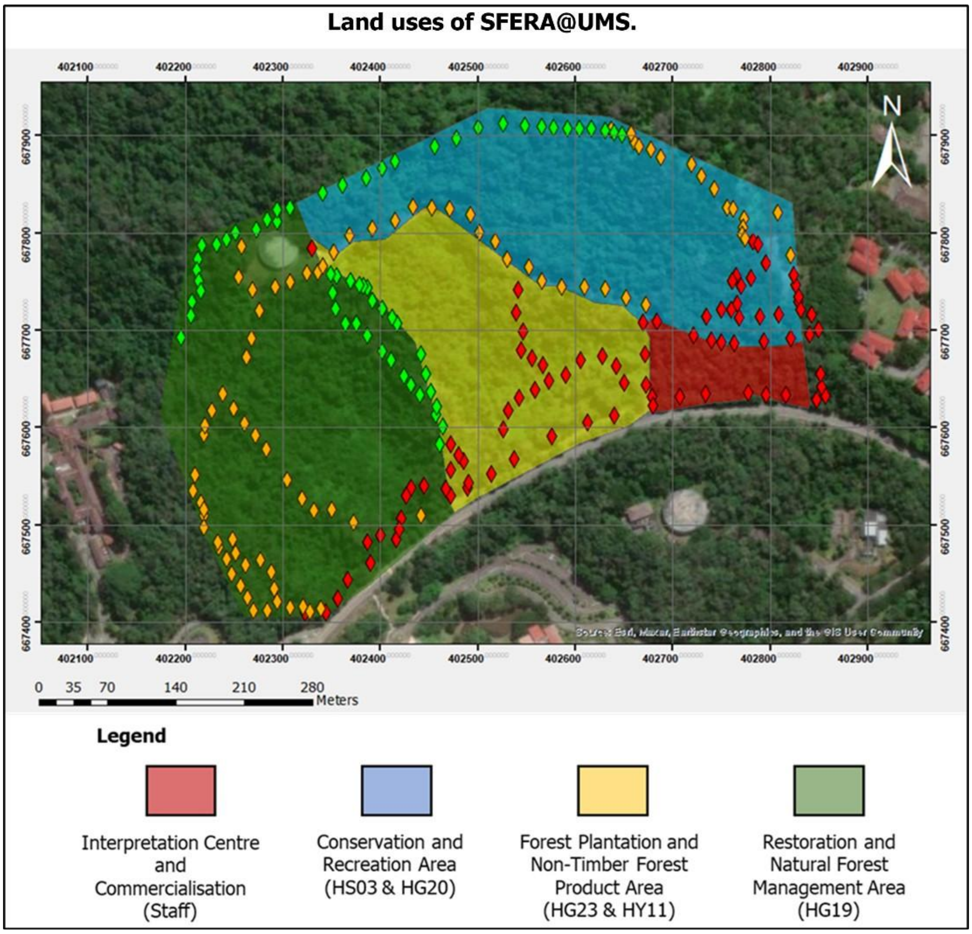


Figure 3. The map of SFERA@UMS land use.

Table 1. A predicted fire risk level based on the elevation, slope, road proximity, urban proximity, tourism hotspot and land use.

Risk level	Land use	Elevation (m)	Slope (%)	Road proximity (m)	Urban proximity (m)	Tourism hotspot (m)
Low	Restoration & Natural Forest - Conservation & Recreation	135 - 200	48 - 70	267 - 400	267 - 400	267 - 400

Moderate	Restoration & Natural Forest - Conservation & Recreation	68 - 134	25 - 47	134 - 266	134 - 266	134 - 266
High	Forest plantation & non-timber forest product - Commercial	1 - 67	1 - 24	1 - 133	1 - 133	1 - 133

Note: Based on the classification report, n=138.

Figure 4. Fire risk prediction map from Random Forest

Fire-related patterns in the study area are strongly associated with low-elevation forest areas, where proximity to access roads, drainage systems, and grassland use increases anthropogenic ignition risk compared to the largely undisturbed higher elevations. The Random Forest (RF) algorithm was selected for its robustness and ability to handle complex datasets, using environmental and anthropogenic factors such as elevation, slope, road proximity, urban proximity, tourism hotspots, and land use. GIS tools complemented this by generating spatial fire risk maps, classifying areas into low, moderate, and high-risk zones. To reduce overfitting, the Random Forest model used bootstrap sampling and feature randomness, where multiple trees are trained on different subsets of the data and aggregated through ensemble averaging. Additionally, k-fold cross-validation was applied to ensure the model generalized consistently across all folds The RF model demonstrated strong predictive performance, achieving 91% overall accuracy. For high-risk areas, precision was 95%, recall was 100%, and the F1-score reached 98%, indicating excellent balance between detection and classification. These results confirm the model's reliability in identifying critical zones where fire occurrence is most likely, ensuring that no high-risk areas were overlooked. The formula for F1-score is:

$$F1 = 2 \times \frac{(Precision \times Recall)}{(Precision + Recall)}$$

Table 2: The classification report of metrics for each fire risk class.

Fire risk level	Precision	Recall	F1-score
High	0.95	1.00	0.98
Moderate	0.84	0.94	0.89
Low	1.00	0.67	0.80
Accuracy			**0.91**

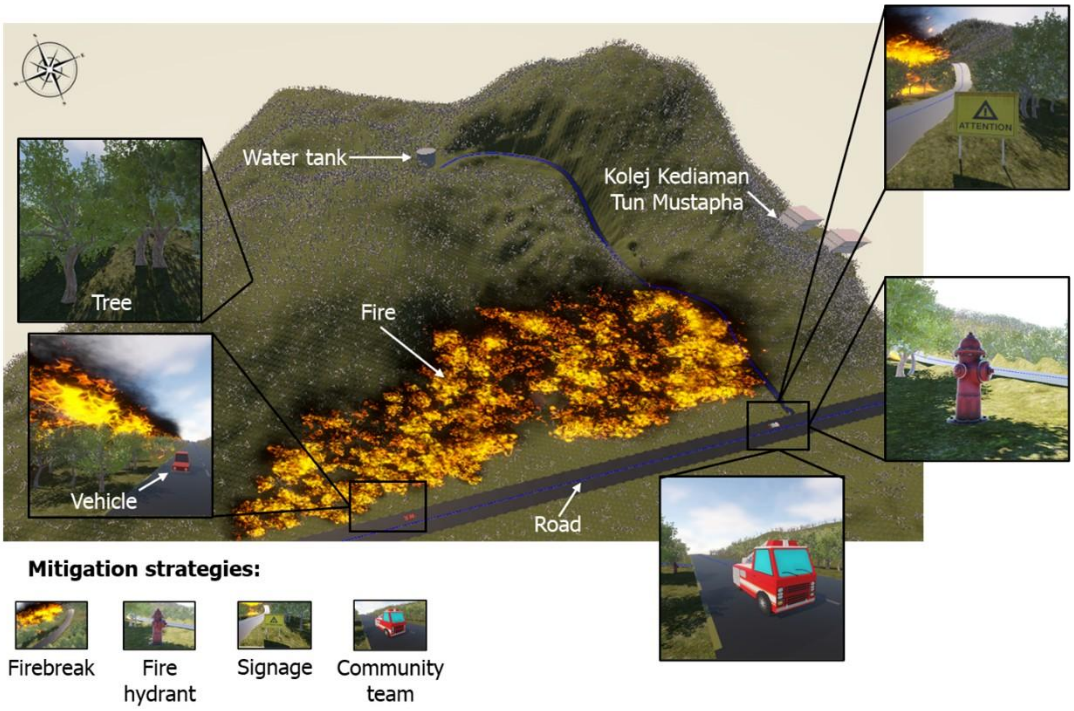
Note: Based on the classification report, the data accuracy is 91%, n=138.

The fire risk map revealed that high-risk zones were concentrated in low-elevation areas with steep slopes and near roads, where human activities increase ignition potential which is limited to the anthropogenic influence data. This study highlight that the lower-elevation areas experience more frequent human activities, making them more prone to ignition, whereas the higher-elevation forested areas remain relatively undisturbed. The fire occurrences will be worsened by the existing small population in the area (Musa et al., 2026) Moderate-risk areas were located between high and low-risk zones, while high-elevation regions generally exhibited lower risk due to higher humidity, despite steep slopes. With a total dataset of 138 samples, the model's ability to achieve 1.00 recall for 'High' risk and 1.00 precision for 'Low' risk indicates a strong capture of the most distinct environmental signatures. While the recall for the 'Low' risk class is 0.67, the model achieves 100% precision for this category and 1.00 recall for the 'High' risk class. This trade-off is acceptable for fire management, as it prioritizes the elimination of false negatives in high-danger zones, ensuring that no high-risk area is erroneously classified as low-risk. This spatial analysis highlights the combined influence of topography and human activity on fire vulnerability. Based on the data from FIRMS and GEE hotspots, the presence does not presence near the SFERA@UMS area. Therefore, the following mitigation measures suggested will be based on the anthropogenic influence that increase the potential ignition risk. In the future work, it was suggested to consider another parameter contribute to the fire risk such as days without rain, wind, temperature and slope.

The application of mitigation strategies in Unity

Fire mitigation and risk-reduction measures are important in fire management strategies, such as canal blocking, firebreak maintenance and active suppression (Musa[b] et al., 2026). The process of visualization of mitigation strategies in SFERA@UMS began with generating the terrain in an empty 3D game object followed by shaping and painting the landscape. Once the terrain was shaped, the vegetations was added and the density of trees were adjusted into the scene to create realistic environments based on SFERA@UMS condition. After the landscape was done, fire simulations were added to achieve the realistic fire effects. Then, the fire dynamic was created to simulate the fire spread between trees and along the terrain where the high-risk levels were predicted.

Figure 5. Visualization of proposed mitigation strategies within the Unity environment for SFERA@UMS



This was where the fire mitigation strategies were proposed and implemented at the scene. Firebreaks that existed in the area are access road, wherein it can mitigate the fire from spreading from the West area to the East of SFERA@UMS. The firebreak availability will prevent the fires from reaching into the nearby student living area, which is closest to the East of SFERA@UMS.

The effectiveness of the model is based to the nearest critical infrastructure of student residential college (Kolej Kediaman Tun Mustapha) which is located near the SFERA@UMS center. Given the high volume of tourist and student activity within SFERA as part of the anthropogenic influence, the proposed mitigation strategy emphasizes preparedness by reducing fire spark potential in assessed as high-risk zones. In the visualization figure, effectiveness is measured by the model's ability to prevent a fire by strategically placing mitigation measures in identified 'High Risk' areas, the simulation demonstrates a significant reduction in the likelihood of fire reaching residential boundaries.

Moreover, this study proposes installing a signage of fire awareness to increase public awareness. Fire hydrant installation is also proposed to be implemented at the roadside of the main road, which is the high-risk area to facilitate fire suppression operations. The fire hydrant installation along the roadside of the main road which is part of the preparedness measures in an area identified as a high-risk. To ensure feasibility, these units will be connected to the existing Universiti Malaysia Sabah water reticulation system, which provides a reliable water source through the campus mains. Maintenance and funding for these installations would fall under the existing university infrastructure budget, managed by the university's development and maintenance division, ensuring long-term operational readiness.

On the other hand, an establishment of community-based fire team in the community, which in this case among students and staff to monitor the area and being a first responder as part of preventive measures before the arrival of the Fire and Rescue Department of Malaysia (JBPM) as described in Figure 5. The establishment of a community-based fire team is proposed among students and staff to monitor the area and serve as first responders. This team will operate under a formal coordination framework with the JBPM, involving basic fire suppression training and the provision of portable equipment such as fire extinguishers and beaters. This proactive measure aims to reduce the fire spark potential in assessed high-risk zones before the arrival of professional firefighters.

Fire simulations confirmed the effectiveness of these measures in slowing fire spread and improving response times. The integration of predictive modeling, GIS mapping, and virtual simulation offers a comprehensive framework for proactive forest fire management and decision-making.

CONCLUSION

This study demonstrates the effectiveness of integrating machine learning, GIS, and digital twin technology for forest fire risk prediction and mitigation planning in SFERA@UMS. The Random Forest model achieved high predictive accuracy (91%), successfully identifying high-risk zones characterized by low elevation, steep slopes, and proximity to roads, areas most susceptible to ignition and rapid fire spread due to environmental and anthropogenic factors. GIS-based spatial analysis provided clear visualization of risk distribution, while Unity simulations enabled evaluation of mitigation strategies, including firebreaks, hydrants, signage, and community engagement. The findings highlight the potential of advanced computational tools to enhance proactive forest fire management and conservation strategies. By combining predictive analytics with spatial and virtual modelling, this approach supports informed decision-making for risk reduction and ecosystem protection. Future research should incorporate dynamic environmental variables and real-world validation to further improve predictive accuracy and operational effectiveness.

Future research should enhance predictive accuracy by incorporating additional environmental variables such as wind speed, humidity, and fuel moisture content. In line with this, the installation of real-time environmental IoT sensors within SFERA@UMS is recommended to continuously feed dynamic weather data (e.g., wind speed, temperature, humidity) into the Random Forest model for improved responsiveness and reliability. Advanced techniques, including hybrid models or deep learning, can be explored to improve performance. Simulation realism can be refined by optimizing fire spread algorithms and integrating dynamic parameters. Finally, validation of mitigation strategies should extend beyond virtual environments through controlled laboratory experiments or field trials to ensure practical effectiveness.

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