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Wildfire Susceptibility Mapping through Machine Learning and Remote Sensing Data with Distance Based Sampling for Fire-Free Points

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ABSTRACT

Wildfire is a common form of natural disaster present in Southeast Asia due to the high temperature and availability of "fuel" during the dry season especially in the form of peat. The negative impact of wildfire can be long lasting to the economy, and environment. Its occurrences are hard to predict given the number of variables that governs it. Thus, due to complex nature of wildfire, a machine learning based approach had seemed like the viable solution to the problem. An ANN model was developed for this study to predict and map out the wildfire susceptibility of the study area, which was Sibu, Sarawak, with data from remote sensing providers sampled through a distance-based approach. Variables chosen for this study to develop the ANN model was aspect, elevation, lithology type, land use and land cover, normalised difference vegetation index, proximity to rivers, and topographic wetness index. The machine learning model was evaluated to have a prediction rate area under the curve score of 0.89, and a precision score of 0.75, making it a viable solution to predict wildfire susceptibility.

1. Introduction

Amongst all countries in Asia, countries that are located around the equatorial line were determined to be highly susceptible to wildfire especially due to the intense seasonal dry weather conditions as well was the abundance of peat as the fuel source [1]. The term peat has been associated with wildfire due to its high organic contents that are highly combustible when dry [2]. Malaysia is one of the countries that fulfils both description as it is in the equatorial line and having a widespread deposits of peat especially around the coastal regions [3]. Being a country with the right

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conditions to have a wildfire occurring particularly in the dry season, Malaysia has been classified as a country with high risks of wildfire by the ThinkHazard organization [4].

One of the direct impact of wildfire is the loss of tree cover, where Malaysia have lost 1680 km^2 tree cover as result of wildfire from 2001 to 2019, with Sarawak receiving the highest rate of tree cover loss due to forest fire with an annual rate of 45 km^2/year [5]. Haze is the immediate impact that came from the burning which significantly increases the Air Pollution Index that are known to cause health concerns [6]. Furthermore, fire in general has a significant impact on the country's economy where the loss in Ringgit Malaysia (Rm) can reach numbers in the billions annually, such as in the year 2016, a loss value of Rm 2.4 billion was recorded due to fire, and amongst the recorded cases, wildfire dominates the category of fire type [7].

As wildfire has been determined to be a big problem in Malaysia, there are several measures that have been implemented by the government to potentially mitigate and control it such as introducing fines for open burning under the Environmental Protection Act of 1974 section 29A [8]. Besides that, under the Malaysian Meteorological Department, a wildfire risk monitoring and mapping system was developed which determines the risk of wildfire through a scoring system adopted from the Canadian Forest Service [9]. Recently, the local authorities are looking forward to implementing an Artificial Intelligence (AI) based approach to predict wildfire susceptibility in Malaysia [10].

A subset of AI that enable data-driven prediction is Machine Learning (ML). Supervised learning approaches in ML is suitable for wildfire susceptibility prediction as it crawls through the training data that is used to develop the ML models predictive capabilities by finding the relationship between the input and the output variables [11]. There are many different ML models each with their own strength and weaknesses such as Artificial Neural Network (ANN), Support Vector Machine (SVM), and Linear Regression (LR). However, ANN stands out when it comes to predicting susceptibility of natural disasters not limited to wildfire as it has been determine to have a consistent accuracy across many different region [12]. Furthermore, in a case study to predict wildfire in Similipal Tiger Reserve, India, the ANN model developed for the study outperform the other deployed model [13].

Although ML models are viable methods to predict wildfire susceptibility, it is unusable if data is unavailable. Thus, through the advancement of free remote sensing data, the publicly available data were incorporated into the training data alongside data that are locally available. Contemporarily, remote sensing data are possible alternative to traditional survey data, albeit a majority of the data having lower accuracy in terms of resolution [14]. Furthermore, the remote sensing data have enabled the mapping process as the provided data are georeferenced [15].

With remote sensing data ensuring the ANN model can be trained to predict wildfire susceptibility as well as mapping it out, what is left is to determine the strategy approach to prepare the data, particularly the target variable of fire-free areas. Based on a recent framework for wildfire mapping in Malaysia which outline the fire-free points approach method, the common approach is to create fire free points randomly in areas that have not been categorised as burnt areas for the past 20 years [16]. However, several problems have been identified when developing the fire free points through this approach, which were the unavailability of historical data, and the changing patterns of wildfire behaviour due to human settlements may cause insufficient amounts of fire free points for training purposes [17].

Thus, this study suggests that the fire free points to be randomly taken at the furthest distance from the fire points within the current year of interest. This approach with the binary target will help the ML model to develop the in-between regression values based on the training data [18]. The study that has been conducted was restricted to the Sibu town area in Sarawak which is widely regarded as having the town that has the most problem with peat in Sarawak to the point that structures would be engulfed by peat when given enough time [19]. Furthermore, the ANN model was developed considering variables that are freely available and related to the problem, which were aspect, elevation, lithology type, land use and land cover (LULC), normalised difference vegetation index (NDVI), proximity to rivers (PTR), and topographic wetness index (TWI).

2. Methodology

2.1 Study Area

Sibu is a town located in central Sarawak with an area of 129.5 km^2, around 60 km from the shoreline, and in the middle of the town flows the Rajang river as in Figure 1 [20]. The town is occupied by 288,000 residents, the third highest in the state behind Kuching with 711,500 and Miri with 356,900 residents, albeit having the smallest area amongst the three where Kuching has 431 km^2, whilst Miri has 997.43 km^2 as of 2020 [21]. Being in close proximity to the coastal line, Sibu geologically to be a place that is not structurally sound, due to the dominant presence of peat throughout the town [22]. These two variables have influenced this research to be conducted in Sibu as population density, and the presence of peats are known to have a large influence on wildfire occurrences. From 22 to 26 July of 2024, there were a total of 42 recorded cases of wildfire throughout Sarawak where Sibu has the highest amount of cases being reported with 30.95% of the total cases, followed by Miri with 26.19% [23]. In the previous year of 2023, out of 2,090 emergency calls regarding wildfire, 705 cases were reported to be related to the burning of shrubs or scrubs, which are abundant on peatland [24]. Sibu was chosen as the study area due to the high number of wildfire cases relative to its size. Furthermore, as Sibu is dominated by the peatlands and as has a high number of residents, successfully predicting wildfire for the town could lead to a better understanding of wildfire behaviour in towns with similar geological and anthropogenic properties such as Miri, and Mukah.

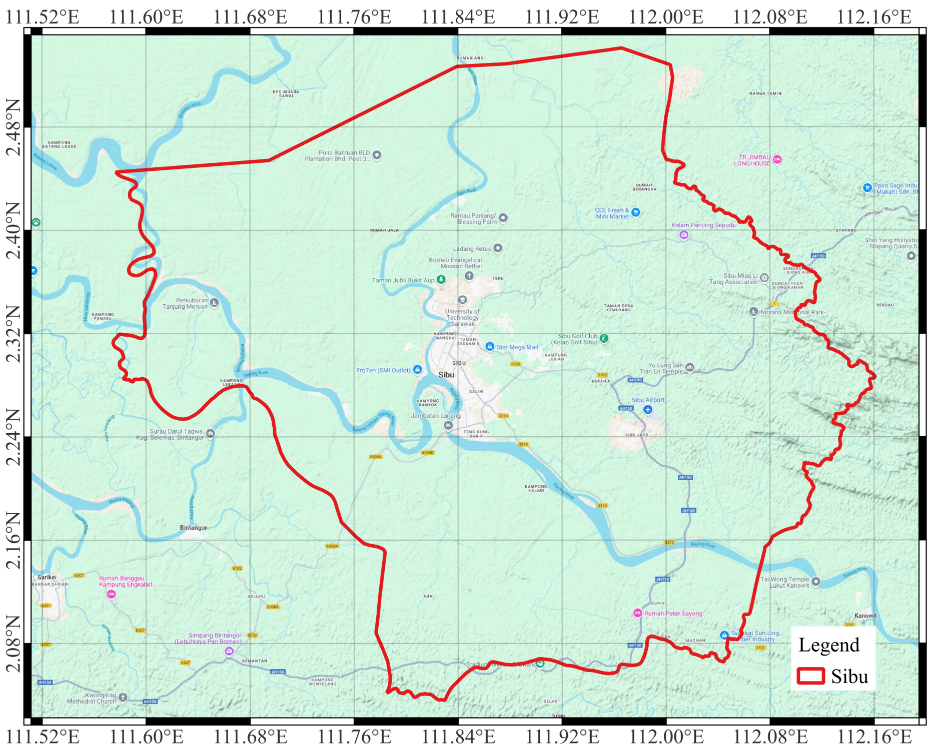


Fig. 1. Study area general location

2.2 Dataset

The ANN model developed in this study was a supervised ML model, thus a labelled dataset is required. The first step after understanding the problem is to collect the data that are related to the problem as seen in Figure 2. The labelled features of the dataset in this study were aspect, elevation, lithology, LULC, NDVI, proximity to river, and TWI, and the target were fire, and fire free points. Post data collection, the data were extracted and checked for multicollinearity [25].

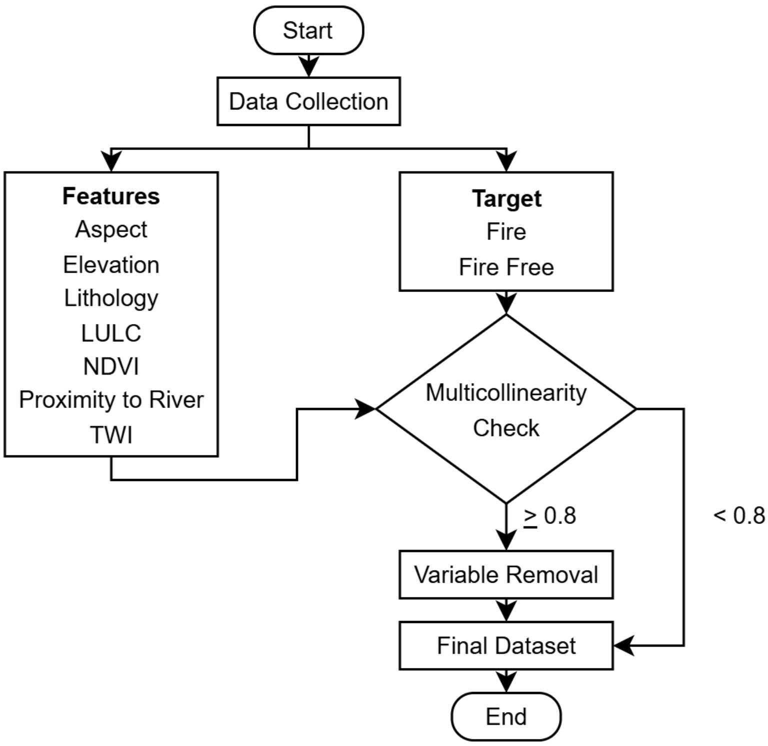


Fig. 2. Data collection

2.2.1 Wildfire and Wildfire-Free Points

The distribution of each variable that was available in the dataset can be seen in Figure 3. The target variable of wildfire and wildfire free (fire free) points is illustrated in Figure 3(a), which were important for the ANN model to be able to develop its understanding on the wildfire susceptibility levels. The historical wildfire points for Sibu were obtained from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) Fire Information for Resource Management System (FIRMS) [26]. The provided data, however, varies in terms of location accuracy, and level of confidence. Thus, cross-referencing with Google's Earth Pro was conducted to ensure that the given location was accurate as well as to increase the level of confidence by confirming the possibility of fire [27].

The fire free points on the other hand were determined by randomly creating points at the furthest distance from the fire points. Although this approach was considered conservative, it was applied in previous studies albeit for a different type of natural disasters, which was landslide [28]. This application in wildfire susceptibility mapping will help the ANN model to understand the in-between risk from the binary target variables. In total, there were 41 historical wildfire points, and 244 wildfire free points in the study area.

2.2.2 Aspect

Aspect refers to the primary orientation of given slope face, with values ranging from 0° to approximately 360° as seen in Figure 3(b). Aspect orientation controls other variables such as the deposition of soil, and local weather conditions where degree of solar variation may varies [29]. Generally, an area with that receives a higher rate of solar radiation are expected to be more susceptible towards wildfire due to the drier conditions. Furthermore, aspect is also known to influence the local wind patterns [30]. This is done through certain aspect may block or allow the wind to flow, thus influencing the wildfire direction through wind. In conclusion, aspect is known to control local weather conditions which are known to be related to wildfire behaviour. The aspect raster in this study was obtained as a terrain product of the elevation raster, extracted through the System for Automated Geoscientific Analyses (SAGA) plugin in Quantum Geographical Information System (QGIS) [31].

2.2.3 Elevation

Elevation is a feature that has a great influence on fuel moisture in this study as it is known be correlated with precipitation and temperature [32]. A previous study has concluded that as elevation increases the likelihood of wildfire decreases [33]. Although, highly elevated areas tends be drier, the risk is mostly mitigated by the low air and oxygen density required for combustion [32]. Furthermore, in a tropical study area such as Sibu, elevation also shows the peat distribution where it is mostly concentrated in low-lying areas, making the lower elevation areas having a higher risk of wildfire [34]. The elevation raster in this study was obtained from NASA's Shuttle Radar Topography Mission where it shows that the elevation of the study area ranges from -9m to 273m as seen in Figure 3(c) [35].

2.2.4 Lithology

Lithology refers to the physical and chemical characteristics of rocks and soils. Certain lithology have a higher possibility of wildfire, especially those with high organic contents and supports dense vegetation which translate to more fuel such as peat [36]. The lithology data of this study was the only data not obtained from a remote sensing data provider, instead, it was obtained through the local Department of Minerals and Geosciences (JMG). From the lithology map as seen in Figure 3(d), there were only two distinct types of lithology present in the study area, which were:

i. Clay, silt, sand, and peat.
ii. Argillaceous rocks, some Arenaceous rocks with Calcareous beds.

Judging by the lithology type alone, the first lithology of clay, silt, sand, and peat seems to have the higher likelihood of wildfire in comparison to argillaceous rocks and some arenaceous rocks with calcareous beds, due to the presence of peat that consists of mostly organic matter [36].

2.2.5 Land Use and Land Cover

Land Use and Land Cover (LULC) depicts the surface properties of an area, which includes the natural land cover type, and anthropogenic land use. Different land covers such as grasslands and trees have different levels of wildlife susceptibility, as grasslands combusts easier in comparison to trees [37]. Furthermore, land use such as built areas, and agricultural fields have different wildfire susceptibility [38]. The LULC raster file was obtained from the Environmental Systems Research Institute (ESRI), which have shown that the LULC of Sibu consisted of water, trees, grass, flooded vegetation, crops, scrub/shrubs, built area, bare ground, and clouds as seen in Figure 3(e) [39].

2.2.5 Normalised Difference Vegetation Index

Normalised Difference Vegetation Index (NDVI) represents the vegetation density, and health of a certain area [40]. A higher NDVI indicates a high density of vegetation which has a higher moisture content due to the healthy vegetation. Low NDVI on the other hand indicates barren areas, dead and dry vegetation, and built areas, which is typically prone to combustion [41]. The NDVI of the study area ranges from -0.579 to 0.861 as seen in Figure 3(f). The NDVI raster file was obtained from the United States Geological Survey (USGS) [42].

2.2.6 Proximity to Rivers

Areas that are near rivers generally have a lower likelihood of wildfire due to the high moisture conditions of the soil in the area as opposed to areas that are further from rivers [43]. The proximity to rivers raster file in this study was obtained by using the river network data from OpenStreetMap (OSM), and determining the distance through the proximity raster plugin in QGIS [44]. The proximity to rivers raster as seen in Figure 3(g) shows that the furthest distance from rivers in Sibu was 19,587.55m.

2.2.6 Topographic Wetness Index

Topographic Wetness Index (TWI) is a measure of the terrain control on hydrological processes that shows the potential of soil moisture accumulation where a higher TWI indicates a wetter area, which are generally less susceptible to combustion as opposed to areas with a lower TWI [45]. The TWI map was another derivative product of the elevation raster file, and it was obtained through the SAGA plugin in QGIS [31]. The TWI of the study area ranges from 2.669 to 9.577 as seen in Figure 3(h).

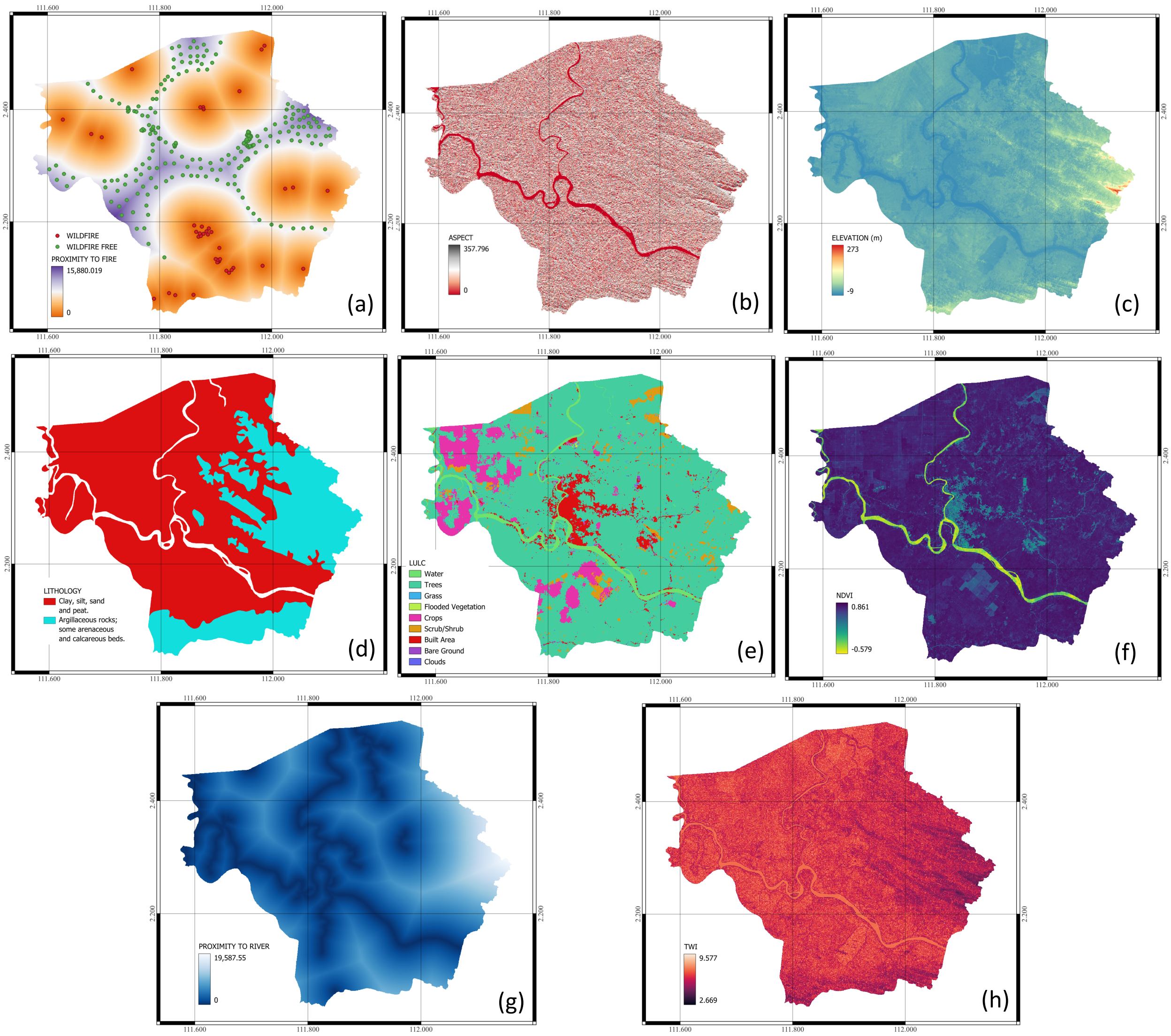


Fig. 3. (a) Proximity to fire map, (b) Aspect map, (c) Elevation map, (d) Lithology map, (e) LULC map, (f) NDVI map, (g) Proximity to river map, and (h) TWI map

2.2.7 Training Data and Testing Data

The previously mentioned feature's variables were used and recommended to develop the dataset required by the ANN model. After extracting the values of each feature variables by using the target variables that has been denoted with 0 as fire free points, and 1 as fire points, the dataset underwent a multicollinearity check. This was done to avoid any issues that could arose due to multicollinearity from the training data made from the primary dataset such as data redundancy that could lead to overfitting [46]. Multicollinearity especially amongst the input variables are very important as it shows how similar the variables are [47]. In this study, whenever two input variables resulted in a multicollinearity score exceeding 0.8 one of the variables would be removed [48]. After no significant multicollinearity has been determined, the primary dataset was split into training data and testing data with a ratio of 90:10.

2.3 ANN Model and Mapping

An ANN model is a form of ML model with the capabilities to simulate a human-brain in the form of statistical model. This was done by mimicking the interconnected neurons of the brain which develops its predictive capabilities [45]. There were numerous studies conducted to evaluate the appropriateness of using an ANN model to predict natural hazards susceptibility with high level of success and not limited to wildfires [49], [50]. To develop the ANN model predictive capabilities, the training data was used which was initially evaluated through Root Mean Squared Error (RMSE), whilst the testing data was used to evaluate the ANN model prediction performance based on the evaluation metrics of Area Under the Curve (AUC) and precision [51]. There were several hyperparameters of the ANN model that were tuned in this study to ensure the predictions were as accurate as possible, which were the number of neurons in the hidden layers, learning rate, learning algorithm, and the maximum learning steps [52]. The flow of the process can be seen in Figure 4.

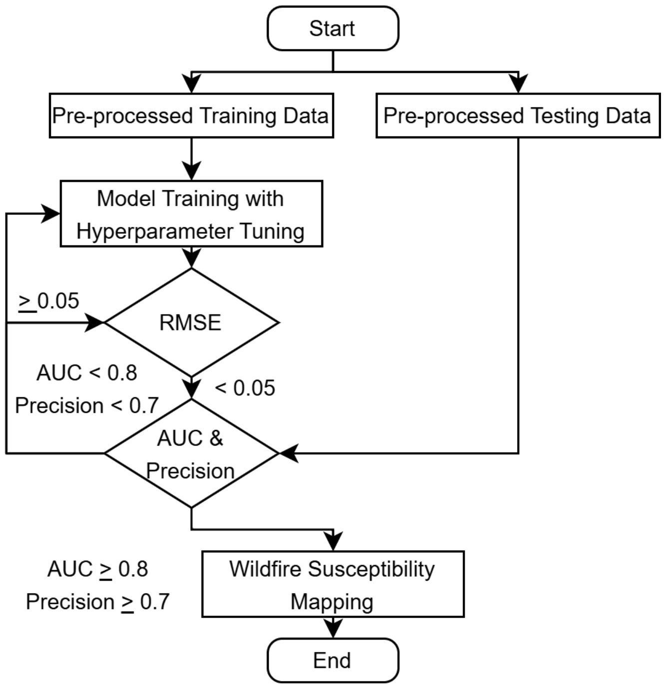


Fig. 4. ANN model development and wildfire susceptibility mapping

2.3.1 Data Pre-processing

Data-preprocessing was conducted before using the raw data to train and test the ANN model. There were two methods applied in the data-preprocessing stage from different variables, which were normalisation for numerical variables, and one-hot encoding for categorical variables. Normalisation was applied to elevation, NDVI, proximity to river, and TWI. Normalisation scales the values of each numerical variables from 0 to 1, to avoid any potential biases resulting from the disparity between the variables values, such as in comparison to the proximity to road, the elevation variable values are smaller [53]. The normalisation equation can be seen in Eq. (1).

$$Y = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

Where X is the raw value of a particular numerical variable, X_{min} is the minimum value of the variable, X_{max} is the maximum value of the variable, and Y is the normalised value of X.

On the other hand, categorical variables of aspect, lithology type, and LULC have underwent one-hot encoding. One-hot encoding is a process where the categorical variables were classified into respective group in a single category. This provides the ANN model with a format that it can understand, as the categorical could not be represented through numbers [54]. The aspect values were categorised with each class having a value of 45°, lithology types were categorised based on the type of lithology, and LULC classes were also organised as such.

2.3.2 Number of Neurons in the Hidden Layers

The hidden layers are located in between the input layer, and the output layer. In this study, a single hidden layer was utilised. The number of neurons in the hidden layer is responsible for the ANN model capability to understand complex relationships amongst the input variables, and the output variables [55]. There are no definite amounts of neurons in the hidden layer making the manual optimisation a necessity, as too many neurons would cause overfitting, and to little neurons would cause underfitting [56]. Thus, hyperparameter tuning for the number of neurons in the hidden layer was done by starting at a small value.

2.3.3 Learning Rate

The learning rate depicts the size of weight adjustments for the learning process of the ANN model. Too large of a learning rate will cause a suboptimal solution, and too small of learning rate will cause a lengthy process that exceeds the optimal training time [57]. For the tuning of learning rate, it is generally acceptable to set it at the value in 0.00n to obtain the performance [58].

2.3.4 Learning Algorithm

Learning algorithm refers to the algorithm used to optimise the loss function, and weights adjustments of the ANN model. An example of the learning algorithm is backpropagation, where weights within the ANN model are adjusted iteratively from the input layer to the output layer until the maximum learning steps has been achieved, or the loss converges to a minimum value [59]. The backpropagation learning algorithm was adopted in this study as it has been widely used in numerous prior studies regarding natural disaster predictions [25,59].

2.3.5 Maximum Learning Steps

Maximum learning steps refers to the maximum number of iterations the backpropagation algorithm can take. Too large of a maximum learning steps will lead to overfitting and a higher computational cost, and too small of a maximum learning steps will lead to underfitting [52].

2.3.6 Root Mean Squared Error

The root mean squared error (RMSE) as seen in Eq. (2) shows the potential deviation in the errors of the predicted value to the actual value. It was particularly useful in the training phase as it indicates the potential success of the phase by the showing the potential error of prediction during the training phase [60].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - y_i)^2} \tag{2}$$

Where n is the number of observations, Y_i is the predicted value, and y_i is the actual value.

2.3.7 Accuracy

The accuracy of the ANN model was evaluated through the AUC method as seen in Eq. (3). AUC shows the ratio of correct prediction of true positive (TP) and true negative (TN), to the total amount of prediction which includes the false positive (FP) and false negative (FN) [61]. In ML, AUC is particularly used to show the overall predictive performance of the ML models [62]. The minimum AUC for this study was set at 0.8, which is the most widely accepted minimum accuracy in ML applications for natural hazards prediction [63].

$$AUC = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

2.3.8 Precision

Precision is an indicator of the ANN model reliability. Precision is determined by calculating the ration between the TP to the TP and FP instances as seen in Eq. (4) [64]. Precision was particularly useful when it comes to mapping out the wildfire susceptibility as the area of Sibu town is relatively small and a low precision could cost the map to be consisted mostly of high-risk areas. The minimum precision for this study was set at 0.7 by considering prior research in the flied [17].

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

2.3.9 Precision

After the ANN model has satisfied all evaluation metrics based on the testing data, then and only then can the wildfire susceptibility map be developed. To develop the map, the georeferenced raster files of the feature variables were converted into a numerical data frame before conducting the same data preprocessing method of the training data and testing data to it [65]. As the pre-processed numerical data frame were in the same format as the training and testing data, the ANN model was able to predict the wildfire susceptibility for the whole area of Sibu town. The final step was to convert the numerical data frame into the wildfire susceptibility map, by removing all of the previous variables except for the longitude, latitude, and the wildfire susceptibility score predicted by the ANN model [66].

3. Results

3.1 Multicollinearity

High multicollinearity amongst the input variables is not a preferable condition for an ANN model training data, and the results for the multicollinearity amongst all variables in this study can be seen in Table 1. Amongst the input variables, elevation and proximity to river achieved the highest score of 0.66, which can be interpreted as elevation increases, the distance to a river also increases. Albeit high, the multicollinearity score did not exceed the threshold of 0.8, thus, no input variables were removed from the dataset [67]. As for the multicollinearity score between the input variables to the output, the highest score was 0.19, which shows that at a certain range, the further the distance from the river, the higher the susceptibility towards wildfire. This can be said as well for the elevation variable, with a multicollinearity score towards the target being 0.12.

Table 1
Multicollinearity matrix

	ASPECT	ELEVATION	LITHOLOGY	LULC	NDVI	RIVER	TWI	FIRE
ASPECT	1.00							
ELEVATION	0.04	1.00						
LITHOLOGY	0.06	0.46	1.00					
LULC	-0.06	-0.12	0.33	1.00				
NDVI	0.07	0.16	-0.20	-0.54	1.00			
RIVER	-0.01	0.66	0.35	-0.27	0.20	1.00		
TWI	-0.13	-0.33	-0.24	-0.02	0.01	-0.18	1.00	
FIRE	0.03	0.12	-0.05	-0.06	-0.05	0.19	0.07	1.00

Note: RIVER refers to proximity to river, and FIRE refers to the occurrences of wildfire.

3.2 RMSE

In this study, the RMSE scores were primarily used as a preliminary assessment towards the ANN model prediction accuracy in terms of potential error in unit based on the different hyperparameter configuration [68]. A total of three trial with different configurations of the ANN model hyperparameters namely the number of neurons in the hidden layer and the maximum steps were conducted, where the learning rate was kept uniform with 0.001, and a learning algorithm of backpropagation as seen in Table 2. Throughout the three trials, the second trial achieved the lowest RMSE score with 0.038. The RMSE results indicated that the final prediction of the ANN model may deviate in magnitude of $\pm$0.038 [69]. Hence, the final hyperparameter configuration of the ANN model was to have 4 neurons in the hidden layer, a learning rate of 0.001, a backpropagation learning algorithm, and a maximum steps of 1e+10. The RMSE was determined to be satisfactory as a prior research in the field of natural hazards predictions has accepted a maximum RMSE score of 0.15 [70].

Table 2
RMSE score based on trials

Trial	Neuron	Learning Rate	Algorithm	Maximum Steps	RMSE
1	4	0.001	Backpropagation	1e+8	0.110
2	4	0.001	Backpropagation	1e+10	0.038
3	6	0.001	Backpropagation	1e+10	0.086

3.3 Accuracy and Precision

The training data and testing were used to evaluate the training success rate, and prediction success rate as seen in **Error! Reference source not found.**. The training success rate evaluates the ANN model accuracy in the phase as well as its precision. Overall, the trainings success rate was determined to have an AUC score of 0.98, with a precision of 1, indicating all TP occurrences were accordingly classified. In total, there were 254 instances in the training data. Thus, it was concluded that the training phase of the ANN model was highly successful [51]. As for the prediction success rate with the testing data, the ANN model was determined to have an AUC score of 0.89 which was faithful to a previous research that deploys other ML models with the highest AUC score of 0.879, with a precision of 0.75 [17]. Based on the never-before-seen testing data, only 1 FP occurrence was observed, leading to the precision score of 0.75. As for the accuracy, it was degraded mainly by 1 FP and 2 FN negative instances. Given the small size of the testing data and the evaluation metrics, the ANN model was considered to be successful in predicting the wildfire susceptibility of Sibu [71].

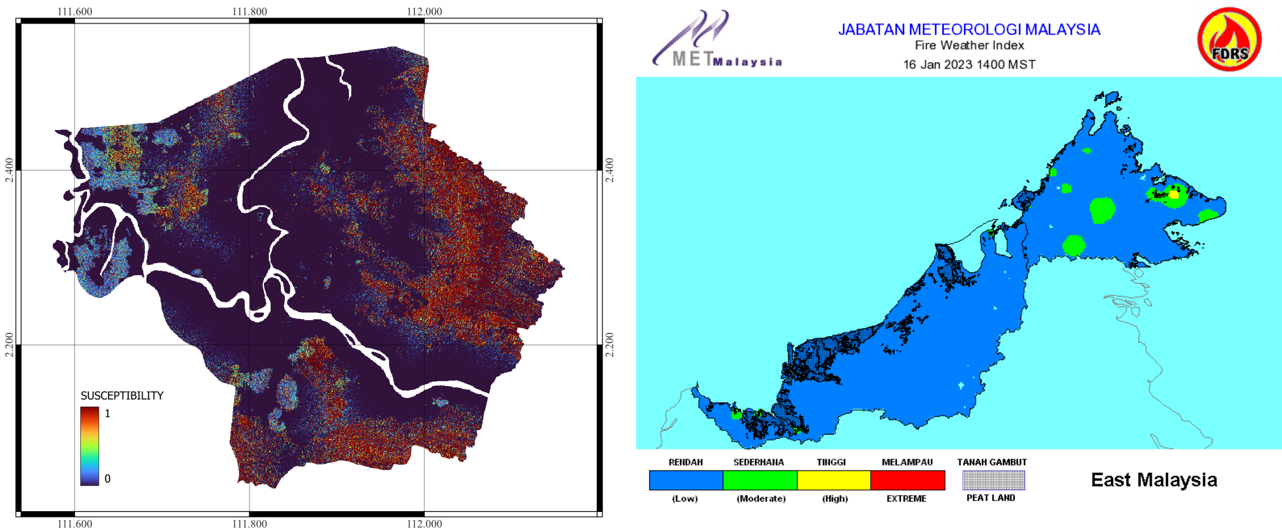
Table 3
Accuracy and Prediction based on data

Metric\Data	Training	Testing
Accuracy	0.98	0.89
Precision	1.00	0.75

3.4 Wildfire Susceptibility Map

The wildfire susceptibility map of Sibu as seen in Figure 3 was the final product of this study. The primary limitation of the map was the exclusion of crucial hydrological data that greatly influences the occurrence of wildfire such as rainfall, and wind patterns [13]. Furthermore, as with most the natural disasters, the susceptibility levels may changes from time to time as certain variables are dynamic in nature, such as rainfall, NDVI, and surface temperatures [72]. Thus, the accuracy of the map was restricted to time of the raster files made available. The wildfire susceptibility map shows that most of the built areas in Sibu are located outside the perimeter of the fire. The most prone LULC type to wildfire in Sibu was deemed to be trees [73]. Furthermore, referring to the elevation map, the highly elevated areas are considered safe from any possibility of wildfire. Most of the highly susceptible areas are in the low to medium elevation. In terms of lithology, albeit having large amounts of organic materials, clay, silt, sand, and peat are in low susceptibility regions, potentially due to the deposition of the lithology being near the rivers. Referencing the NDVI map, regions with high NDVI correlated highly with high susceptibility regions likely due to the availability of burn fuel.

Unlike the current map of fire weather index developed by the Meteorological Department of Malaysia, the wildfire susceptibility map was developed through an ML approach whereas the fire weather index map was developed through a scoring system [74]. The wildfire susceptibility map provides a more detailed level of wildfire susceptibility in comparison the fire weather index map. Furthermore, the fire weather index map did not consider variables such as lithology type, NDVI, and elevation, with the variables used were the meteorological variables of temperature, relative humidity, rainfall, and wind speed [9]. As for the ANN model, if high resolution data of meteorological variables used by the fire weather index are to be made available to the public, it can be easily added to the training data of the ANN model for update, as compared to establishing new scores for new variables for the fire weather index [75]. Nevertheless, the data pool size for the ANN model was relatively small, thus it should be used in conjunction with the government supplied fire weather index map to provide a more trustworthy prediction.



(a) (b)

Fig. 5. (a) Wildfire susceptibility map of Sibu, and (b) East Malaysia fire weather index

4. Conclusions

In conclusion, for a small-scale wildfire susceptibility map, the ANN model developed through the incorporation of remote sensing data with distance-based fire free points sampling was successful. There was no significant multicollinearity amongst the input variables that could degrade the ML model predictive performance with the highest score being amongst elevation and proximity to river with a score of 0.66. This study has greatly supported the national peatland fire prevention programme which was initiated by the Department of Environment. Based on the evaluation metrics of RMSE, AUC, and precision the ANN model has been greatly successful and faithful to the previous studies in the field with a score of 0.038, 0.89, and 0.75 respectively. The final product of the wildfire susceptibility map can be used as a preliminary assessment alongside the fire weather index map developed by the authority to provide a better mitigation effort when it comes to combating wildfire in Sibu. Finally, the ANN model could provide insights on wildfire behaviour in other regions of Sarawak, specifically those with similar geological, and topographical properties such as Kota Samarahan in the Kuching division down South, and Miri up North, where both areas are known to have large distribution of peatlands as well as flat areas.

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