Comparative Assessment of Machine Learning Algorithms for Wildfire Susceptibility Mapping in South Wales, Australia

Alireza Rostami[1], Parham Pahlavani[1*], Omid Ghorbanzadeh[2]

[1]School of Surveying and Geospatial Engineering, College of Engineering, University of Tehran, Tehran, Iran
(alireza.rostami, pahlavani)@ut.ac.ir
[2]Institute of Geomatics, University of Natural Resources and Life Sciences (BOKU), Vienna, Austria -
omid.ghorbanzadeh@boku.ac.ir

Keywords: wildfire, satellite imagery, random forest, support vector machine, extreme gradient boosting, categorical boosting, adaptive boosting, natural gradient boosting, light gradient boosting machine

Abstract

Wildfire susceptibility mapping is an essential tool for proactive fire management in regions prone to wildfires. This study aims to determine areas of South Wales, Australia, that are susceptible to wildfires using a comprehensive set of environmental parameters and multiple machine learning (ML) models. A geospatial data set of topographical (digital elevation model, slope, aspect), climatic (temperature, precipitation, wind speed, soil moisture), vegetative (normalized difference vegetation index, forest cover, land use), and anthropogenic (distance to roads and rivers) attributes was created. Seven ML classifiers were developed: Random Forest, Support Vector Machine (SVM), Adaptive Boosting (AdaBoost), Light Gradient Boosting Machine (LightGBM), CatBoost, Extreme Gradient Boosting (XGBoost), and Natural Gradient Boosting (NGBoost). Four-fold cross-validation was used to test the models, with area under the receiver operating characteristic (ROC) curve (AUC) being the primary model performance metric. Results indicate that ensemble tree-based models were superior to other approaches in performance. CatBoost, LightGBM, and XGBoost were the best performers, with maximum mean AUC values higher than 0.9. The least effective model among those tested was the SVM model. Across all the models tested, NDVI was determined to be the top predictor of wildfire susceptibility.

1. Introduction

Forests are an integral part of the Earth's ecosystems and play an essential role in maintaining climatic balance and supporting biodiversity. However, wildfires pose a significant threat to this valuable asset. Every year, wildfires consume millions of hectares of forest, resulting in severe ecological and economic impacts (Shi et al, 2023, Tymstra et al, 2020, Zhang et al, 2019). Wildfires can disrupt ecosystems, releasing substantial amounts of greenhouse gases, causing soil erosion, and altering hydrological processes (Burke et al, 2021). In recent decades, the frequency and intensity of wildfires have increased in many regions around the world, a trend associated with climate change influences such as rising temperatures and prolonged dry periods, as well as anthropogenic factors (Pourtaghi et al, 2014). This escalating hazard underscores the necessity of effective prevention and mitigation strategies. A critical aspect of wildfire disaster management is identifying areas susceptible to wildfire occurrence (Moghim et al, 2024, Shmuel et al, 2022). Mapping wildfire susceptibility is an essential tool for effective prevention planning. Such maps delineate regions with varying fire risks based on environmental factors and historical conditions. They help land managers identify high-risk areas that require focused monitoring, targeted resource allocation, and proactive fuel management (Leuenberger et al, 2018, Moghim et al, 2024, Yu et al, 2023). Previously, wildfire susceptibility mapping methods relied largely on ground observations and simple statistical models; however, in recent years, innovative and more advanced techniques have emerged. Developments in geospatial technologies have greatly improved wildfire analysis in recent years by enhancing the quality and availability of data (Tavakkoli Piralilou et al, 2022).

Satellite remote sensing has particularly transformed wildfire observation by illuminating large areas through extensive and timely data concerning vegetation, surface conditions, and active fires. Mid and High-resolution satellite multispectral images from Landsat, MODIS, and Sentinel facilitate efficient detection of fire hotspots and accurate highlighting of burned areas, which is superior to the traditional ground methods. Various recent studies have utilized satellite sensors such as Landsat and MODIS for mapping burned areas, VIIRS for active fire detection, and Sentinel-2 in combination with deep learning techniques for fire-affected area detection.(Bahadori et al, 2023, Iban et al, 2022, Schroeder et al, 2014, Shi et al, 2023).This widespread geospatial information forms a strong foundation for current wildfire susceptibility modelling. During the past decades, machine learning (ML) techniques have become versatile tools for wildfire susceptibility mapping.

Compared to traditional statistical approaches, machine learning (ML) techniques can more effectively capture the complex, non-linear relationships among diverse environmental variables, leading to significantly improved accuracy. General supervised ML methods—including decision trees, support vector machines, ensemble methods, and logistic regression—have been extensively applied and consistently outperform traditional or expert-based methodologies.

The objective of this study is to produce a reliable wildfire susceptibility map for South Wales, Australia, by employing and comparing several advanced machine learning algorithms. We systematically evaluate multiple ML models to effectively capture the complex relationships among various environmental factors influencing wildfire occurrences. Our approach integrates detailed environmental variables derived from

* Corresponding author

satellite imagery and other geospatial sources, providing comprehensive coverage of topographic, climatic, and vegetative influences. The primary contributions of this research include a comparative analysis of state-of-the-art machine learning algorithms for wildfire susceptibility mapping, ultimately achieving high predictive performance with an area under the curve (AUC) of approximately 90%. The results of our comparative approach not only validate the effectiveness of ML methodologies in the context of wildfire management but also deliver practical guidance for land managers and policymakers. Moreover, our study introduces a locally tailored susceptibility assessment for New South Wales—an area relatively understudied in existing wildfire literature—thus providing crucial information in Australian wildfire research.

2. Methodology

2.1 Study Area

The research focuses on New South Wales, Australia. It is famous for the varied landscapes that make up the rolling hills, the thick forests, and the broad agricultural plains. Altitudes here range from sea level to an elevation of up to about 2,228 meters above Mount Kosciuszko(Government, 2025a). Most of the population of South Wales lives in the coastal areas, and Sydney holds over five million residents. Climatic range makes the area support a range of different vegetation from closed forest to open grassland. Among the great rivers, some course their way through the area, performing fundamental tasks in local ecosystems. Moreover, South Wales also sometimes witnesses outbreaks of fire in the form of wildfires during hot and dry conditions with significant effects on ecosystems, human communities, and economic activities. These instances of wildfires serve to demonstrate the susceptibility of the region and to emphasize the need for a managed approach to fire control.

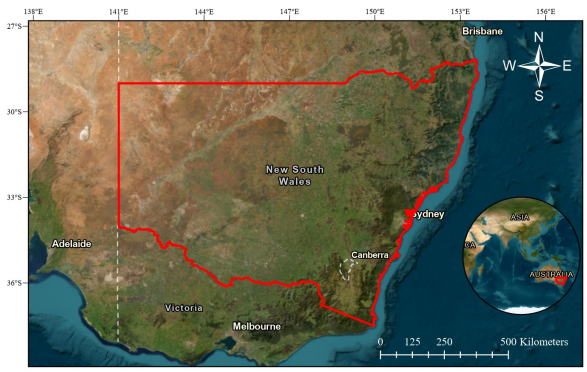

Figure 1. New South Wales, Australia

2.2 Dataset

2.2.1 Historical Fires: The wildfire history dataset for New South Wales (NSW), Australia was obtained from the NSW Government's open data portal (Government, 2025b) (accessed August 2024) and provides records of fire events across the region from 1920 to 2025, categorized as either wildfires or prescribed burns. For this study, only wildfire events from 2019 to 2024 were selected from the dataset, while all prescribed burn records were excluded, to focus on recent unplanned fire activity. A total of 625 wildfire events were used to represent areas affected by recent fire activity in the study area. These wildfire records represent areas affected by past fire activity and served as the fire class in model training, denoting locations of known fire occurrence in the susceptibility model.

2.2.2 Environmental Factors: We used a high-resolution (~30 m) SRTM DEM accessed through Google Earth Engine to record topographic effects on wildfire vulnerability. Slope and aspect were extracted from the DEM to denote terrain steepness and orientation. Elevation affects climate and vegetation distribution, where increased elevation is generally cooler and more humid, damping fire intensity, while lower elevation areas tend to be drier, supporting fire spread. Steep slopes increase fire spread velocity since heat travels upward more rapidly, and aspect affects sunlight exposure and fuel dryness. North-facing slopes in the Southern Hemisphere receive greater amounts of sunlight, leading to drier, more flammable vegetation (Bahadori et al, 2023, Sun et al, 2023, Tavakkoli Piralilou et al, 2022).

Monthly climatic data, including precipitation, temperature, wind speed, and soil moisture, were derived from TerraClimate data. Low humidity and temperature dry out vegetation and make fuels flammable and susceptible to ignition. Loss of soil moisture during dry periods adds to the enhancement of wildfire risks by stressing vegetation. Wind strongly influences wildfire behaviour by drying out fuels, enhancing fire spread, and enabling embers to be blown. Conversely, high rainfall periods increase vegetation moisture, lowering fire susceptibility. These variables comprehensively characterize regional climatic conditions critical to wildfire dynamics (Sim et al, 2023).

We combined land cover and vegetation indices to define fuel condition and availability. Sentinel-2 NDVI values indicated greenness of the vegetation, where low NDVI indicates dry, burnable vegetation that would be prone to catching fire. Land use information was obtained from ESA WorldCover 2021, taking into consideration variation in fuel load and burnability across landscape types like forests, grasslands, and urban environments. Secondly, forest cover data of high resolution were sourced from the ABARES Forests of Australia dataset (ABARES, 2024). Forest and dense shrubland are likely to consist of continuous, high biomass fuel loads, which pose much higher levels of risk of fire compared to sparsely vegetated or developed environments (Suryabhagavan et al, 2016).

Anthropogenic and hydrological factors consisted of road and river distances of Open Street Map data (accessed 2024). Proximity to roads is likely to be linked with higher human-induced ignitions as roads facilitate access for wildland use. Similarly, proximity to rivers signifies higher recreational use, adding chances of ignition from humans. Rivers also serve as natural firebreaks, where greater distances might denote lesser availability of moisture and fewer physical barriers to the spread of fire.

Factor	*Data Source*	*Resolution*
DEM	SRTM	30 m
Slope	Derived from DEM	30 m
Aspect	Derived From DEM	30 m
Land use	ESA WorldCover	10 m
Distance from Roads	Open Street Map	30 m
Distance from Rivers	Open Street Map	30 m

This contribution has been peer-reviewed. The double-blind peer-review was conducted on the basis of the full paper.
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Forest	Australian Bureau of Agricultural and Resource Economics and Sciences	-
NDVI	Sentinel-2	10 m
Average Temperature	TerraClimate	~4 km
Rainfall	TerraClimate	~4 km
Soil Moisture	TerraClimate	~4 km
Wind Speed	TerraClimate	~4 km

Table 1. Environmental Factors

2.3 Methods

2.3.1 Train and Test Dataset Preparation: We employed a common four-fold cross-validation procedure in this study. The data were randomly partitioned into four roughly equal-sized folds; three folds (~75% of the data) were used for training the model for each iteration of the folds, and another fold (~25%) was left as the validation set. This process was repeated four times (each fold as the validation set once) for robustly evaluating model performance. Notably, the same fold splits were used on all machine learning models to provide a fair and uniform basis for comparison across models. Model hyperparameters were selected based on internal cross-validation performance on training folds, and final model results were reported in held-out fold predictions. Our approach is guaranteed to make the assessment robust and model performance be tested on balanced subsets of the data, essential for the imbalanced nature of data for instances of wildfires.

2.3.2 Random Forest: Random Forest classifier is an ensemble learning method that constructs a large collection of decision trees and averages their outputs for a final prediction. All trees are bootstrapped with one sample from the data and split on a random subset of features, a process that decorrelates the trees and avoids overfitting. The model's prediction in the case of classification is computed through majority voting across the set of trees. It is based on the "wisdom of the crowd" and yields better accuracy and stability than single decision trees. Random Forests, in turn, are known to possess improved performance values compared to single trees and have shown robust performance in many classification tasks (Ballings et al, 2013).

2.3.3 Support Vector Machine (SVM): SVM is a supervised learning method that identifies the optimal hyperplane to separate data points of different classes with the largest margin. It transforms input features to a higher-dimensional space (using kernel functions in non-linear situations) and determines the decision boundary with maximum distance to any class's closest data points (the support vectors). The maximum margin concept helps to generalize better on unseen data. SVMs are founded on statistical learning theory and are effective in high-dimensional spaces or where the data points are sparse relative to features. They have been employed widely as one of the best-performing classification techniques for the past decades, with continuously competitive performance on a wide range of fields (Khan et al, 2024).

2.3.4 Adaptive Boosting (AdaBoost): AdaBoost is an ensemble technique that combines multiple weak learners to form a strong classifier. AdaBoost trains a sequence of shallow decision trees (or stumps), where each tree is trained on the data based on the errors of the previous trees. Misclassified samples by earlier iterations are increasingly allocated higher weights, and hence, later learners learn to focus on such hard-to-classify instances. The contribution of every weak learner is weighted in terms of its accuracy, and a weighted vote across all the learners yields the final prediction. Recursive re-weighting of this type allows AdaBoost to reduce training errors gradually and improve generalization. One of the earliest practical boosting algorithms, AdaBoost remains much studied and utilized, with numerous papers documenting its strong performance on classification problems across many application domains (Ding et al, 2022, Schapire, 2013).

2.3.5 Light Gradient Boosting Machine (LightGBM): LightGBM is a modern gradient boosting library that has gained popularity because of its efficiency and high-performance features. It supports a leaf-wise tree construction policy and histogram-based binning for continuous features, which significantly speeds up tree construction and reduces memory usage. By expanding leaf-wise (first expanding the most loss-reducing leaf) rather than level-wise, LightGBM is able to achieve lower loss within fewer iterations, albeit with careful regularization to avoid overfitting. The algorithm uses methods like Exclusive Feature Bundling and Gradient-Based One-Side Sampling (GOSS) to improve efficiency in dealing with large-scale data. Because of these improvements, LightGBM is likely to outperform typical gradient boosters both in training time and precision. It has been very successful in classification tasks and is frequently employed because it is computationally cost-efficient and has great predictive performance (Ke et al, 2017).

2.3.6 Categorical Boosting (CatBoost): CatBoost is a gradient boosting approach tailored to handle categorical variables seamlessly and to combat overfitting. Like other boosting algorithms, CatBoost builds an ensemble of decision trees in an iterative manner but adds the concept of an ordered boosting process and a permutation-based approach for the encoding of categorical features. Instead of naive one-hot encoding of categories (which may lead to high-dimensional data and target leakage), CatBoost employs target statistics and random permutations to map categories to numbers at training time such that each mapping depends only on the previously processed data, without inducing bias. Ordered boosting and the use of oblivious decision trees (symmetric trees with the same splitting criterion at all levels) help stabilize training the model. Through these innovations, CatBoost can directly utilize categorical data and will often need minimal pre-processing. The algorithm has demonstrated exceptional accuracy at classification problems, with successful applications ranging from engineering system fault diagnosis to financial application anomaly detection (Prokhorenkova et al, 2018, Wu et al, 2023).

2.3.7 Extreme Gradient Boosting (XGBoost): XGBoost is an extremely optimized gradient boosted decision tree that has gained extremely high praise for speed and high prediction ability. XGBoost incorporates second-order gradient information (Hessian) in its optimization, enabling more precise and faster convergence in tree boosting. It includes a regularization term on the objective function (L1 and L2 penalties) as well to control model complexity in order to prevent overfitting even for large trees. Additional features like shrinkage (learning rate reduction), column subsampling, and a tree building algorithm that is aware of sparsity further increase its efficiency and generalization. XGBoost is particularly scalable to big data and has been thoroughly tested across a variety of areas with consistently great performance on classification benchmarks. Its good engineering and regularized learning objective make it the go-to model for most real-world classification problems (CHENT, 2016).

2.3.8 Natural Gradient Boosting: NGBoost is a version of gradient boosting that is designed to give probabilistic predictions instead of point predictions. It uses the concept of natural gradients with the boosting algorithm, which improves in updating models, making predictions about probability distribution parameters. In an NGBoost classifier, the model may be set up to predict parameters of a Bernoulli or SoftMax distribution for class probabilities, basically making its outputs probabilistic in nature. This allows NGBoost not only to classify but to provide uncertainty estimates of its predictions. Although it aims at probabilistic prediction, NGBoost has also been competitive in point-estimate accuracy. Previous research employed NGBoost within binary classification contexts – i.e., to classify fraudulent vs. normal instances – and reported high precision and accuracy, outperforming typical classifiers within those studies. These results suggest that NGBoost can be an effective classifier while simultaneously offering the benefit of uncertainty quantification in predictions (Duan et al, 2020, Kavzoglu et al, 2022).

3. Results

3.1 Multicollinearity Analysis of Data

Collinearity diagnostic using Variance Inflation Factors (VIF) also indicated that none of the 12 predictor variables had an issue with problematic multicollinearity (see Table 2). All VIF scores were well below the widely used threshold of 5 (ranging from 1.02 for Aspect to 4.86 for mean temperature), whereas VIF > 5 is commonly considered as a marker of excessive multicollinearity (Al-Najjar et al, 2019, Kalantar et al, 2020). Since there were no values of VIF greater than this value, all the variables were included in the model for wildfire susceptibility. Overall, these low VIF values indicate that predictors are not much intercorrelated, and this justifies the suitability of the dataset for multivariate analysis.

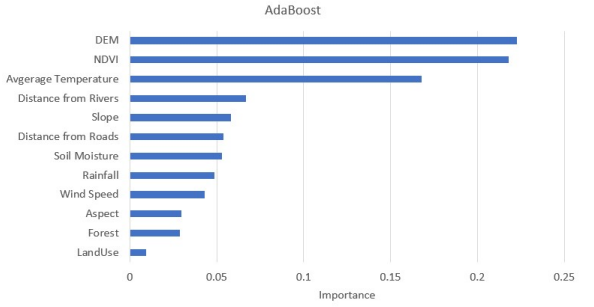
Variable	*VIF*
DEM	3.18
Slope	1.38
Aspect	1.02
Land Use	2.16
Distance from Rivers	1.82
Distance from Roads	1.92
Forest	3.21
NDVI	1.74
Average Temperature	4.86
Rainfall	2.62
Soil Moisture	2.18
Wind Speed	2.95

Table 2. VIF results for each environmental variable

3.2 Feature Importance

Across the seven models, one feature of consistency across feature importance is evident: certain environmental predictors consistently turn up strong, while others are marginal and algorithm-specific. NDVI (Normalized Difference Vegetation

Index) is a leading variable in nearly all models, which points to its strong link to vegetation health and fuel availability – a key driver of wildfire vulnerability. This consistency means that NDVI is capturing underlying fuel condition signals, and consequently, it is a good wildfire event predictor regardless of the technique employed to model. Temperature and elevation were also quite consistently ranking relatively high in multiple models (though with some difference), adding evidence that climatic and terrain variables matter to wildfire risk. Aspect (slope orientation) and Wind Speed were substantially lower and more model-specific in significance. These variables were at the lower end of most models, which suggests that their impact is either relatively minor or swamped by the more substantial predictors. Such low, variable importance of topographic features such as aspect is consistent with research that shows that climate and vegetation controls tend to have a larger influence on fire prediction than do lesser terrain characteristics.



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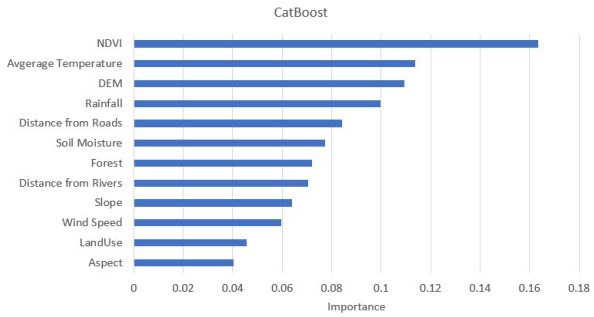

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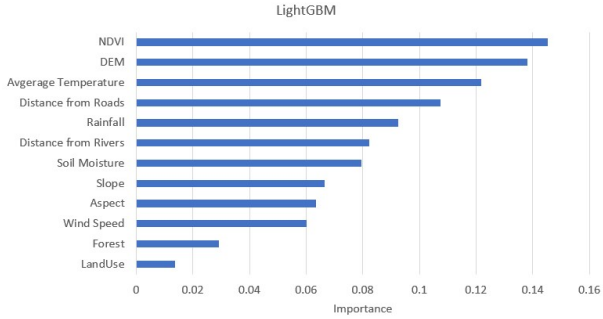

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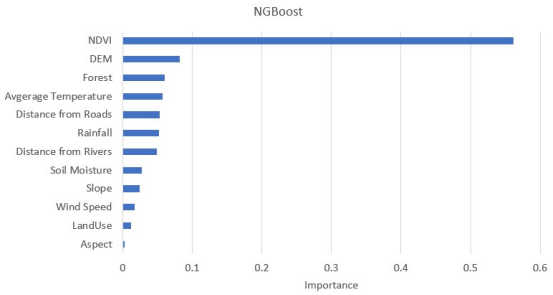

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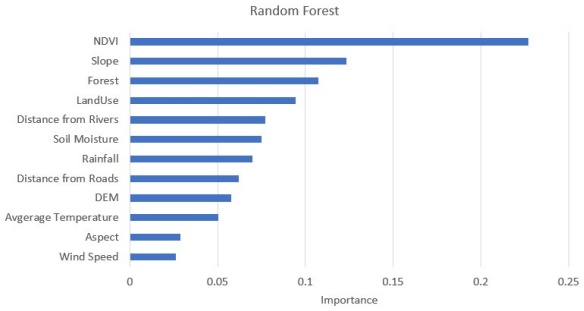

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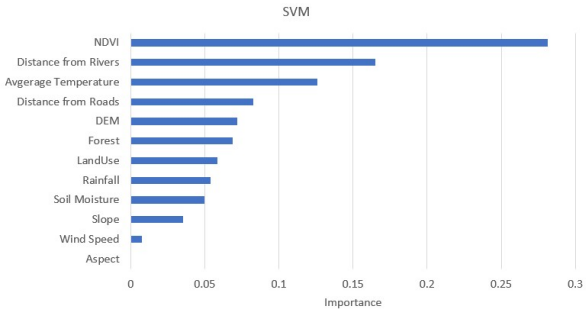

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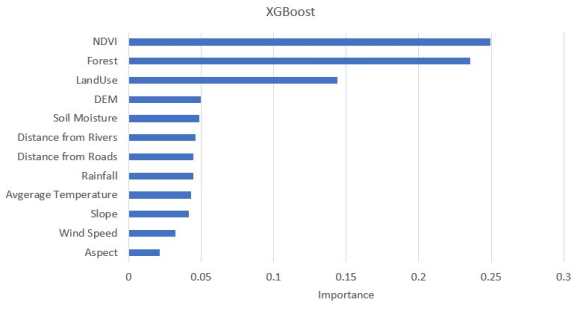

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Figure 2. Importance degrees of features: (a) AdaBoost (b) CatBoost (c) LightGBM (d) NGBoost (e) Random forest (f) SVM (g) XGBoost

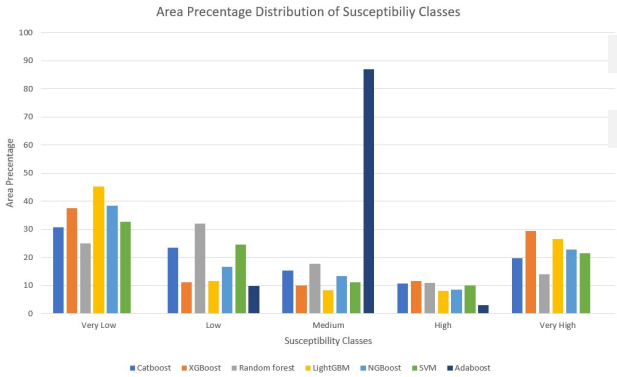


Figure 3. Area percentage of each susceptibility class

3.3 Models Performance Assessments

Model performance was kept in check by 4-fold cross-validation, under which the training and testing were done across various data splits for each model in a manner such that the performance measures remained intact and unbiased. This strategy gave individual values for each fold as well as mean estimates on which the comparison of model overall performance can be made directly. The most important test measure was Receiver Operating Characteristic's Area Under the Curve (AUC) for the ability of each model to differentiate between fire-prone and non-fire-prone areas. The AUC measures the ability of each model to discriminate between fire-prone and non-fire-prone areas, with values ranging from 0.5 (no discrimination ability) to 1 (perfect discrimination). Mathematically, the AUC can be expressed as:

$$AUC = \int_0^1 TPR(t)dFPR(t) \quad (1)$$

Where:

$$TPR = \frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (2)$$

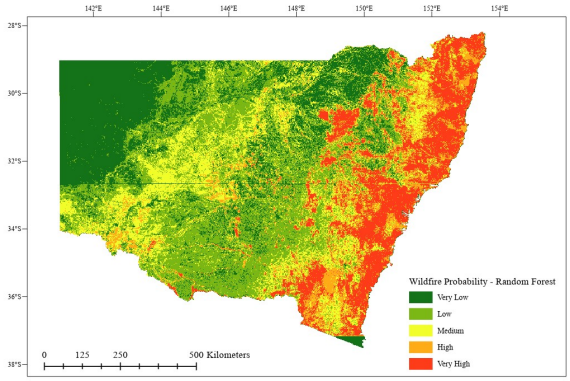
$$FPR = \frac{False\ Positives}{False\ Positives + True\ Negatives} \quad (3)$$

Most of the models had high AUC scores, with CatBoost and LightGBM overall top-ranked, all with mean AUC values over 0.9 (see Table 3). Random Forest and XGBoost ranked similarly but lower than those top-performing gradient boosting models, while AdaBoost and NGBoost ranked with moderate predictive ability, and Support Vector Machine (SVM) recorded the lowest AUC. For all models, cross-validation results were consistently low in variance, which indicated that the measures were stable and not greatly influenced by the division of data. In Table 3, the AUC metric for each fold, as well as the mean AUC across all folds, is reported for each model.

Model	*Fold-1*	*Fold-2*	*Fold-3*	*Fold-4*	*Mean*
AdaBoost	0.9053	0.8791	0.9129	0.8597	0.8892
CatBoost	0.9129	0.8961	0.9337	0.8841	0.9067
LightGBM	0.9102	0.8955	0.9217	0.878	0.9014
NGBoost	0.9048	0.8667	0.9119	0.865	0.8871
Random Forest	0.903	0.8843	0.9179	0.8923	0.8994
SVM	0.9085	0.8364	0.8696	0.8139	0.8571
XGBoost	0.9009	0.8902	0.9264	0.878	0.8989

Table 3. AUC values for each fold

Beyond the quantitative measures related to model prediction interpretability, the practical interpretability in a spatial sense was assessed by analysing the spatial distribution within the pixel-wise classification over the predefined susceptibility classes (very low, low, medium, high, very high) through graphical presentations for all candidate models (see Figure 3). The spatial analysis showed noteworthy differences between the different models. Of particular note was the fact that AdaBoost assigned roughly 87% of the pixels in the "medium" susceptibility class and had low representation in the extreme susceptibility classes (the "very low" and "very high" classes), creating a distinctly skewed spatial distribution which seemed inexplicable in relation to the anticipated variability in susceptibility over the landscape. Conversely, the more complex gradient boosting models—CatBoost and LightGBM—showed a more balanced spatial class distribution that aligned well with expected landscape variability.



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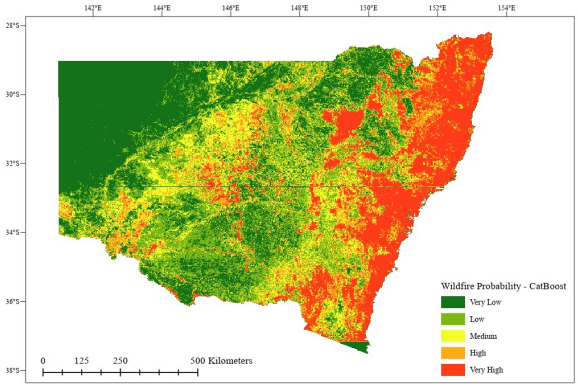

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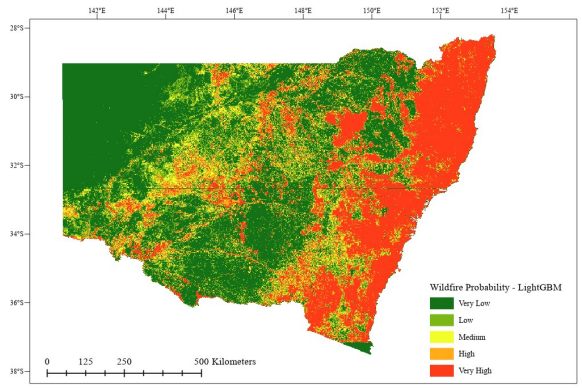

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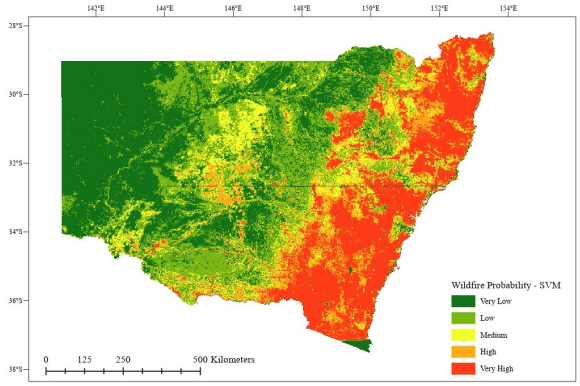

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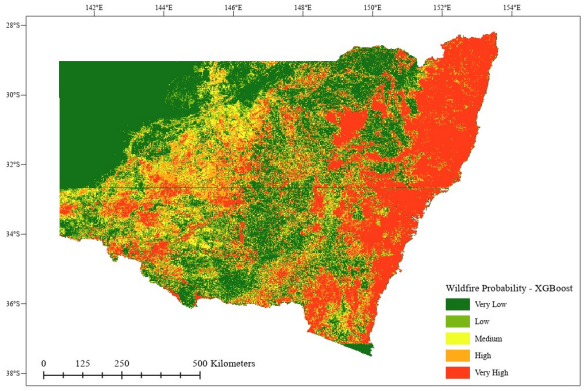

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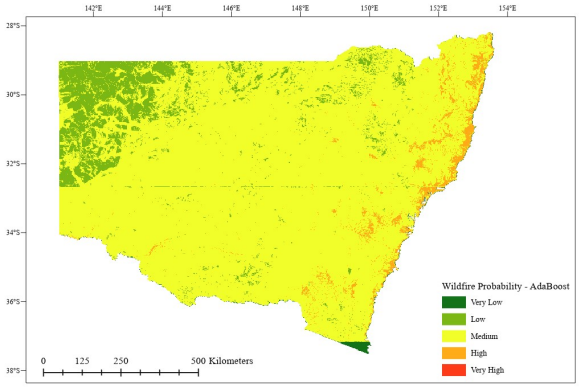

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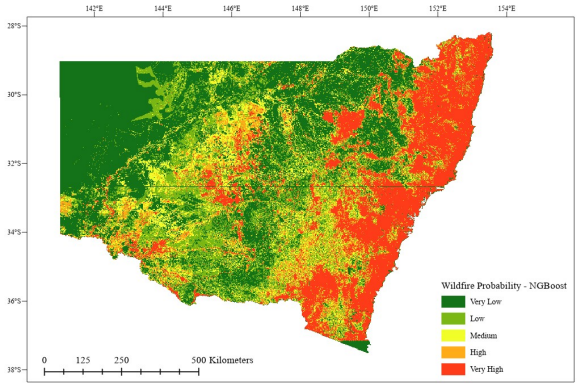

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Figure 4. Wildfire susceptibility mapping: (a) Random Forest (b) CatBoost (c) LightGBM (d) SVM (e) XGBoost (f) AdaBoost (g) NGBoost

The superior predictive performance of the boosting algorithms, particularly CatBoost, LightGBM, and XGBoost, can be attributed to their enhanced capacity to model complex, nonlinear relationships and higher-order interactions among predictor variables. Wildfire susceptibility in NSW arises from the combined influence of vegetation condition (e.g., NDVI), climatic factors (temperature, rainfall, soil moisture), and terrain characteristics, which interact in intricate and non-additive ways. Through iterative residual correction, boosting frameworks progressively refine decision boundaries and effectively capture these dependencies, resulting in improved discrimination between fire-prone and non–fire-prone areas. This behaviour contrasts with algorithms such as SVM and Random Forest, which are comparatively limited in representing multi-dimensional feature interactions, thereby explaining their lower predictive performance.

4. Conclusion

This study evaluated several machine learning models (RF, SVM, AdaBoost, LightGBM, CatBoost, XGBoost, NGBoost) trained on terrain, vegetation (e.g. NDVI), climate, and human accessibility data to predict wildfire susceptibility in South Wales, Australia. Utilizing 4-fold cross-validation in conjunction with AUC statistics for model validation, the gradient-boosting algorithms CatBoost and LightGBM exhibited considerably higher predictive accuracy, thus

substantially outperforming AdaBoost and other baseline models. More importantly, the feature importance analysis systematically identified NDVI as the leading predictor, in concordance with the widely reported positive correlation between the vegetative cover and the potential of fuel. While AdaBoost reported an acceptable level of general accuracy, its spatial risk contrasts proved less discriminatory in comparison to the highest-performing boosting algorithms. The general framework—bringing together heterogeneous predictor variables with strict cross-validation—provides a solid basis for modelling wildfire susceptibility.

The susceptibility maps obtained using optimal modelling successfully distinguish areas with high levels of risk within the study region, with a specific focus on zones of potential influence. Maps of this nature are intended to serve as useful decision-support tools; according to earlier research, *"accurate wildfire susceptibility maps [are] an important primary step in efficient wildfire risk management"* thus supporting the planning and subsequent analysis of risk.(Thies, 2025). As a result, this research provides practical information for fire management authorities in South Wales, including a detailed listing of susceptible areas to aid in planning and mitigation efforts.

In applied contexts, the comparative multi-model approach improves multi-temporal wildfire susceptibility analysis by incorporating sophisticated algorithms with extensive environmental data sets. High AUC values and concordant model reproducibility enhance the reliability of hotspot identification. The analytical spatial model can be expanded by including temporal parameters (e.g., seasonal climatological predictions or fuel moisture variation), further predictive variables (e.g., ignition sources or local weather conditions), or with scalable cloud computing for near real-time mapping. By combining these advancements, the method can be further advanced to serve as an operational early warning system. Overall, this paper shares general methodological advancements related to wildfire susceptibility maps, which have strong potential to maximize fire management planning and mitigation of wildfire risk in the South Wales area and other regions similarly prone to wildfires.

5. References

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