Explainable Artificial Intelligence to Unveil Intrinsic Characteristics of Conditioning Factors Governing Forest Fire Susceptibility

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Abstract

Forest fires are typically triggered by natural factors or human negligence and accidents, spreading across vast areas and causing extensive damage to vegetation, wildlife, and ecosystems. Machine learning algorithms have recently become important tools for their efficiency in generating high-quality wildfire susceptibility maps in the literature. Despite their success in achieving promising thematic accuracies, they are typically criticized for their black box structure and their limited ability to interpret the resulting susceptibility maps. This study aims to address these limitations by exploring the inherent characteristics of geospatial covariates controlling the wildfire phenomena with local and global underlying factors of wildfire phenomena with the application of explainable artificial intelligence (XAI). For this purpose, three ensemble machine learning algorithms, including random forest, XGBoost, and NGBoost, were initially inputted with 11 conditioning factors to produce wildfire susceptibility maps. The internal mechanisms of these models were then interpreted using global and local XAI techniques. The results showed that the NGBoost had the highest predictive performance with an overall accuracy of 81.42%, and outperformed the other algorithms by approximately 5% to 8%. The global explainability analysis with the SHAP technique revealed that topographical parameters, such as elevation and valley depth, were the most influential factors in wildfire susceptibility. On the other hand, local analyses conducted with the LIME technique for three randomly selected instances highlighted the significant influence of parameters such as elevation, wind speed, and valley depth on individual wildfire cases.

1. Introduction

Housing an estimated 80% of terrestrial biodiversity, forests are of utmost importance in the sustainability of ecological systems, and play a significant role in vital tasks from nutrient cycling to various atmospheric process (Aerts & Honnay, 2011; Seniczak et al., 2021; Tonbul et al., 2022). They also help alleviate the harsh impacts posed by climate change by sequestering carbon dioxide, a major greenhouse gas that is typically blamed for global warming. In addition to these ecological services, forests provide many benefits such as supporting biodiversity, fostering economic activities, and promoting energy conservation.

With the ongoing influence of external factors such as climate change and global warming, greater frequency, severity, and impact of the wildfires have recently exacerbated. This interaction between climate change and global warming has further led to the emergence of increasingly uncontrollable forest fires. According to the European Forest Fire Information System data, Turkey was the most affected country by forest fires in 2021, while a total area of 206,013 hectares was affected. One of the most notable recent examples is the 2021 mega forest fires, which significantly affected the Mediterranean countries, including Turkey. These fires, which first ignited in Manavgat district in Antalya on July 28, 2021, subsequently spread across various regions of the country, affected many cities in the southern and south western sections (Kavzoğlu et al., 2021).

The negative effects caused by forest fires have led to taking a number of measures, such as policy development (Xanthopoulos, 2007) and early fire detection system planning (Barmpoutis et al., 2020). Among these, generating susceptibility maps has emerged as a fundamental tool for alleviating the above-mentioned adverse effects, preparing disaster response plans, and conducting emergency management in post-disaster phase. In principle, they spatially represent the probability of a forest fire occurring in a certain geographical location depending on local terrain conditions. Additionally, the cost of the process of producing susceptibility maps can be typically lower than its alternatives. Consequently, the production of forest fire susceptibility maps has gained widespread recognition in the literature.

A series of approaches from heuristic methods to data-driven algorithms have been applied to reliably predict the wildfire susceptibility in the literature. Presently, the scientific literature is largely focused on ensemble machine learning models, including random forest (Noroozi et al., 2024), XGBoost (Tonbul, 2024), CatBoost (Haydar et al., 2024), and gradient boosting machines (Singha et al., 2024). Although ensemble machine learning algorithms are reported to achieve high predictive performance in the production of wildfire susceptibility maps, their black-box nature can make it challenging to comprehend the rationale behind their predictions. In turn, this lack of explainability poses problems for all actors who use these models to carry out efficient disaster management and formulate relevant policies. Also, analyzing the importance of factors both globally and locally is crucial in the context of wildfire susceptibility as it helps to understand fire risk in greater specificity from different patterns across wider areas. Explainable artificial intelligence (XAI) serves as a vital solution for such scenarios by providing the predictions made by complex machine learning models. The XAI techniques can also elucidate which factors are most influential at both global and local levels.

Motivated by the aforementioned challenges, this study mainly focuses on generating forest fire susceptibility maps for the Manavgat district in Antalya by using three machine learning algorithms, including Random Forest, XGBoost, and NGBoost.

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To develop the susceptibility map for this region, a total of 11 geospatial covariates contributing to the wildfire activities were employed. Also, the correlation analysis and multicollinearity test were initially performed to assess potential correlations between these factors. Furthermore, McNemar's test was conducted to quantify whether the differences in the accuracy of the resulting maps produced by the three models were statistically significant. After generating susceptibility maps using these black-box machine learning models, two XAI techniques (SHAP and LIME) were applied to identify the most dominant factors driving wildfire risk in the study area.

2. Study Area and Dataset

The study was conducted in Manavgat district located in the Antalya province of the Western Mediterranean Region of Turkey (Figure 1). Covering approximately 2283 km², the study area is geographically bordered by the 36° 39′ 45″ and 37° 26′ 15″ N latitudes and 31° 01′ 30″–31° 45′ 51″ E longitudes. The region is under the impact of the Mediterranean climate, with hot and dry summers and mild and humid winters. While the average temperature rises to 28°C in summer, the average temperature drops to 8°C in winter. The Western Mediterranean Since the Mediterranean climate is observed in Manavgat district, the hot and dry summers make the region riskier in terms of forest fires.

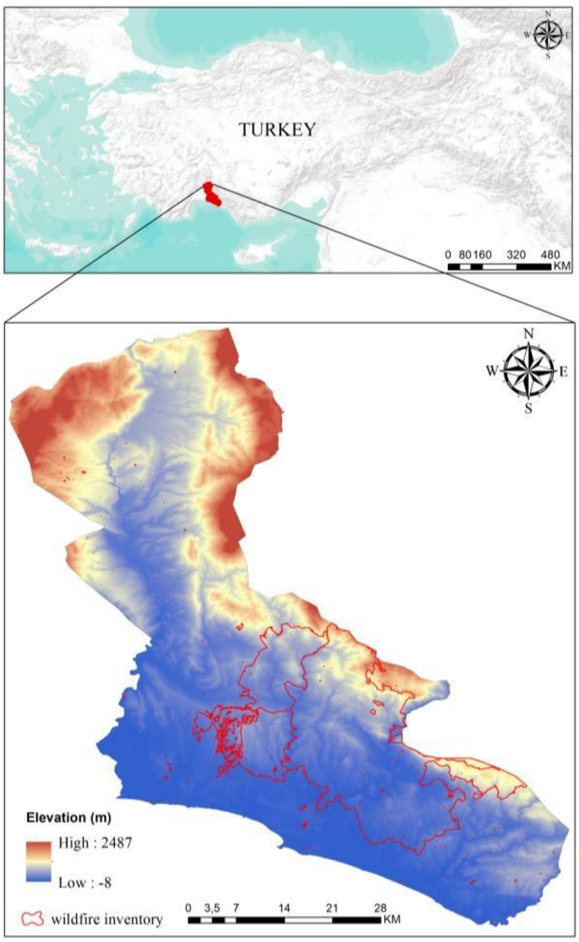

Figure 1. Geographical location of the study area.

Main Factors	Geospatial Covariates	Data Source
Topographical	Elevation	SRTM
	Aspect	
	Curvature	
	Slope	
	Valley Depth	
Hydrological	TWI	
	Distance to Rivers	OSM
Anthropogenic	Distance to Roads	
Meteorological	Temperature	Turkish State Meteorological Service
	Precipitation	
	Wind Speed	

Table 1. Data sources of geospatial covariates used to predict forest fire susceptibility.

Forest fire inventory maps are the maps containing information about the locations, dates, and the extent of wildfires previously occurring in a certain area, the causes of these fires, the type of fire, and the work done in this region. For this study, an inventory map covering forest fire events from 2019 to 2021 was obtained from the General Directorate of Forestry. Within the study area, 197 forest fires were recorded, collectively damaging approximately 6,171 ha of forest. The largest recorded fire affected 42,725 ha in the southern part of the study area, while the smallest fire, impacting 427.25 km², occurred in the northern part. In addition, considering the fundamental characteristics of the region and previous research, a total of 11 parameters, namely elevation, aspect, curvature, slope, valley depth, TWI, distance to rivers, distance to roads, temperature, precipitation, and wind speed, were selected (Table 1). The topography-related parameters (elevation, aspect, curvature, slope, valley depth, TWI) were extracted from the SRTM digital elevation model. The maps of distance to rivers and roads were thematically created in the GIS environment using the existing road network and the Euclidean distance function. Meteorological parameters (temperature, precipitation, and wind speed) for local stations within the study area were procured by the General Directorate of Meteorology.

3. Methodology

The literature offers a wide range of methods for generating forest fire susceptibility maps. A systematic workflow comprising five essential steps was employed in the study. In the first step, the key geospatial covariates contributing to the wildfire activities were identified by taking into consideration the specific characteristics of the study area. Then, the thematic maps of the factors were stacked to establish a multi-layer image composite. In the second step, the created dataset is divided into two subsets: 70% for training and 30% for testing. In the third step, potential correlations among the independent variables were examined to prevent any issues that could negatively affect the performance of the machine learning algorithms through multicollinearity testing and correlation analysis. The fourth step involves the application of three ensemble-based machine learning algorithms, namely Random Forest, XGBoost, and NGBoost, to produce wildfire susceptibility maps for the study area. These maps were then evaluated using performance metrics and statistical significance tests to ensure their reliability and validity for practical fire risk management applications. Ultimately, both local and global XAI analyses were conducted to provide insights

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into the inner mechanisms of the ensemble machine learning algorithms, enhancing the interpretability of the models and their predictions.

3.1 Random Forest (RF)

Proposed by Breiman (2001), the random forest (RF) is a machine learning algorithm combining the output of multiple decision tree models. The algorithm can also be recognized an improved version of the bagging methodology since it includes the randomness concept in the model prediction phase. The working mechanism of the RF initially starts by dividing a given dataset with different instances to create a decision tree form from each dataset. These randomly selected individual trees are trained on random subsets. To provide a low correlation among features and a high predictive model, the algorithm selects the best variable from a randomly chosen subset of variables at each node without branching each node based on the best variable overall. Upon construction of the model with the individual trees, the predictions are combined with a majority voting or averaging approach (Kavzoglu, 2017).

3.2 Extreme Gradient Boosting (XGBoost)

XGBoost is a member of gradient boosting family in which multiple weak estimators are sequentially trained (Chen & Guestrin, 2016). With the boosting mechanism, each new learner aims to iteratively correct the errors (i.e., residuals) made by the previous ones. By estimating the gradient of the loss function, the algorithm tries to update the model parameters and aims to minimize the error at each step. Since it can be optimized for performance and supports parallel processing, this makes it much faster compared to the regular gradient boosting algorithms. The algorithm also uses regularization terms to prevent overfitting by penalizing large values of model parameters.

3.3 Natural Gradient Boosting (NGBoost)

The Natural Gradient Boosting (NGBoost) algorithm is an advanced machine learning technique incorporating natural gradients for capturing probability distribution within a given space of the predictions (Duan et al., 2019). However, the NGBoost does not only provide a single point estimation but instead provides a deterministic representation of the potential predictions (Kavzoglu & Teke, 2022b). Moreover, probabilistic forecasting plays a critical role in assessing model uncertainties, which often arise due to the nonlinear and complex nature of real-world problems. This approach enables a deeper understanding of uncertainty, making it essential for reliable decision-making in various fields.

3.4 Hyperparameter Optimization

A machine learning model is essentially made up of two main components: parameters and hyperparameters. The former is learned directly from the training data, and it represents the internal structure of the model. The latter are generally higherlevel structural elements; they guide the learning process and shape critical components of the models, including their behavior, speed, and complexity. However, hyperparameters need to be adjusted by the designer since they are not directly inferred from the data. This process, often referred to as hyperparameter optimization or hyperparameter tuning, involves systematically selecting the ideal model architecture to achieve the best performance. Numerous hyperparameter optimization techniques exist in the literature, including grid search, random search, Bayesian optimization, and hyperband (Kavzoglu & Teke, 2022a). Though grid search is generally more computationally intensive compared to other methods, it was chosen for this study due to its ability to guarantee optimal accuracy within the defined search space.

3.5 McNemar's Test

To rigorously compare the produced resulting maps, a statistical significance test (McNemar's test) was used in addition to the regular accuracy assessment metrics. Based on the chi-square distribution, McNemar's test essentially compares the classification errors of two classifiers on the same paired dataset by using 2x2 confusion matrix in the calculations. When the calculated statistic value is higher than the critical threshold value from the distribution table within the determined confidence interval, the null hypothesis is rejected. Consequently, it can be concluded that the difference in the classification performance and error rates of the algorithms is statistically significant. In other words, this result is a statistical indication that the two classification results are significantly different from each other. It has been widely used in remote sensing and susceptibility assessment studies (Hasan et al., 2024; Kavzoglu et al., 2018).

3.6 Shapley Additive Explanations (SHAP)

Theoretically founded on cooperative game theory, the Shapley additive explanations (SHAP) is an explainable artificial intelligence method used to make transparent of inner structures of the machine learning models with black-box nature (Lundberg & Lee, 2017). The main focus of the theory is to estimate how to fairly distribute a payoff (prediction) among players (features) working as a team. Similarly, the SHAP aims to calculate the Shapley values to reveal the contribution of each feature in a given dataset to the difference between the model's prediction and the baseline (i.e., usually the average model prediction). The contribution is typically quantified by analyzing how the prediction changes when each feature is added to various subsets of features (Kavzoglu & Bilucan, 2023). The marginal contribution for each feature is ultimately calculated by considering all possible feature interactions.

3.7 LIME

LIME is a model-agnostic explainable artificial intelligence technique that can be applied to any machine learning algorithm. It is an interpretable model that approximates the model predictions of the model (Ribeiro et al., 2016). The algorithm initially creates perturbed samples by marginally changing the instance to be explained. The so-called complex model is used to predict these perturbed samples, and they are later transferred to train the local surrogate model (Teke & Kavzoglu, 2024). The algorithm applies a weighting scheme to these created samples based on their statistical vicinity to the instance under examination. The trained model is analyzed to extract an explanation of the original complex model's prediction. This explanation typically includes a summary of the most important features and how they influence the final prediction.

4. Results and Discussion

In this study, two approaches were used to assess potential statistical correlations among the factors and identify any adverse effects on the performance of the machine learning models: multicollinearity testing and correlation analysis. For the multicollinearity test, two key indicators, namely Variance Inflation Factor (VIF) and Tolerance (TOL), were calculated (Figure 2). A VIF value exceeding 10 or a TOL value below 0.1

would indicate significant multicollinearity between the independent variables. The analysis showed that the highest TOL value was 0.915, and the lowest VIF value was 1.093, both for the aspect parameter, indicating no multicollinearity issues among the factors.

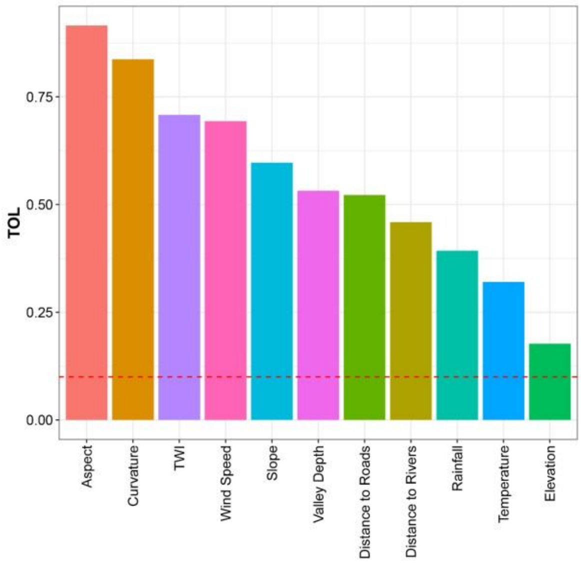

Figure 2. TOL values of multicollinearity test for geospatial covariates.

In the correlation analysis, the highest correlation coefficient was 0.66 (between distance to the river and elevation), and the lowest was -0.68 (between elevation and temperature) (Figure 3). Since all values calculated for factor pairs were below the 0.7 threshold value, all 11 geospatial covariates potentially influencing the forest fire susceptibility were retained as independent variables in the prediction phase.

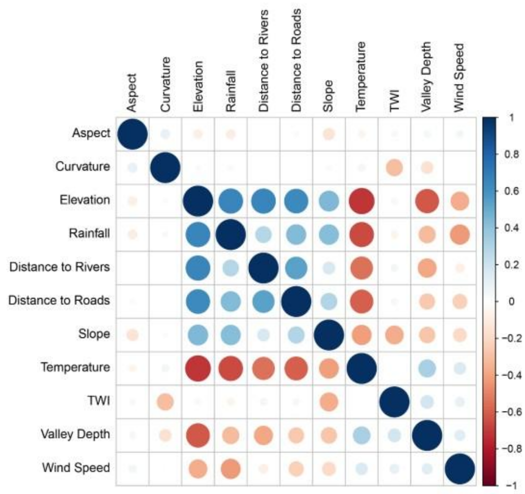

Figure 3. The heat map illustrating the correlation between the geospatial covariates.

The wildfire susceptibility maps for the study area were generated using three ensemble-based machine learning algorithms. To optimize their predictive performance, the hyperparameters of each algorithm were fine-tuned using the grid search method. Overall accuracy was chosen as the fitness function during optimization, and three-fold cross-validation was applied. The reliability of the resulting maps was later evaluated using four accuracy assessment metrics: overall accuracy (OA), area under the curve (AUC), precision, and recall (Figure 4). NGBoost achieved the highest prediction accuracy with an overall score of 81.42%, while Random Forest had a lower overall accuracy of 73.50%.

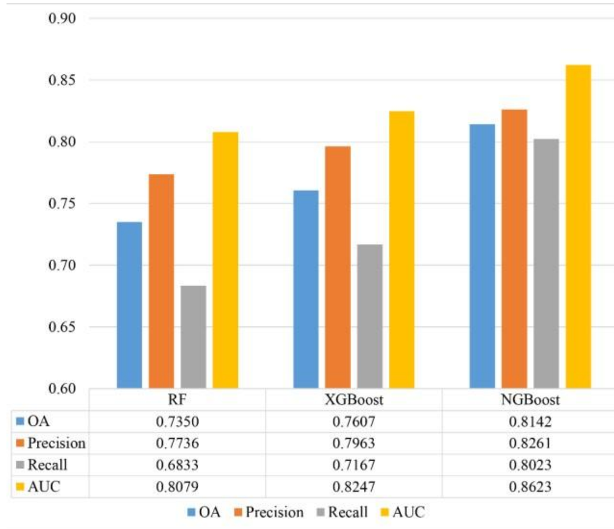

Figure 4. Accuracy assessment results of machine learning models with OA, precision, recall, and AUC scores.

In addition to the accuracy assessment, McNemar's test was used to assess the statistical significance of performance differences between the algorithms (Table 2). The results showed a statistically significant difference between NGBoost and Random Forest, whereas the performance differences between the other algorithms were not statistically significant.

	RF	**XGBoost**	**NGBoost**
RF	—	2.722	5.042
XGBoost		—	3.704
NGBoost			—

Table 2. Pairwise comparison of estimated statistical values for algorithm pairs with McNemar's test.

The produced forest fire susceptibility maps were later thematically analyzed after reclassified using a quantile-based discretization approach (Figure 5). The thematic analysis of the maps revealed that forest fire susceptibility generally increased in the central and southern parts of the study area while the northern and northwestern parts corresponded to the low and very low susceptibility categories. In the central and southern regions of the study area, higher wind speeds and temperatures, combined with lower rainfall compared to other parts of the district, were identified as factors contributing to the increased forest fire susceptibility.

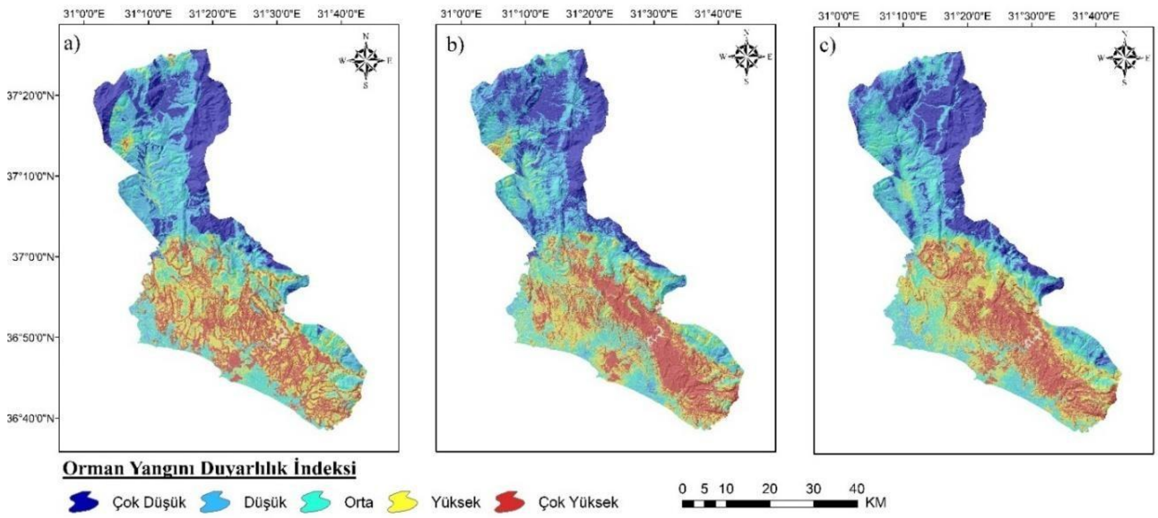

Figure 5. Forest fire susceptibility maps produced by (a) RF, (b) XGBoost, and (c) NGBoost.

After producing forest fire susceptibility maps using three machine learning algorithms with black-box characteristics, two explainable artificial intelligence (XAI) methods, SHAP and LIME, were applied to identify the most influential parameters affecting forest fires. The SHAP analysis was conducted to analyze the influence of parameters at a global scale across the entire study area while LIME was applied to three randomly selected samples to explore the impact of specific parameter values at a local level.

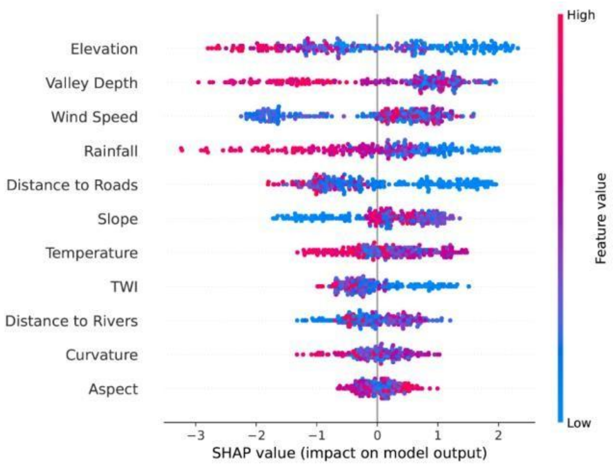

Figure 6. SHAP beeswarm graph illustrating the importance of geospatial covariates for the NGBoost algorithm.

The SHAP analysis revealed that elevation and valley depth were the top two factors with the greatest influence on model accuracy, while aspect had the least impact. Overall, the SHAP results indicated that the climatic and topographic factors identified in the study area played an important role in influencing forest fire susceptibility (Figure 6).

Three samples were randomly selected from different locations within the study area, and the local explainability results were evaluated using the LIME algorithm on the forest fire susceptibility map with the highest prediction performance, generated by the NGBoost. The first sample, covering 81,002.872 m², was classified as a forest fire with a prediction probability of 0.91 (Figure 7). LIME revealed that the top five factors influencing this prediction were elevation, wind speed, slope, precipitation, and temperature. The sample's elevation of 103 meters, within the LIME-determined range of 58 to 362.15 meters, increased the prediction probability by 0.15. Additionally, the wind speed of 2.72 m/s, exceeding the LIME threshold of 2.45 m/s, raised the prediction probability by 0.11.

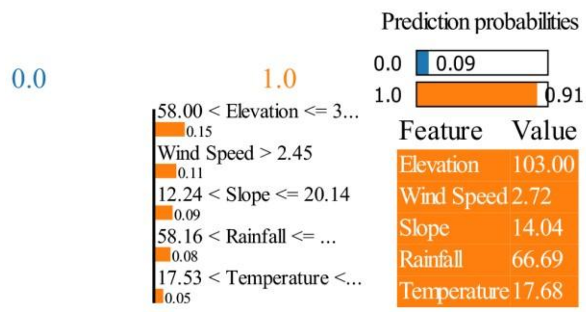

Figure 7. Local explanation with LIME for the first randomly selected sample.

The second sample, from a forest fire event in the Manavgat district of Antalya, covered 73,560.555 m² and was classified as a non-forest fire event (Figure 8). The five key factors identified by LIME were wind speed, elevation, precipitation, distance to road, and valley depth. The wind speed of 2.04 m/s, within the LIME-calculated range of 1.92 to 3.02 m/s, reduced the prediction probability by 0.27. Similarly, the sample's elevation of 1275 meters, higher than the LIME threshold of 860.25 meters, further decreased the probability by 0.27.

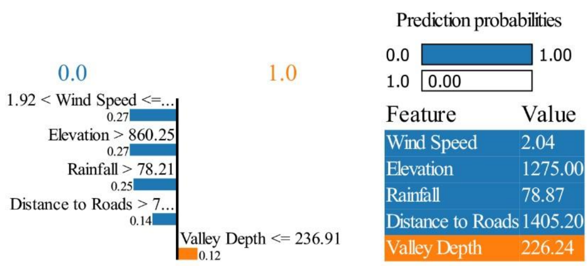

Figure 8. Local explanation with LIME for the second randomly selected sample.

The third sample, covering 260,029.584 m², was also classified as non-forest fire activity, with a prediction probability of 0.88 (Figure 9). LIME indicated that the most influential factors were valley depth, elevation, distance to road, curvature, and wind speed. The valley depth of 525.3 meters, within the LIME range, reduced the prediction probability by 0.23. The distance to the road, being greater than the 60-meter threshold, slightly increased the fire prediction probability by 0.04.

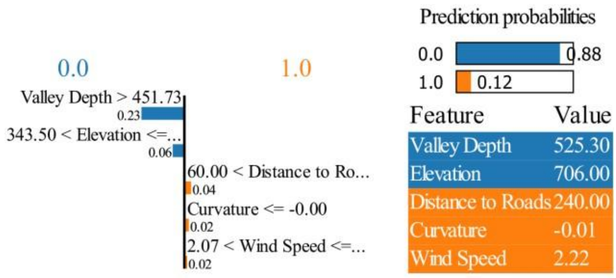

Figure 9. Local explanation with LIME for the third randomly selected sample.

5. Conclusions

This study aims both to produce forest fire susceptibility maps for the Manavgat district, one of the areas in Turkey where forest fires are most frequently observed and to make the decision-making mechanisms of the black-box nature of the machine learning algorithms used more transparent, thereby examining the factors affecting forest fires both globally and locally. According to the findings obtained, the most significant results in line with the main objective of this study can be summarized as follows.

- The correlation analysis and VIF/Tolerance values obtained from the collinearity test indicated that there is no potential statistical linearity problem among the factors contributing to wildfire activities.

- Considering a total of four accuracy assessment metrics, the NGBoost algorithm outperformed the XGBoost and RF algorithms in predicting wildfire susceptibility, achieving higher overall accuracy by approximately 5% to 8%.

- The statistical test results demonstrated that the performance differences between the NGBoost and other machine learning algorithms were statistically significant within the 95% confidence interval, further validating the superiority of the NGBoost algorithm.

- The SHAP method was applied to enhance the interpretability of the NGBoost model's decision-making mechanism. The results revealed that precipitation, altitude, and valley depth had the highest influence on the model.

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