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FOREST FIRE HAZARD ASSESSMENT USING REMOTE SENSING DATA AND MACHINE LEARNING, CASE STUDY OF JIJEL, ALGERIA

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Abstract

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Climate change, particularly in vulnerable areas such as the Mediterranean hotspot, exacerbates the risk of wildfires, turning these regions into true danger zones. In Algeria, where climatic conditions are rapidly evolving, these risks are especially pronounced in the northern coastal regions. Wildfires, which are already frequent, are becoming increasingly difficult to control due to rising temperatures and prolonged periods of drought. In this context, wildfire hazards in Algeria, particularly in the northern coastal regions, present significant challenges. Despite frequent forest fires, effective management strategies are lacking. This paper assesses wildfire hazards in Jijel, Algeria, using advanced machine learning techniques combined with spatial analysis of environmental and anthropogenic factors. Two algorithms, K-Nearest Neighbours (KNN) and Histogram-Based Gradient Boosting (HGB), were employed. Evaluation metrics such as Receiver Operating Characteristic Area Under the Curve, F1 score and accuracy, supported by repeated cross-validation, were used to gauge performance. Both models performed well (with an average area under the curve of 0.977 and 0.984, respectively), with HGB maintaining a marginal but consistent advantage over KNN, with relatively low standard deviations, suggesting stability in its predictive capability. The study offers valuable insights for wildfire management and land-use planning in Algeria, highlighting the need for tailored risk mitigation strategies.

Key words: wildfire susceptibility mapping, remote sensing, machine learning, Jijel, Algeria, SHAP.

Introduction

The conservation of forests and forest vegetation in the Mediterranean basin presents a complex challenge due to the heterogeneity of the situations and the multiple anthropogenic pressures exerted by various Mediterranean cultures over millennia (Quézel, Médail, 2003; Kheir et al., 2021). With climate change exacerbating these pressures, the current situation in Mediterranean countries has become even more concerning. This global climate change has led to an increased frequency of wildfires worldwide, not only resulting in significant economic losses and environmental destruction but also posing a major threat to human safety (Ghorbanzadeh et al., 2019). Only ambitious programs of integrated ecological management, which account for the impacts of climate change, will enable preservation of the remaining forest fragments and protection of the few areas that have miraculously escaped these destructions (Quézel, Médail, 2003; Dahmani et al., 2023).

Forest fires are a significant environmental hazard, particularly in Mediterranean regions like Algeria, where climatic conditions and human activities converge to create high-risk scenarios (Belgherbi et al., 2018; Djellouli et al., 2024). The northern coastal regions of Algeria, including the Wilaya of Jijel, are especially prone to wildfires, which have devastating impacts on ecosystems, biodiversity, and human settlements (Moussaoui et al., 2022). Despite the frequency and severity of these events, effective wildfire management strategies remain underdeveloped in the region (Chicas, Østergaard Nielsen, 2022). This gap highlights the critical need for advanced tools and methodologies to assess and mitigate wildfire hazards.

The increasing frequency and intensity of wildfires globally, exacerbated by climate change, underscore the urgency of developing robust hazard assessment frameworks. In Mediterranean climates, characterised by hot, dry summers and mild, wet winters, the risk of wildfires is particularly acute. Algeria has seen a rising trend in wildfire incidents (Curt et al., 2020), with significant loss of forest cover and damage to agricultural lands. The social and economic repercussions of these fires are profound, affecting livelihoods and contributing to environmental degradation (Sahar et al., 2018; Allam et al., 2020). The need for precise and reliable wildfire susceptibility models is, therefore, pressing.

Efforts to improve alert systems, communication, and preventive silviculture are crucial in reducing forest vulnerability to fires in Algeria. By integrating advanced technologies, such as machine learning (ML) algorithms, with comprehensive wildfire hazard assessments, it is possible to develop effective strategies for wildfire management and mitigation tailored to the unique environmental conditions and landscape characteristics of the region. This paper aims to contribute to this endeavour by conducting a thorough assessment of wildfire hazard in the Wilaya of Jijel. Despite its ecological significance, Jijel has not been comprehensively studied in terms of wildfire occurrences and susceptibility. This study aims to address this gap by conducting a thorough assessment of wildfire hazard in the region.

Forest fire susceptibility mapping using ML has gained traction as an effective approach to predict and manage fire risks. Research indicates that various ML algorithms have been employed to analyse environmental variables and historical fire data, yielding high accuracy in susceptibility predictions (Le et al., 2021; Zhao et al., 2024; Yu et al., 2024). For instance, Yu et al. highlighted the integration of remote sensing data and socioeconomic factors, which enhances the predictive capability of models (Yu et al., 2024). Moreover, Alkan Akıncı et al. emphasised the importance of feature selection in improving model performance, suggesting that the inclusion of topographical and climatic variables significantly influences susceptibility outcomes (Akinci et al., 2024). However, limitations exist, such as the need for extensive datasets, effective optimisation and effective validation methodology to avoid overfitting.

While significant progress has been made in wildfire modelling, there remains a lack of comprehensive studies focusing on Algeria, particularly in the Wilaya of Jijel. This region's unique landscape, climate and socioeconomic conditions demand tailored approaches for wildfire risk assessment. Moreover, the application of cutting-edge ML techniques, such as K-Nearest Neighbours (KNN) and Histogram-Based Gradient Boosting (HGB), in this context has been limited. They were chosen for this study due to their complementary strengths in wildfire susceptibility assessment. KNN, a simple and interpretable algorithm, is well suited for capturing local patterns in small to medium-sized datasets without assuming a specific data distribution, making it ideal for initial analysis in complex environments (Cover, Hart, 1967). However, HGB offers high predictive power and efficiency with large datasets, thanks to its ensemble learning approach and histogram-based method, which effectively handles non-linear relationships, missing data and outliers (Guryanov, 2019).

This study aims to fill this gap by conducting a detailed assessment of wildfire susceptibility in the Wilaya of Jijel using advanced ML algorithms. By integrating spatial analysis with ML, this research seeks to provide actionable insights into the factors driving wildfire occurrences in the region. The ultimate goal is to contribute to the development of effective wildfire management strategies that can be implemented at both local and national levels.

Material and methods

Study area

The study area encompasses the Wilaya of Jijel, a region located along the northern coast of Algeria, characterised by its rich biodiversity and diverse landscapes. Covering an area of 2385.65 km^2 and boasting a 120-km coastline, the Wilaya of Jijel is positioned between parallels 36°30'N and 36°60'N and meridians 5°25'E and 6°30'E (Fig. 1). Its Mediterranean climate, typified by hot, arid summers and mild, wet winters, coupled with periodic droughts and prevailing strong winds, renders the region susceptible to wildfires. The topography of the area, featuring coastal plains, rugged mountains and lush forests, further exacerbates wildfire risk, presenting unique challenges in wildfire management and hazard assessment. Forests, covering 57% of the total area of the wilaya, are a prominent feature, with oak woodlands comprising cork oak, zean oak, afarès oak, Aleppo pine and maritime pine species. In addition, maquis shrubland thrives in the region.

Wildfire data

Fire point data were collected from remote sensing, specifically Moderate Resolution Imaging Spectroradiometer (MODIS). The dataset was filtered to include observations with a confidence level of 100 and a day/night indicator of 'D' (daytime). The dataset provides a monthly average Fire Radiative Power (FRP) recorded in Jijel, Algeria, from 2001 to 2022. FRP is a measure of the rate of radiant energy release per unit area from a fire, commonly expressed in megawatts per square meter (MW/m^2).

Analysis of the data (Fig. 2) revealed a noticeable concentration of detected fires during the summer and early autumn months, particularly in July, August and September. This temporal pattern aligns with the typical fire season in many regions, characterised by hot and dry weather conditions conducive to fire ignition and propagation. Variations in the number and intensity of detected fires were evident from year to year. Some years exhibited higher FRP values, indicating more intense or widespread fire activity, while others showed lower values. Notably, certain years stood out with notably high FRP values, indicative of significant fire events during those periods.

Conditioning factors

In this analysis, 12 factors that are recognised to play crucial roles in influencing the occurrence of wildfires were incorporated (Yue, 2023). A range of environmental and anthropogenic variables, including Aspect, Elevation, Distance to stream, Landform, Land Surface Temperature (LST), Normalised Difference Vegetation Index (NDVI), Population density, Rainfall, Road density, Slope, Stream density and Topographic Wetness Index (TWI), alongside Wind speed, were encompassed by these factors. Uniquely contributing to our understanding of the landscape's susceptibility to wildfires, the intricate interplay between natural features and human activities is captured by each of these factors.

The spatial distribution of these conditioning factors is visually depicted in Fig. 3, which provides a clear representation of their geographic patterns and gradients across the study area. Valuable tools for identifying areas of heightened wildfire risk and guiding targeted mitigation efforts are served by these maps. To ensure transparency and facilitate further research, detailed sources for each conditioning factor have been included in Table 1.

The results in Fig. 4 show the distribution of the density of wildfire and non-wildfire points for each of the selected factors. The analysis of this finding reveals significant correlations between wildfire occurrence and the following:

- Elevation: Wildfire density appears highest at medium elevations, potentially due to increased fuel availability, fa-

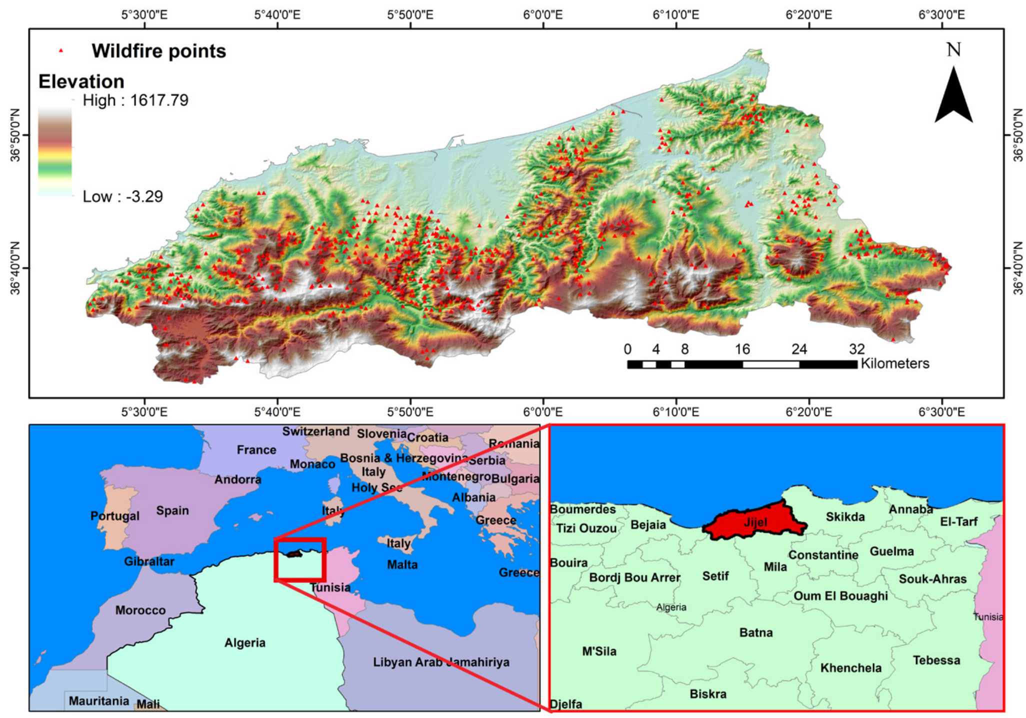

Fig. 1. The study area with the location of wildfire points.

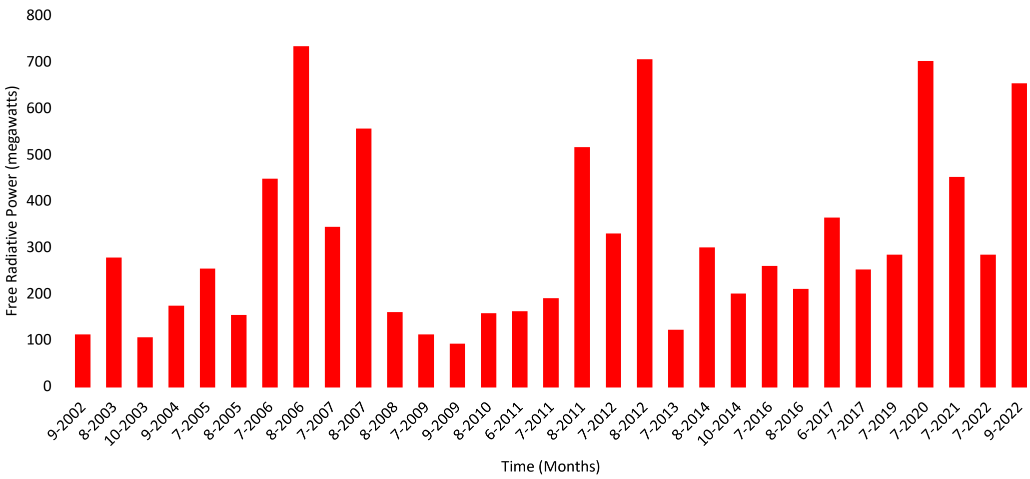

Fig. 2. Monthly FRP records according to MODIS fire data.

Table 1. Sources of data used in the study.

Data	Sources
Historical wildfire	https://doi.org/10.5067/FIRMS/MODIS/MCD14DL.NRT.0061
Elevation, Aspect, Slope, Stream density, TWI	https://doi.org/10.5067/Z97HFCNKR6VA
LST	https://doi.org/10.5067/MODIS/MOD11A2.061
Rainfall	https://doi.org/10.1038/sdata.2015.66
Wind speed	https://doi.org/10.1038/sdata.2017.191
NDVI	https://doi.org/10.5067/MODIS/MOD13Q1.061
Roads	https://gadm.org/
Landform	https://doi.org/10.1371/journal.pone.0143619
Population density	https://hub.worldpop.org/

Notes: LST - Land Surface Temperature; NDVI - Normalised Difference Vegetation Index; TWI - Topographic Wetness Index.

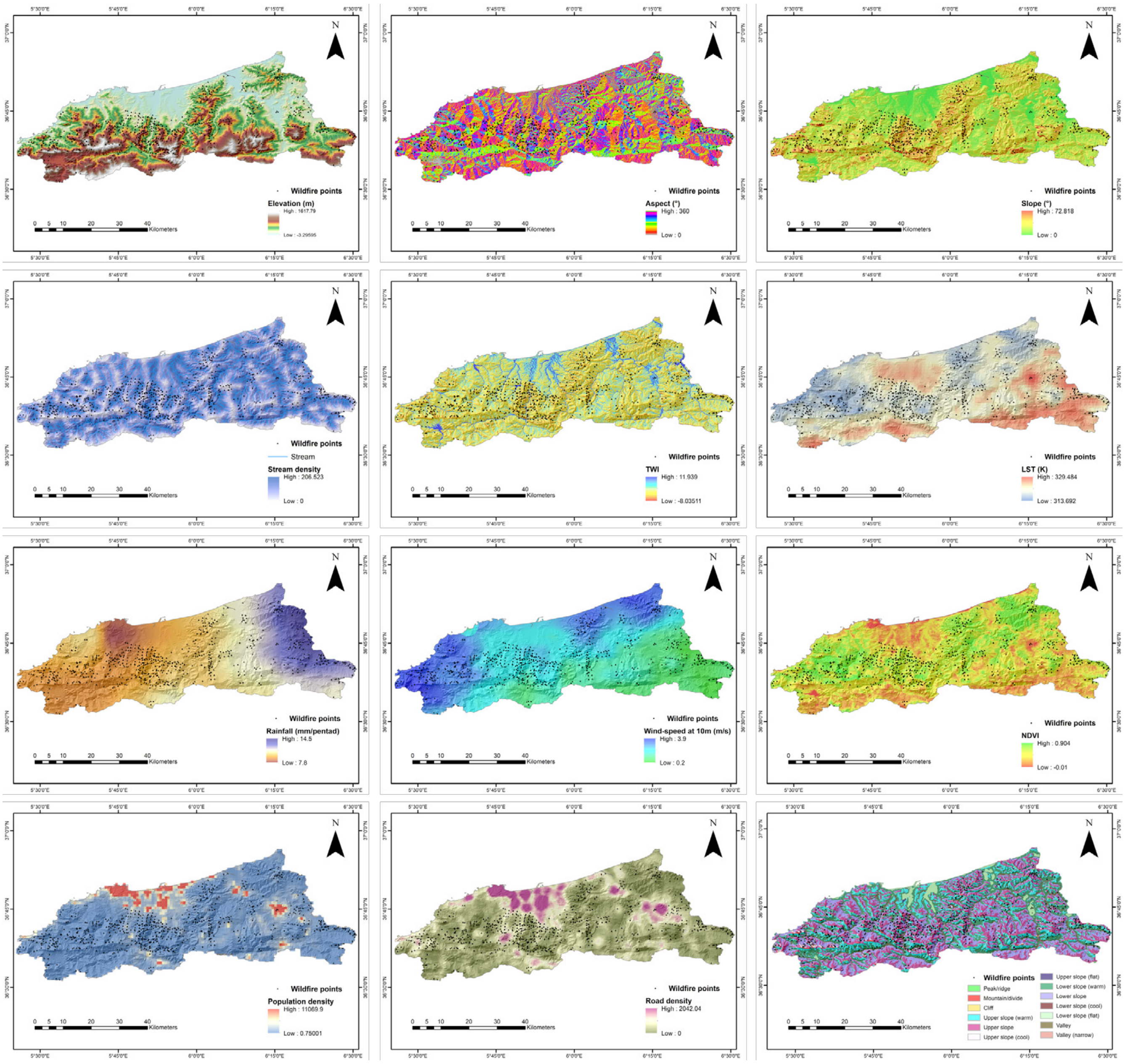

Fig. 3. Maps of wildfire conditioning factors.

vourable wind patterns and topographic influences on fire behaviour.

- Slope Aspect: South-facing slopes exhibit a higher density of wildfires compared to other aspects. This can be attributed to greater direct sunlight exposure throughout the day, leading to drier and hotter conditions. Conversely, north-facing slopes show a lower density likely due to reduced solar exposure, resulting in cooler and moister environments. East- and west-facing slopes have intermediate wildfire densities, reflecting their sunlight exposure between north and south aspects.
- Slope Gradient: Wildfire points are more concentrated on slopes with a medium incline, whereas non-wildfire points are more prevalent on low slopes. This suggests a potential link between ignition sources (lightning strikes, human activity) and the ability of these slopes to sustain wildfires.
- Stream Density: Areas with lower stream density (potentially drier) exhibit a higher density of wildfires compared to areas with higher stream density. This suggests a correlation between moisture availability and wildfire susceptibility.
- LST: A seemingly counterintuitive pattern emerges with wildfire points being more concentrated in areas with low-to-medium LST. This can be explained by spatial collinearity between vegetation and LST. Denser vegetation cover in these areas may act as a buffer against sunlight, leading to lower surface temperatures despite potentially higher moisture levels and shading.

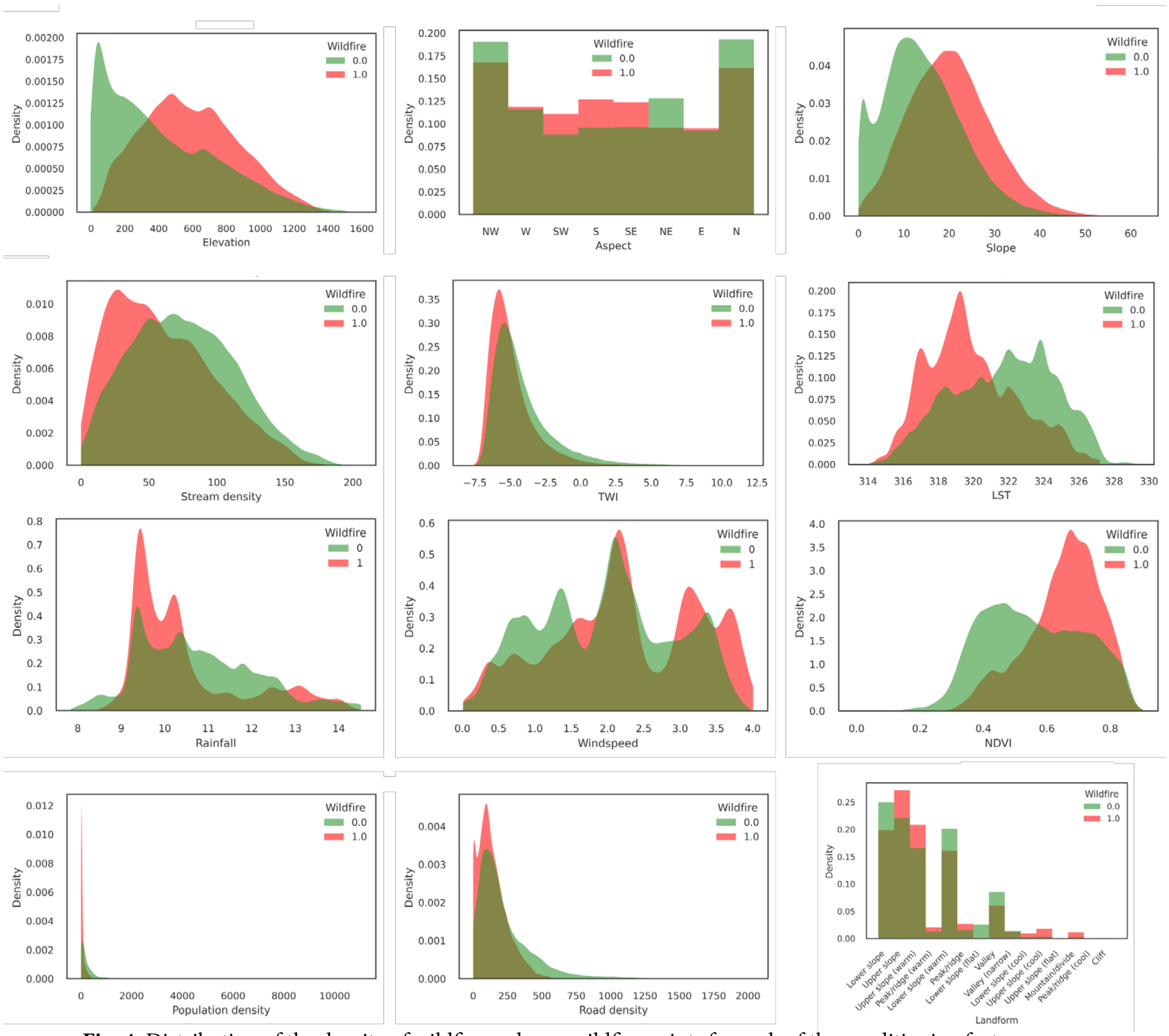

Fig. 4. Distribution of the density of wildfire and non-wildfire points for each of the conditioning factors.

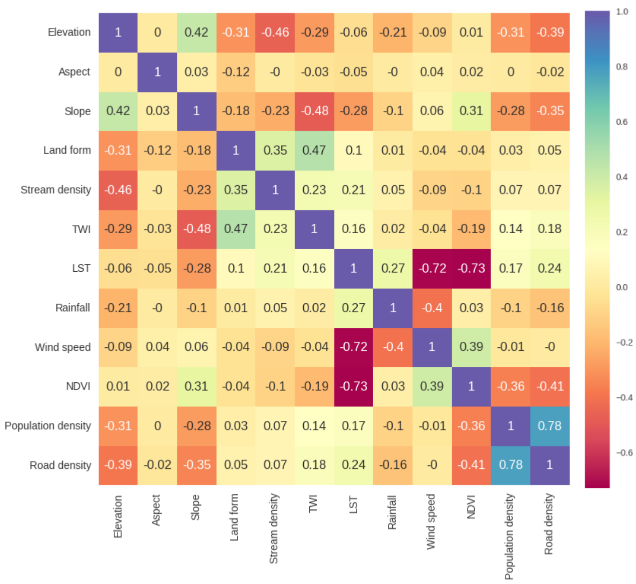

Fig. 5. The correlation matrix between the proposed factors.

- Rainfall: Wildfire frequency is higher in areas with low rainfall, suggesting a link between moisture availability and wildfire occurrence.
- Wind Speed: Wildfire points are more concentrated in areas with high wind speeds, implying that strong winds contribute to the spread of wildfires by fanning flames.
- NDVI: An unexpected relationship exists between NDVI and wildfire occurrence. While high NDVI typically indicates denser vegetation, potentially reducing fire risk, our study revealed a concentration of wildfire points in such areas. This suggests that dense vegetation may not necessarily hinder wildfire ignition or spread.
- Population Density: Both wildfire and non-wildfire points show concentration at low population densities. However, wildfire density is significantly higher at very low population densities, suggesting a link between human activity and wildfire occurrence in remote areas.
- Road Density: Wildfire points are less frequent in areas with high road density, whereas non-wildfire points are spread more evenly. This suggests that remote areas with lower road density may be more susceptible to wildfires.

- Landform: Wildfire densities vary across different topographic zones. Upper slopes and peaks experience higher densities likely due to drier conditions and abundant fuel. Conversely, valley bottoms exhibit lower densities due to higher moisture content and denser vegetation. In addition, flat areas show lower densities compared to slopes, as fire propagates more readily uphill.

Methodology

The methodology employed in this study involved the implementation of two distinct ML algorithms: KNN and HGB. These algorithms were selected based on their ability to effectively handle large datasets with relatively low computational time requirements. To optimise the performance of the models, hyperparameter tuning was conducted using the Randomised Search CV approach. This method allows for an efficient exploration of the hyperparameter space, ultimately identifying the optimal combination of parameters for each algorithm. Following hyperparameter tuning, the performance of the models was evaluated using three key metrics: Receiver Operating Characteristic Area Under the Curve (ROC AUC), F1 score and accuracy. Evaluation was conducted using cross-validation, ensuring robustness and reliability of the results across multiple folds of the dataset.

K-Nearest Neighbours

KNN is a powerful and straightforward ML algorithm that belongs to the field of non-parametric supervised learning. It operates by assigning a new data point to the majority class among its KNN, based on a distance metric such as Euclidean distance. KNN is particularly suitable for moderately large datasets and is known for its ease of implementation and tuning (Cover, Hart, 1967; Yue et al., 2023).

Histogram-Based Gradient Boosting

HGB is a powerful ensemble learning technique that combines the strength of decision trees with gradient boosting. HGB builds an ensemble of decision trees sequentially, where each tree is trained to correct the errors of its predecessors. By iteratively improving the model's predictions, HGB achieves high predictive performance and is capable of handling complex, non-linear relationships in the data (Guryanov, 2019; Iban, Sekertekin, 2022).

Results and discussion

Collinearity analysis

The collinearity analysis is a crucial aspect of the ML modelling process, necessitating thorough evaluation. The correlation matrix presented provides insight into the relationships between predictor variables, shedding light on potential multicollinearity issues that could affect the model's stability and interpretability.

The correlation matrix between the factors is shown in Fig. 5, where each cell represents the correlation coefficient between two variables, ranging from −1 to 1. A correlation close to 1 indicates a strong positive linear relationship, while a correlation close to −1 signifies a strong negative linear relationship. A correlation near 0 indicates no linear relationship between the variables. Examining the correlation matrix reveals several noteworthy patterns. The correlation matrix helps identify potential redundancies among predictor variables, guiding feature selection and dimensionality reduction efforts. For instance, high correlations between variables such as LST and NDVI indicate multicollinearity. This collinearity should be at the origin of the misleading result for the distribution of LST forest fires, which led to the exclusion of the variable to reduce redundancy in the model.

Forest fire susceptibility maps

The maps generated using HGB and KNN are depicted in Fig. 6, alongside wildfire density distribution plots for each model. This innovative approach, aimed at enhancing susceptibility classification methods (Matougui et al., 2024), illustrates the number of wildfires per unit area on the Wildfire Susceptibility Index (WSI) scale, offering valuable insights into the models' ability to capture the spatial distribution of wildfires.

Both wildfire susceptibility maps exhibit a visually realistic portrayal, with a notable concentration of fire points observed in high-susceptibility areas. This observation is corroborated by the wildfire density distribution plots, which demonstrate a clear positive correlation between WSI and wildfire density. However, distinct patterns emerge in the plots: the HGB plot displays a relatively smooth curve, while the KNN plot features a staircase-shaped curve. This difference in curve shapes suggests variations in how each model predicts wildfire occurrences across different susceptibility levels. The smoother curve of HGB indicates a more gradual transition in wildfire density as susceptibility levels change, while the staircase pattern of KNN suggests distinct thresholds or boundaries between susceptibility classes.

Overall, the combination of susceptibility maps and wildfire density distribution plots provides a comprehensive understanding of the models' performance in capturing spatial wildfire patterns.

Performance of the models

The models were meticulously fine-tuned to optimise their performance. For HGB, the parameters were set as follows: max − iter = 200, max − depth = 6, loss = 'log − loss', and learning − rate = 0.1. Similarly, for KNN, the parameters were configured as weights = 'distance', n − neighbours = 5, leaf − size = 30, and $p = 2$.

Various key metrics were used to assess the performance of the models: ROC AUC, accuracy and F1 score. These metrics provide comprehensive insights into the models' predictive capabilities, assessing their ability to discriminate between positive and negative instances, overall correctness of predictions and balance between precision and recall, respectively. To ensure robustness and reliability, the evaluation was conducted using repeated cross-validation. This method involves repeatedly splitting the dataset into training and testing subsets, training the model on one subset and evaluating its performance on the other. This process is repeated multiple times to mitigate the impact of random variability in the data, yielding more stable and generalisable results (Matougui et al., 2023). The performance of the models is summarised in Table 2.

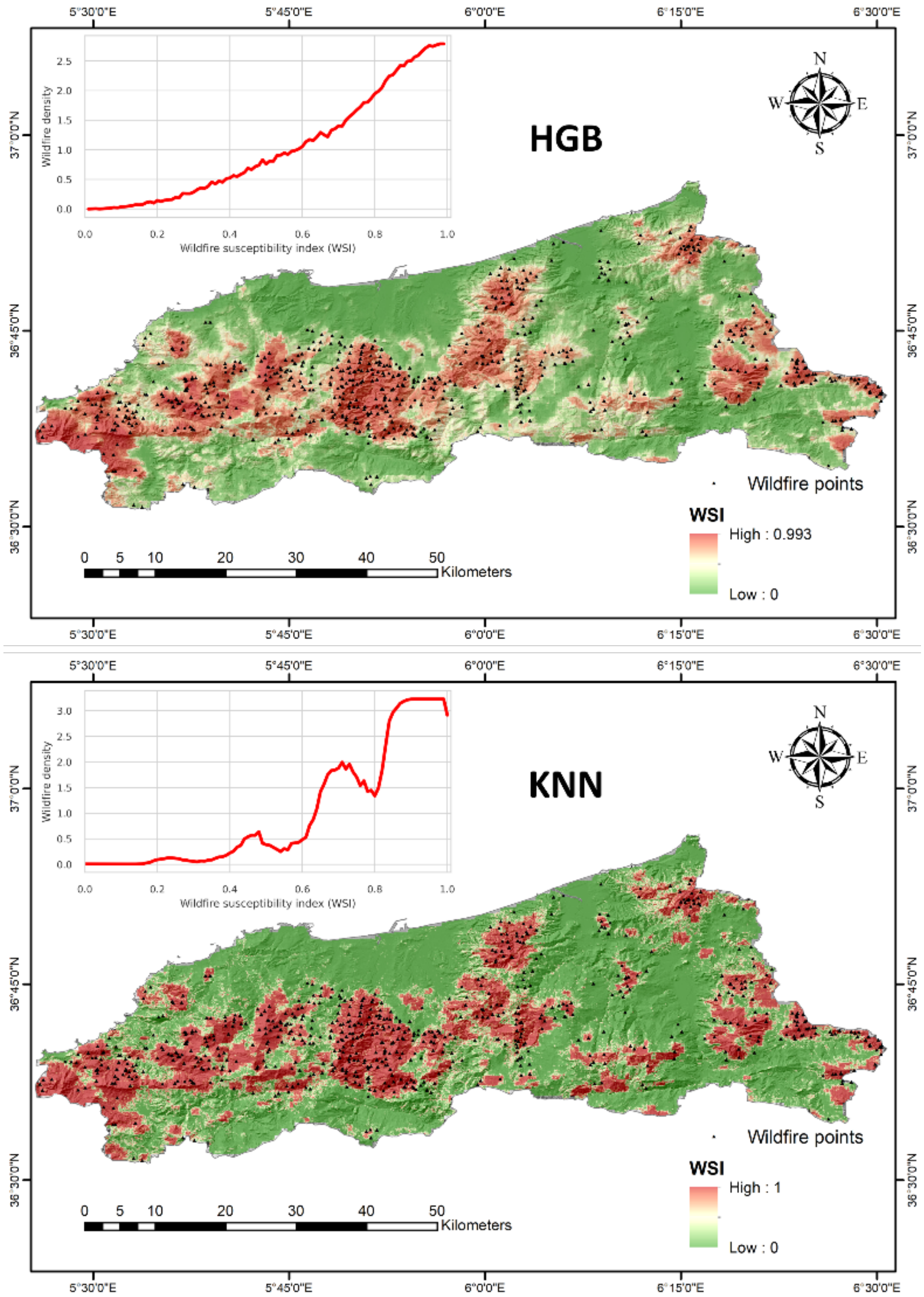

Fig. 6. Wildfire susceptibility maps with density distribution plots.

Table 2. Predictive performance of each model.

Metrics	KNN		HGB	
	Mean	SD	Mean	SD
ROC AUC	0.977	0.00085	0.983	0.0006
Accuracy	0.936	0.0018	0.938	0.0015
F1 Score	0.884	0.0029	0.884	0.0028

Notes: HGB – Histogram-Based Gradient Boosting; KNN – K-Nearest Neighbours; ROC AUC – Receiver Operating Characteristic Area Under the Curve; SD – standard deviation.

Both the KNN and HGB models exhibited commendable performance across various metrics, particularly in terms of ROC AUC scores. While the difference in ROC AUC performance between the two models was relatively modest, a more substantial contrast emerged when examining the F1 score and accuracy metrics. HGB demonstrated superior performance in area under the curve (AUC), F1 score and accuracy, compared to KNN. Specifically, HGB achieved an F1 score of 0.884 with a standard deviation of 0.0028, whereas KNN matched this F1 score. Similarly, HGB exhibited higher accuracy (0.938 with a standard deviation of 0.0015) compared to KNN (0.936 with a standard deviation of 0.0018).

These discrepancies suggest that the HGB model excels in classification tasks compared to KNN. While both models effectively distinguish between positive and negative instances, the superior performance of HGB is evident in its higher accuracy metrics. Interestingly, these results align with the wildfire density distribution diagrams associated with each model. The relatively smooth curve observed for HGB implies a direct correlation between wildfire density and susceptibility index. In contrast, the stepped curve characteristic of the KNN model suggests a more categorical classification approach. These findings underscore the importance of evaluating models using qualitative and quantitative metrics to gain a comprehensive understanding of their performance.

These results are consistent with, and in some cases exceed, those reported in other studies on wildfire susceptibility using ML techniques. For instance in Antalya, Türkiye, Mediterranean environments with similar conditions have reported AUC values ranging between 0.83 and 0.85. AUC scores in this study suggest that the chosen models (Akinci et al., 2024), particularly HGB, may offer superior accuracy in predicting wildfire-prone areas.

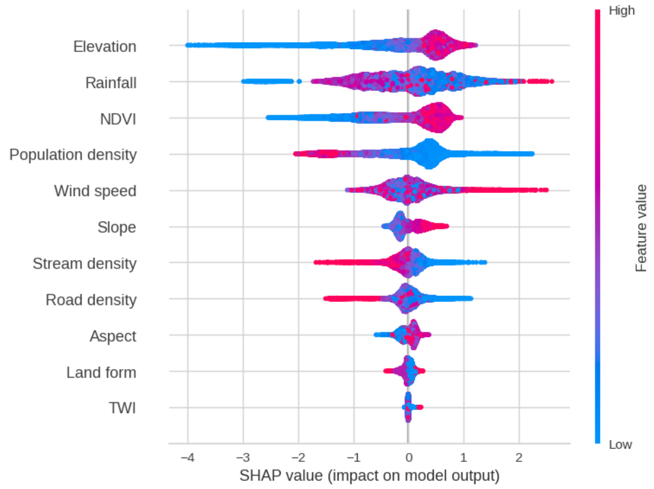

Fig. 7. Summary plot of Shapley values of HGB.

SHapley Additive exPlanations for wildfire susceptibility assessment

SHapley Additive exPlanations (SHAP) is a technique used to explain the predictions of any ML model (Lundberg, Lee, 2017). It is particularly useful for understanding complex models like gradient boosting, which can be like black boxes. In the context of wildfire susceptibility assessment, SHAP helps us understand how different factors contribute to the prediction of whether a particular location is susceptible to wildfires. The summary plot of Shapley values for wildfire susceptibility assessment using HGB is presented in Fig. 7. The plot shows the impact of various features on the model as follows:

- Elevation: Higher elevation values correspond to a lower susceptibility to wildfires. This aligns with the result of a previous study (Aini et al., 2019).
- Rainfall: Higher rainfall amounts correspond to a lower susceptibility to wildfires. This suggests that areas with more rainfall are likely to be wetter, making them less prone to fires. However, it seems that this hypothesis is not entirely consistent with the model.
- NDVI: Higher NDVI values, indicating denser vegetation, correspond to a higher susceptibility to wildfires (Pereira-Pires et al., 2021). This aligns with the understanding that areas with more vegetation are more prone to fires.
- Population density: Higher population density corresponds to a lower susceptibility to wildfires. This could be due to a number of factors, such as human activity leading to land development or fire suppression efforts in densely populated areas.
- Wind speed: Higher wind speeds correspond to a higher susceptibility to wildfires. This is likely because strong winds can fan flames and spread fires more rapidly. Wind plays a crucial role in controlling the spread of fires, which is influenced by the exposure and slope of an area (Pazmiño et al., 2019).
- Slope: The impact of slope is less pronounced. Sensitivity increases slightly with steeper slopes and decreases with lower slopes. According to Güngöroğlu (2017), steeper slopes can promote fire spread by increasing the speed at which the fire moves, facilitating the supply of oxygen, and allowing the fire to climb more quickly in altitude.
- Stream density and road density: The influence of these two factors is quite similar. Lower stream density and road density corresponds to a higher susceptibility to wildfires. This aligns with the understanding that these areas are more likely to have dry fuels that can ignite due to human action and support wildfires.
- Aspect: The relationship between aspect and wildfire susceptibility shows a higher susceptibility at aspects with values closer to 0° (north) and 180° (south). This aligns with the understanding that north-facing slopes receive less sunlight and tend to be cooler and moister, while south-facing slopes receive more direct sunlight and are drier and hotter.

Overall, the summary plot suggests that the most important factors influencing wildfire susceptibility in the Jijel region are elevation, rainfall, NDVI and wind speed. Areas with lower elevation, lower rainfall, lower NDVI and higher wind speed are more susceptible to wildfires according to the model. It is important to note that this interpretation is based on the specific model and data used to generate the Shapley values. Other models or datasets might identify different factors as being most important.

Conclusion

This study provides a detailed assessment of wildfire hazard in the Wilaya of Jijel, Algeria, by integrating advanced ML techniques with spatial analysis. The results underscore the critical role of environmental and anthropogenic factors, such as elevation, slope aspect and population density, in influencing wildfire susceptibility. Both KNN and HGB models exhibited strong performance in classifying wildfire risk in a Mediterranean context, with HGB demonstrating slightly higher accuracy and robustness, while KNN showed commendable effectiveness in wildfire classification tasks. The innovative application of spatial factor analysis in this study provides a better understanding of the impact of various individual risk factors, offering a level of interpretability that is often lacking in complex models. The study also reveals complex and sometimes counterintuitive relationships in variables like LST and NDVI, highlighting the intricate nature of wildfire dynamics in the region.

These findings offer valuable insights for the development of targeted wildfire management strategies. To effectively incorporate these insights into existing wildfire management strategies, it is crucial to integrate the risk assessment models into Algeria's decision-making frameworks. Specifically, the generated susceptibility maps should be used to inform land-use planning, resource allocation and emergency preparedness efforts. Decision-makers can leverage these maps to identify high-risk areas, prioritise monitoring efforts and guide the deployment of firefighting resources. Furthermore, integrating this data with early warning systems could enhance the timeliness and accuracy of fire alerts, enabling quicker and more targeted responses.

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