Machine Learning Methods for Fire Risk Assessment in Wildland Urban Interfaces - Case Study Attica Region, Greece

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Abstract. Wildfires' severity and frequency, further deteriorating due to Climate Change, are currently gaining great attention due to the devastating damages these may cause in the natural/built environment. Thus, proactive planning, targeting mitigation, preparedness, response and recovery, has become a necessity and needs to embrace Disaster Management perspectives, originating from wildfires. In support to this emergency, this study aims to develop a fire risk assessment framework relevant to Wildland-Urban Interfaces (WUIs), i.e., highly vulnerable areas due to their close proximity to forested ones. Towards this end, insights from the case study area – Attica region, Greece – and the inherent WUIs' characteristics has led to the establishment of an exhaustive fire-related variables' dataset. This has formed the ground for comparing robustness of a number of Machine Learning (ML) Methods towards fire risk assessment. Six literature-driven Individual ML Methods – Random Forest (RF), eXtreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), Logistic Regression (LR), Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) – and one Integrated Ensemble Method (Voting Ensemble) are used in this respect. Results obtained witnessed strong predictive performance of all methods, with XGBoost and LightGBM demonstrating the best overall results across multiple evaluation metrics. Worth noticing is also the minimal divergence between Test AUC and Spatial Cross-Validation AUC, indicating robustness to spatial generalization. Finally, contrasting fire risk assessment results to burned areas in the time span 2000–2024 revealed strong spatial alignment of all methods.

Keywords: Climate Change · Wildland Urban Interfaces (WUIs) · Fire Risk Assessment · Machine Learning Methods · Attica Region/Greece

1 Introduction

In the Climate Change (CC) era, incidents of natural disasters around the globe display escalating trends, raising thus concerns as to the severity, intensity and frequency of these phenomena; and the devastating consequences these cause in the natural/cultural

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and built environment. Reports of IPCC on future climatic projections demonstrate the prevalence of hot extremes and extended heat waves, droughts and decreasing precipitation rates in the years to come, particularly in the Mediterranean, an area marked as a CC "hotspot" [1]. That said, weather conditions in particular are expected to amplify the number of fire incidents in the Mediterranean, thus extending the fire season and the number of consecutive days with high or extreme fire danger [2, 3], affecting region's vulnerability and exposure to forest fires.

The rising frequency and severity of natural disasters in the CC era has raised research interest and risk assessment endeavours in, among others, the Mediterranean Region [2]. Thus, apart from indulging into the specificities of Mediterranean as a CC hotspot, research interest and relevant works are also focusing on the human factor and, more precisely, on the continuously escalating, poorly-planned urban sprawl along the Mediterranean coast. This is due to urbanization trends and the rising pressure for expanding mass tourism accommodation infrastructure, with both reinforcing vulnerability and exposure to wildfire incidents [4]. Urban sprawl, in particular, has given rise to the *Wildland Urban Interfaces* (WUIs), lying at the heart of this work. These are land compartments in close proximity to fire prone forested and vegetated areas. In fact, WUIs in the Mediterranean have so far witnessed the devastating consequences of severe wildfire outbreaks in their natural and socioeconomic environment. For instance Greece, along with other Mediterranean countries, every fire season is confronted with extreme wildfire events and their repercussions in both forested areas (e.g., Evia Island in 2021, area of Alexandroupolis in 2023) [5, 6] and the neighbouring urban constellations. Attica region, i.e., the case study of this research, is also one of the most affected areas in this respect. This area is marked by expanded WUIs throughout its territory, which have gone through severe wildfire disasters, with immeasurable repercussions in both the natural and built environment, but also human losses and deterioration of the quality of life of local population [2, 6, 7].

The escalating number of disaster incidents in the CC era and their severe consequences highlight the need to assess risk and set up proactive strategies in pursuing resilience objectives of both the natural and the man-made environment. A great ally in this effort is the immense technological developments, which have shifted scientific interest towards state-of-the-art and more reliable methodologies in support of disaster management enhancement. Speaking of wildfires, the need for more efficient fire risk assessment methodologies that are capable of coping with complexity inherent in this research topic is particularly evident [8, 9]. The advent and rapid growth of Artificial Intelligence (AI) and Machine Learning (ML) tools represent a valuable step towards this direction, proved also by their widespread adoption across relevant scientific fields. Due to their capability to manage large volumes of complex data [10], minimize human bias and deliver promising and reliable results in complex research endeavours [9, 11], state-of-the-art methodologies are increasingly replacing conventional ones. Enabled by technological evolution and computing power, the adoption of more automated procedures is shifting the focus towards more advanced technological solutions [7, 8].

As literature demonstrates, the implementation of ML methods in fire risk assessment appears to be rather extensive. Such methods are largely depended on the quality and quantity of available data [10], especially in research fields such as the wildfire risk,

which is driven by interactive factors that can affect the outcomes produced. Many recent studies have advocated the efficiency of ML methods by highlighting their geospatial predictive capacity; whereas other studies undergo comparative analyses among such methods [12]. ML methods are also used for elaborating on various research dimensions of wildfires, such as fire susceptibility, risk and behaviour prediction [10]. For instance, classification by means of ML methods is used in many fire risk studies in order to identify or distinguish fine prone from non-fire prone areas, due to the accuracy of results produced by them [11].

That said, this research work attempts to compare a range of ML methods as to their robustness and comparative advantages in assessing wildfire risk in WUIs. In doing so, results produced by six literature-driven *Individual Learning Methods* [Random Forest (RF), eXtreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), Logistic Regression (LR), Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP)] and one *Integrated Ensemble Method* (Voting Ensemble) are compared, using a set of evaluation metrics. In addition, GIS technologies are an integral part of the spatial analysis and mapping. Implementation of ML methods uses as case study area a representative Mediterranean urbanized landscape, namely the Attica region, Greece.

The structure of the paper has as follows: Sect. 2 elaborates on the methodological framework; features aspects of the study area and establishes the dataset feeding the ML methods; and presents the theoretical ground of these methods and the metrics used for assessing their performance. Section 3 presents results obtained from the implementation of the ML methods and their performance, based on relevant evaluation metrics. Finally, in Sect. 4, critical discussion on the outcomes obtained is provided, commenting on the performance and predictive results of each single ML method in both the study area in general and the WUIs in particular.

2 Materials, Methods and Data

2.1 The Methodological Approach

The stages of the methodological approach have as follows (Fig. 1):

- *Stage I* aims at: gaining insight into the attributes of the study area; overviewing wildfire incidents and burned areas in the time span of 2000–2024; exploring literature as to the WUIs' fire-related factors; and establishing the dataset of variables relevant to the study area for implementation in the fire risk assessment methods.
- *Stage II* elaborates on: data acquisition, description and processing; short theoretical discussion on Machine Learning Methods; metrics used in the evaluation process; and selection of ML methods to be tested in Stage III.
- *Stage III* involves: overview of the dataset; implementation of the ML methods in the study area; mapping/comparison of fire risk estimations produced by the ML methods in the WUIs inherent in the study area; evaluation of results based on metrics' assessment; and validation of results through their comparison with burned areas due to wildfire incidents, taking place in the time span 2000–2024.

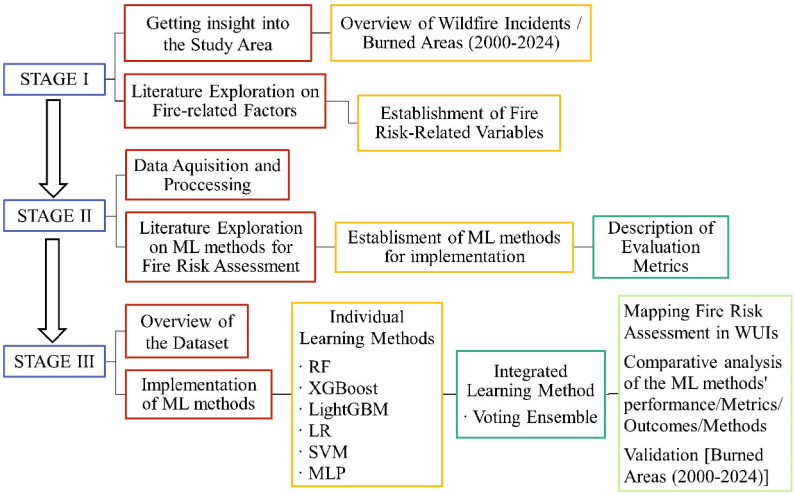

Fig. 1. Stages of the methodological approach

2.2 Delving into the Study Area for Dataset Establishment

Attica Region (Fig. 2) is selected as the study area of this work due to the recurring fire incidents, occurring in this area in the recent past. The region consists of eight Regional Units and sixty-six Municipalities. It covers an area of 3808 km^2 and, according to the 2021 Census of the Hellenic Statistical Authority (ELSTAT), gathers a population of approximately 3.81 million inhabitants [13]. The mountainous complexes prevail in the region's landscape, with the mountains of Geraneia, Pateras and Kithairon defining the western border of the region; and the mountains of Poikilo, Aigaleo, Parnitha, Penteli and Hymettus encircling the Attica basin from west to east. Furthermore, the south/south-western seaside area is washed by the Saronic Gulf, whereas the eastern/north-eastern seaside area from the South Euboean Gulf and the Gulf of Petalioi, both favouring mass tourist development of related coastal areas. The climate of the region is characterized as maritime, with dry, very warm summers [14].

A critical attribute of Attica region is the extensive urban sprawl towards the mountainous parts. This is due to the population growth in peri-urban areas, coupled with the seasonal population increase in the coastal part during summertime, i.e. from May to October, a period that coincides with the fire season. Due to the region's topographical diversity and the noticeable urban sprawl, extended WUIs are inherent in this area, i.e. urban and peri-urban areas highly exposed to wildfire risk due to their proximity to flammable vegetation [2]. The continuously expanding urban sprawl, the shift towards touristic activities in the extended coastal part and the abandonment of traditional agriculture leave the region vulnerable to wildfires and highlight the need for fire risk assessment that can properly feed proactive fire-preventing strategies [7].

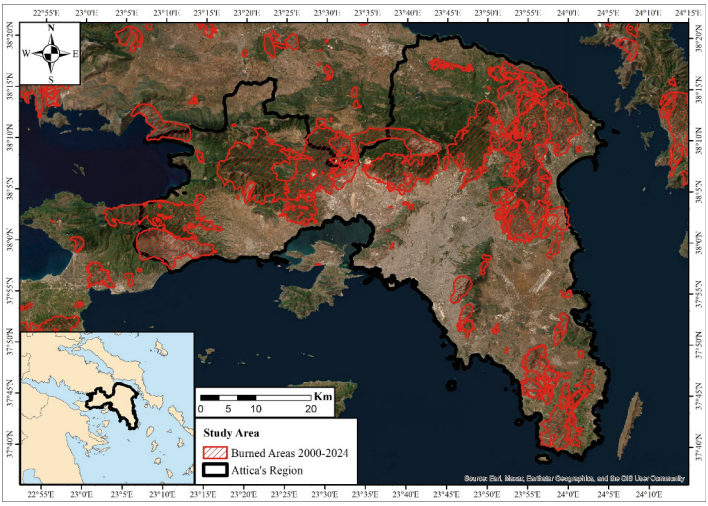

Fig. 2. Location of the Attica Region – Burned Areas in the time span 2000–2024. Source: Own Elaboration based on data from [13] and [16]

Indeed, data from the Hellenic Fire Service indicate a high frequency of fire incidents since 2000, remarkably impacting both the natural – extensive burned areas across the region, leading to the degradation of local ecosystems– and the urban environment and infrastructures, affecting thus quality of life of local population and leading to severe human losses [7]. In Fig. 3 the number of incidents occurred in this region in the time span 2000–2024 is demonstrated, coupled with the surface of burned areas [15]. Worth noticing in Fig. 3 is that although the number of incidents shows a decreasing pattern, the burned areas display an opposite one. This unveils the severity of recent wildfires, leading to extensive landscape degradation. Despite the intensive and ongoing efforts for early response and the recurrent reinforcement of fire fighting forces, the intensity of these phenomena and the size of the affected areas witness the imperative need for integrating disaster management practises in proactive strategies in order for effectively coping with today's urgencies [7].

2.3 Fire Risk Assessment Factors and Variables

The selection of fire risk related factors, as literature unveils, is a crucial task directly linked to each single study area and its particularities. Thus, choice of the most critical factors in each single case study, coupled with the successful collection of relevant data forms the ground for grasping interrelationships among these factors. This, in turn, provides important information regarding fire occurrence [8] and directly contributes to accurate and successful outcomes [17].

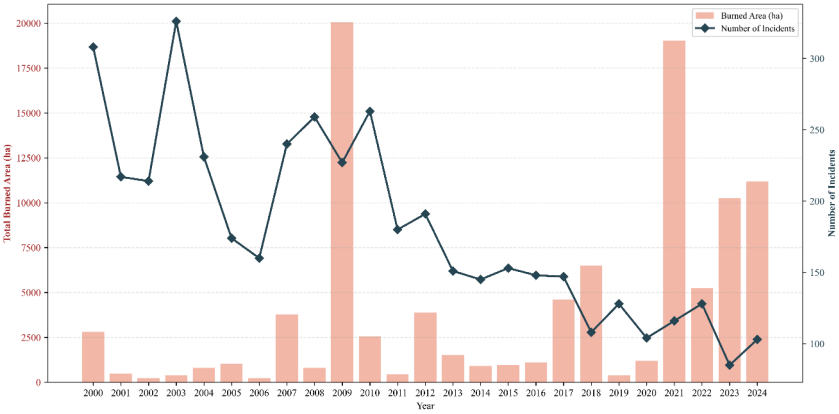

Fig. 3. Dual-axis temporal analysis of the frequency (N) of wildfire incidents and the cumulative Burned Areas (ha) in Attica Region during the Fire Season (May – October) for the time span of 2000–2024 – Data Source: Hellenic Fire Service [15]

Aksoy et al. [11] have studied a significant number of fire risk related studies and provided an extensive variables' list. Out of this list, scientists are able to select the most suitable ones, based on the specific attributes of the area at hand [7, 17]. These variables are of use regardless of the methodological approach, followed by the various studies; and are roughly categorized under a range of factors, namely Topography, Climate, Environment and Urban Space, used also in the context of this research.

Topography is closely associated with variables that refer to area's topographical and morphological attributes. It includes variables such as 'Elevation', 'Slope' and 'Aspect', which affect the behavior and progress of a forest fire, while play a decisive role in terms of accessibility to fire events and response rate of the fire fighting forces [7]. Specifically, 'Elevation' correlates with the climatic conditions of the area and the fire behaviour, whereas 'Slope' affects the speed and spread of forest fire, with steep slopes displaying a greater impact to fire spreading [18]. As for 'Aspect', the percentage of sunlight that an area receives increases the propensity of fire occurrences, making the south-southwest aspects of the study area more susceptible [19].

Climate consists of variables, such as 'Temperature', 'Wind Speed', 'Relative Humidity' and 'Precipitation', which relate to fire weather conditions [3]. Climatic conditions mostly affect the state of the environment and vegetation, both playing a decisive role in fire ignition and progress. High 'Temperatures' as well as extreme heat waves during summer time and fire season affect the vegetation's moisture, leading to higher flammability [19]; whereas low rates of 'Precipitation' affect soil moisture and area's 'Relative Humidity' [19]. The combination of decreased 'Precipitation' with high 'Temperatures' affects area's vulnerability by increasing fuel load availability and favouring fire ignition conditions [20]. Furthermore, 'Wind Speed' contributes to forest fire spreading by enhancing the fire speed and hindering fire suppression [7, 18].

Environment includes variables associated with the type, density and health of vegetation, all of decisive role in its general flammability. Specifically, 'Dominant Leaf Type' [DLT], 'Tree Cover Density' [TCD] and 'Normalized Difference Vegetation Index'

[NDVI] are the most commonly used variables in fire risk studies as they impact fire ignition and progress, i.e., significant factors to a forest fire event. 'Dominant Leaf Type' is a crucial variable since, according to various studies, coniferous trees due to their leaf structure and pine needles are significantly more prone to fire ignition in comparison to broad-leaved trees [18]. Respectively, 'Tree Cover Density' determines availability of the fuel load [18]. Thus denser vegetation in an area leads to rising fire risk [7, 11]. In recent studies, NDVI has been identified as one of the most influential fire risk variables, as vegetation's health is associated with fuel availability and vegetation's fire susceptibility [20]. NDVI provides information about vegetation's health condition. Higher values show healthy vegetation, whereas lower ones correspond to dry vegetation with higher fire risk [7, 19].

Urban Space is the factor that correlates with the urban environment and neighbouring population; and highlights the intricate involvement of the human factor in fire occurrences. As literature demonstrates, human negligence is one of the main reasons of forest fire ignition, with the number of incidents indicating a rising trend [4]. Some of the most widely used variables in forest fire research endeavours are 'Distance from Road Network', 'Distance from Rivers', 'Distance from Settlements', 'Population Distribution' and 'Land Use'. Distance variables are closely related to fire ignition as proximity of human activities to fire prone vegetation correlates with increased susceptibility [18]. In particular, proximity of WUIs' to forested areas constitutes the main reason for their high risk of ignition, being further amplified by dense population and poorly planned urban sprawl [7, 20].

Taking into consideration the particularities of the study area and the WUIs, *14 independent variables* are selected for establishing the dataset to be used in fire risk assessment (Table 1). These are: Elevation, Slope, Aspect, TCD, NDVI, Temperature (maximum), Wind Speed, Precipitation, Humidity, Distance from Road Network, Distance from Settlements, Population Distribution, Distance from Rivers and Land Use, and represent all four aforementioned factors.

2.4 Machine Learning Methods - Theoretical Background and Usability

Within the scope of this study, six *Individual Learning Methods* [five Machine Learning – Random Forest (RF), eXtreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), Logistic Regression (LR) and Support Vector Machine (SVM) – and one Deep Learning (Multi-Layer Perceptron (MLP)] and one *Integrated Ensemble Method* [Voting Ensemble (Voting Classifier)] have been used to assess fire risk in the study area; and are shortly presented in the following paragraphs.

Table 1. Data and Variables used as input in the selected ML methods

Raw Data	Factor	Variables	Source	Time Span
Digital Elevation Model (DEM)	Topography	Elevation (m) Slope (%) Aspect (°)	Copernicus	-
Tree Cover Density (TCD)	Environment	TCD (%)	Copernicus	2023
Normalized Difference Vegetation Index [NDVI]		NDVI	Copernicus	2024
Temperature Wind Speed Precipitation Relative Humidity	Climate	Temperature (° C) Wind Speed (m/s) Precipitation (mm/y) Humidity (%)	E-OBS, Copernicus	2000-2024 Fire Season (May – Oct)
Population	Urban Space	Population Distribution (Nr)	ELSTAT	2021
Settlements		Distance from Settlements (m)	ELSTAT	2021
CLCplus Backbone		Land Use	Copernicus	2023
Road Network		Distance from Road Network (m)	Geofabrik [21]	2026
Hydrographic Network		Distance from Rivers (m)	Geofabrik	2026
Burned Areas	-	Fire/No Fire (Dependent Variable)	EFFIS, Copernicus	2000-2024

Random Forest (RF), developed by Breiman and Cutler [22], is a widely used ML algorithm. RF can handle both classification and regression problems by means of either categorical or continuous variables. It builds multiple decision trees at the same time, utilizing a "parallel ensembling" approach. By use of the Bootstrap Aggregation (Bagging) technique, every decision tree uses a different subset of the data's sample for training, while results occur from majority voting (for classification tasks) or averaging (for regression analysis). This significantly reduces variance, contributes to the avoidance of overfitting and enhances the prediction accuracy. Unlike simple decision trees, RF's robustness is grounded in the number of decision trees that are used to provide stable and efficient outcomes [10, 23].

eXtreme Gradient Boosting (XGBoost) is a powerful ML model, introduced by Chen and Guestrin [24], and is recognized for its high performance and versatility [25]. It is applicable for conducting both classification and regression tasks. Its high predictability stems from the gradient boosting framework, which iteratively combines predictions from multiple weak learners (Decision Trees). It constructs new Decision Trees sequentially, and provides more advanced ones by accounting for and minimizing the residuals of the preceding ones, thus targeting the most optimal outcomes [11, 23, 25]. Furthermore, its robustness and computational speed, as well as its regularization capability and proficiency in handling large scale and complex datasets strengthens its appropriateness to various research applications [25].

Light Gradient Boosting Machine (LightGBM) is an advanced framework, developed by Microsoft in 2017 [25, 26]. A key feature of the method is the leaf-wise tree

growth strategy, in contrast to the level-wise tree development, used by other tree-based models. LightGBM also utilizes a gradient-based one-side sampling (GOSS) technique, focusing on data instances with larger gradients (higher error), thereby enhancing models' efficiency, accuracy and training speed. Moreover, due to its speed and robustness of execution, it can handle large datasets and is applicable to both classification and regression research problems [25].

Logistic Regression (LR) is a probabilistic statistical ML model, primarily used for classification tasks. LR employs a logistic function to map the dependent variable to a probability range between 0 and 1 and is more effective when the data can be linearly separable. However, the model is susceptible to overfitting with complex data. The assumption of a linearity between input and output data can be a LR's limitation to model complex, non-linear relations between data [23].

Support Vector Machine (SVM) is a supervised ML model, applicable to classification, regression and other research applications. As a classifier, its primary objective is to define the optimal hyperplane (decision boundary) within high dimensional data, aiming to achieve the greatest distance (margin) between the hyperplane and the nearest training data point of each class, known as support vectors. In doing so, it leads to the best class separation and the lowest generalization error. In contrast to Deep Learning models that require a large amount of training samples, SVMs are more efficient and robust with limited number of training samples [10, 23].

Multi-Layer Perceptron (MLP) is a foundational Artificial Neural Network (ANN) model and a key component of Deep Learning (DL). For DL models, performance is data-driven, as both the efficiency and predictive accuracy rises with larger datasets [23]. The basic unit of a MLP are the neurons (nodes), with their architecture consisting of input, hidden and output layers. Using a feed-forward approach, every neuron of a layer connects with the subsequent one with an adjustable weight. The model reaches to the final weighted sum output layer through activation functions in order to identify complex, non-linear patterns. A significant difference with other models is that MLP uses the "Backpropagation" technique, which provides the ability to compare the predicted values to the actual ones and iteratively adjust the weights to optimize predictive accuracy [10, 23].

Finally, *Voting Ensemble (Voting Classifier)* is a ML method that aggregates the individual base learners' predictions in order to determine a prediction for the dependent variable. There are two voting strategies, namely the Hard Voting, with its prediction occurring from the majority voting of the class labels; and the Soft Voting, with its result occurring from the average of the predicted probabilities of all models. The combination of the outputs of multiple models aims at reducing variance error of individual ones and enhance predictive accuracy and robustness [27].

With regard to the evaluation of performance of the aforementioned models – accuracy and reliability – a variety of metrics can be employed. As literature demonstrates, the most commonly ones are: 'Accuracy', presenting the model's overall predictive capability and being defined as the ratio of correctly predicted instances to the total number of instances (Eq. 1) [25]; 'Precision', reflecting the model's reliability by calculating the ratio of the true positive predictions to the total number of positive predictions (Eq. 2) [25]; 'Recall', referring to the model's ability to correctly identify and predict actual

positive instances (Eq. 3) [25]; 'F1 Score', representing a balanced metric of model's performance and being the harmonic mean of Precision and Recall, ranging from 0 to 1 (Eq. 4) [27]; 'MCC' (Matthews Correlation Coefficient), being a robust statistical measure that is used to evaluate the model's binary classification quality and is particularly effective for overcoming potential issues of imbalanced datasets with values ranging from −1 to +1 (Eq. 5) [28].

The Eqs. 1 to 5 are given below:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 = 2\frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{5}$$

where TP: True Positive Predictions, TN: True Negative Predictions, FP: False Positive Predictions and FN: False Negative Predictions, according to the confusion matrix categories.

Additionally, the AUC – ROC (Area Under the Receiver Operating Characteristic curve) works as a measure of the model's classification performance; the ROC curve plots the True Positive Rate [TPR (TP/(TP + FN) - correctly identified fire instances] against the False Positive Rate [FPR (FP/(FP + TN) - Non-fire instances incorrectly identified as Fire] across all possible thresholds; the AUC quantifies the overall performance within a range between 0–1 [27]; while the Spatial CV AUC (Spatial Cross-Validation AUC) assesses the model's predictive power on geographically independent data, estimating spatial generalization. This is derived as the average AUC from a k-fold cross-validation process, using spatially separated folds based on geographic groups [25, 27, 29].

3 Implementation of the Methodological Framework - Results

In this section, results obtained from the implementation of the methodological framework and the aforementioned ML methods are presented. The 14 independent variables, used as input in the fire risk assessment methods, are presented in Table 1. By use of the Burned Areas dataset for the period 2000–2024 [16], provided by the European Forest Fire Information System (EFFIS), fire occurrence points were derived and were supplemented with non-fire points (unburned areas) in order for the binary dependent variable (Fire = 1; No Fire = 0) to be established. This variable consisted of 475 points, with 222 of them being classified as 'Fire' (46.7%) and 253 as 'No Fire' (53.3%); thus, the dataset was interpreted as relatively balanced for the modelling process. All necessary

preprocessing procedures and modifications were conducted in order for the dataset to be unified and be appropriate for implementation by use of the ML methods, resulting in the final *fire risk maps*. Implementation of the selected ML methods was carried out in Python, whereas the spatial analysis and the fire risk maps were developed by use of the ArcGIS Pro 3.3.

In order for a comprehensive overview of the dataset, used in the empirical part, to be provided, descriptive statistics for all independent variables are presented in Tables 2 and 3. For the continuous variables of the dataset (Table 2), the calculated statistics are Mean value, Standard Deviation (Std), Maximum and Minimum value; while for the categorical one – i.e., Land Use – the distribution of land use classes was calculated (Table 3). As evident, the Sealed and Permanent Herbaceous categories, which correspond to urban space and permanent vegetation, are the ones that appear to have the highest frequency in the study area.

Table 2. Descriptive Statistics and Multicollinearity Assessment (VIF) for the 14 Independent Variables

Independent Variables	Count (N)	Mean	Std	Min	Max	VIF
Elevation (m)	475	239.83	223.45	0.00	1115.87	3.469
Slope (%)	475	13.39	13.91	0.00	72.94	2.018
Aspect (^{o})	475	162.89	92.33	−1.00	357.05	1.119
TCD (%)	475	9.95	19.80	0.00	87.00	2.216
NDVI	475	0.27	0.17	−0.49	0.80	1.819
Temperature (^{o} C)	475	27.80	0.78	25.84	29.80	3.150
Wind Speed (m/s)	475	3.14	0.51	2.41	4.91	4.486
Precipitation (mm/y)	475	271.15	17.42	231.44	299.78	7.820
Humidity (%)	475	57.36	1.45	53.25	59.65	5.024
Distance from Road Network (m)	475	89.14	134.32	0.00	1037.11	1.489
Distance from Settlements (m)	475	1710.97	1129.48	0.00	5393.72	1.342
Population Distribution (Nr)	475	12114.25	16723.88	148.72	64779.15	3.451
Distance from Rivers (m)	475	796.55	806.51	0.00	5803.46	1.253
Land Use	475	–	–	–	–	1.570

Table 3. Frequency Distribution and Percentage of Land Use Categories

Land Use Category	Frequency (N)	Percentage (%)
Sealed	155	32.64
Permanent Herbaceous	101	21.26
Low-growing Woody Plants	85	17.89
Woody Needle Leaved Trees	62	13.05
Non and Sparsely Vegetated	36	7.58
Woody Broadleaved Deciduous Trees	14	2.95
Woody Broadleaved Evergreen Trees	10	2.11
Periodically Herbaceous	8	1.68
Water	3	0.63
Coastal Seawater Buffer	1	0.21
Total	**475**	**100**

To ensure strong *statistical soundness* and *predictive accuracy*, Multicollinearity and Correlation Analysis was conducted. More specifically, Variance Inflation Factor (VIF) was calculated in order for multicollinearity among all independent variables to be examined and the final dataset for implementation to be determined. According to the literature, variables with VIF values greater than 10 should be eliminated due to high collinearity and redundancy [30]. As shown in Table 2, however, VIF values for all independent variables remained below the aforementioned threshold, ranging from 1.119 to 7.820. Furthermore, Spearman's rank correlation analysis was conducted to examine pairwise relationships among the continuous independent variables (Fig. 4). All variable pairs maintained correlation coefficient values within the range of 0.80 to −0.80, values which, as literature states, constitute the critical elimination thresholds. Thus the final dataset for further implementation displayed no threats or inefficiencies that could compromise produced outcomes [30, 31].

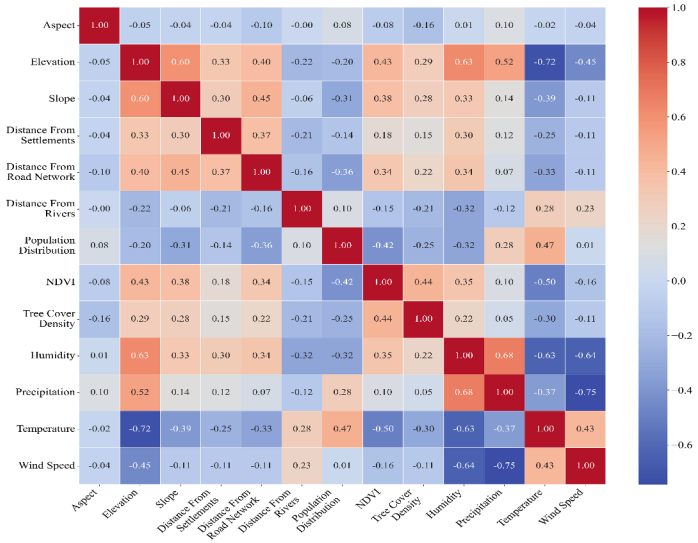

Fig. 4. Spearman Correlation Matrix for the continuous independent variables of the dataset

The aforementioned ML methods were implemented to derive the final *Forest Fire Risk Assessment maps.* The dataset was randomly partitioned into training (70%) and testing (30%) subsets. Models' training was performed using a 10-fold Spatial Cross-Validation and a GroupKFold technique in order to ensure geographical independence of the folds and avoid spatial overfitting. As for the Integrated Ensemble method, Soft Voting was implemented in this study.

Speaking of the ML methods' performance, the evaluation metrics presented in Table 4 show that all methods display high predictive accuracy and robustness. XGBoost (0.860) and Voting Ensemble (0.860) achieved the highest overall accuracy. These are followed by LightGBM (0.853), RF (0.839) and LR (0.839), while the remaining methods appear to have a slightly more conservative performance. Regarding quality achievements, XGBoost achieved the highest values in MCC (0.720) and F1 Score (0.853), indicating a robust balance between precision and recall; while MLP and SVM have the lowest values among all methods. Inspection of Test AUC values, ranging between 0.904 to 0.936, and the ROC curves (Fig. 5), verifies that all methods show strong classification performance and high capability in distinguishing between fire and non-fire instances. As for the Spatial CV AUC, Voting Ensemble (0.927), RF (0.924) and LR (0.924) exhibit the most robust performance regarding spatial generalization capabilities, slightly outperforming SVM (0.915) and XGBoost (0.913). Conversely, LightGBM (0.905) and MLP (0.906) appear to have the lowest comparative performance among all ML methods.

Table 4. Performance Evaluation Metrics for the ML Methods used in this work

Method	Accuracy	Precision	Recall	F1 Score	MCC	Test AUC	Spatial CV AUC
RF	0.839	0.833	0.821	0.827	0.677	0.930	0.924
XGBoost	0.860	0.841	0.866	0.853	0.720	0.936	0.913
LightGBM	0.853	0.811	0.896	0.851	0.710	0.926	0.905
LR	0.839	0.855	0.791	0.822	0.677	0.935	0.924
SVM	0.832	0.831	0.806	0.818	0.663	0.904	0.915
MLP	0.818	0.815	0.791	0.803	0.635	0.922	0.906
Voting	0.860	0.851	0.851	0.851	0.719	0.933	0.927

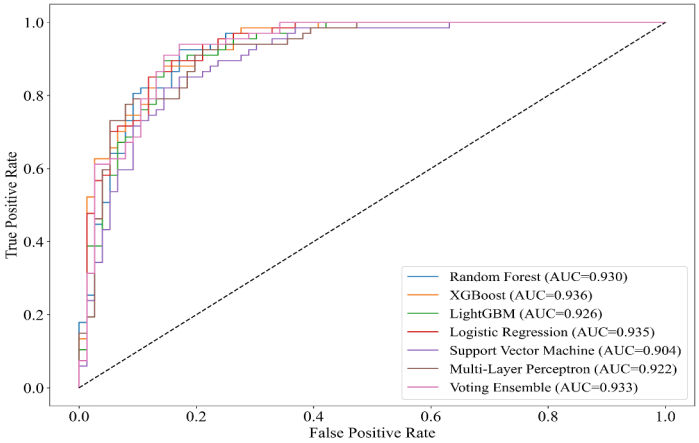

Fig. 5. ROC curve comparison and AUC values for all implemented methods

Furthermore, maps for the 14 independent variables (Fig. 6) as well as the Final Forest Fire Risk Assessment maps (Fig. 7), displaying the probability and the spatial pattern of Fire Risk in the study area, are generated. The latter are demonstrated for all methods and are coupled with Burned Areas for the time span of 2000–2024.

Worth noticing is that in the Forest Fire Risk maps, generated by the ML methods tested in this work (Fig. 7), the fire risk probability values indicate a similar range across all methods. RF (Fig. 7a) and Voting Ensemble (Fig. 7g) display a peak with a value of 0.97 and 0.98 respectively, whereas LR (Fig. 7d) reaches the maximum value of 1.0. Spatial patterns of fire risk appear to be consistent, with RF and MLP's patterns being slightly different (Fig. 7a and 7f respectively). In all ML methods, forested areas across the study area appear to have very high fire risk (brown color), while urban areas seem to have low fire risk (blue color). Areas with moderate to high fire risk (green to yellow color) appear to be at the mountain foothills, marking the transition to the urban space, i.e., Wildland Urban Interfaces (WUIs).

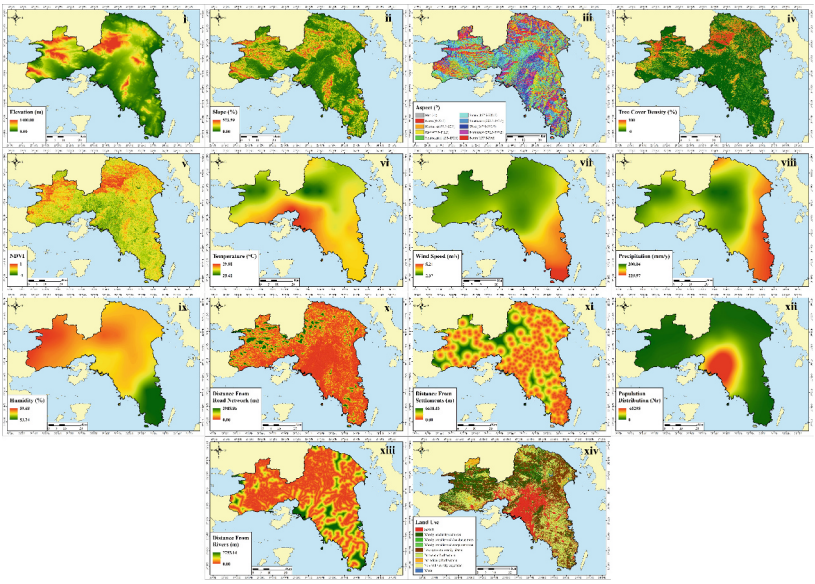

Fig. 6. Maps of the 14 independent variables: i) Elevation, ii) Slope, iii) Aspect, iv) TCD, v) NDVI, vi) Temperature, vii) Wind Speed, viii) Precipitation, ix) Humidity, x) Distance from Road Network, xi) Distance from Settlements, xii) Population Distribution, xiii) Distance from Rivers and xiv) Land Use. Source: Own elaboration.

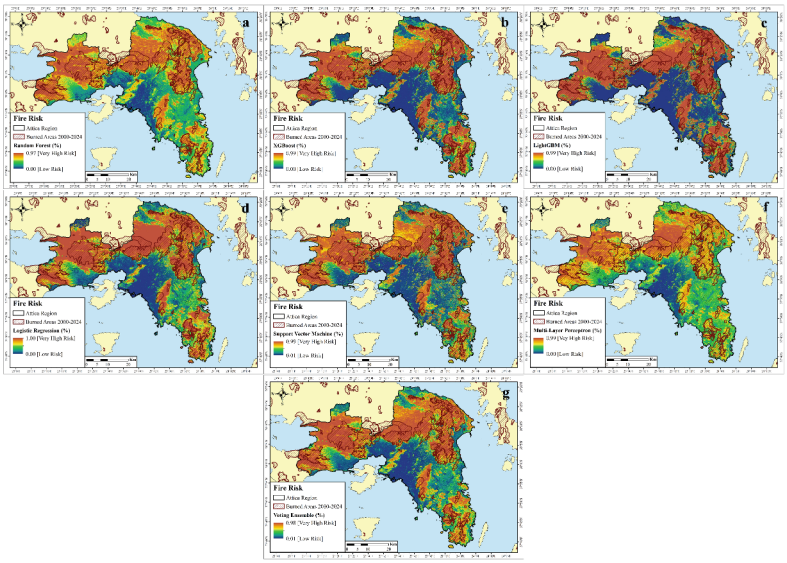

Fig. 7. Forest Fire Risk Maps produced by the selected ML methods – a) RF, b) XGBoost, c) LightGBM, d) LR, e) SVM, f) MLP and g) Voting Ensemble. Source: Own elaboration. (Color figure online)

4 Discussion and Conclusions

Vulnerability of Wildland Urban Interfaces (WUIs) and their exposure to high fire risk seems to go hand in hand with the rising number of wildfire incidents, witnessed in such areas around the globe. Mediterranean Region, as a noticeable "Hotspot" in CC terms [1], is the 'theater' of a large number of such WUIs' fire incidents, being highly noticeable due to the rising intensity, frequency and destructive outcomes in the natural and manmade environment. These highlight the need for reshaping urban planning directions in general as well as fire management strategies in particular, especially in WUIs, with a focus on a more proactive direction [4]. Of critical importance, in this respect, is to delve into efficient fire risk assessment methodologies in support of more informed policy articulation [7]. ML methods for fire risk assessment is an important improvement in fire disaster management, since state-of-the-art technologies are capable of successfully handling the complexity of this research topic [9].

That said, this study conducts a comparative analysis of fire risk assessment performance among seven ML methods, mapping respective outcomes in WUIs located in the Attica region, Greece. Results obtained as to the spatial patterns of Forest Fire Risk (Fig. 7) exhibit a high degree of consistency across all ML methods, with the highest risk values (brown color) appearing in mountainous areas, i.e. areas covered by forests and permanent vegetation, reflecting the influence of vegetation and topography in fire risk vulnerability and exposure. The lowest risk values (blue color) in all models appear to cover the urban fabric areas. The spatial patterns of XGBoost, LightGBM, LR and SVM (Fig. 7b to 7e) demonstrate more well-defined boundaries around the very high risk areas, while LR and SVM (Fig. 7d to 7e) result in minor differentiation of fire risk pattern, especially in the southern part of the study area. On the other hand, RF and MLP (Fig. 7a and 7f) demonstrate a more gradual fire risk distribution from urban to forested space, indicating the rising vulnerability of the transitional urban zones that are closely related to WUIs' distribution across the Attica region as a whole. For the study area in particular, where the WUIs consist of a large part of the region, those two methods appear to identify the area's particularities more efficiently, highlighting the important role of WUIs in the region's vulnerability and exposure, even though MLP demonstrates a slightly more conservative performance. Voting Ensemble represents an aggregate pattern, smoothing the variances of all methods. An additional strength of the high predictive performance of the ML methods is the identification of vegetated low hills within the Attica basin as high risk areas, reflecting a high level of geographical sensitivity. Fire risk assessment of all methods appears to be in alignment with the past burned areas (time period 2000–2024) (Fig. 7), a fact that serves as a qualitative validation of the methods' capability to capture the particular environmental conditions that affect fire occurrence.

Comparative analysis by means of the evaluation metrics shows that gradient boosting methods (XGBoost, LightGBM) display the highest predictive efficacy in classification tasks, with XGBoost achieving a superior level in overall predictive accuracy (0.860). Although RF performed slightly more conservatively than the gradient boosting methods, it demonstrated strong predictive capability, establishing the tree-based methods as the most efficient ones in capturing the complex, non-linear patterns of fire occurrence. In contrast, SVM and MLP demonstrate lower classification performance

(0.832 and 0.818 respectively). An important finding is the minimal divergence between Test AUC and Spatial CV AUC (ranging from −0.011 to 0.023). This indicates high spatial stability, generalization capability and robustness against spatial autocorrelation. Specifically, Voting Ensemble (0.927), RF (0.924) and LR (0.924) show the most significant performance, a fact that suggests that they are less prone to spatial overfitting and more capable of identifying the drivers that stay consistent across different geographic parts of the region. In contrast, the lower stability of LightGBM (0.905) and MLP (0.906) suggests less spatial flexibility. The Voting Ensemble represents a balanced approach as it mitigates individual variances and weaknesses, without compromising the overall predictive performance and geographical reliability. Overall, all methods demonstrate superior performance, stressing the suitability of tree-based methods (XGBoost, LightGBM and RF) as frontrunners for fire risk assessment and fire-related research.

The efficacy of ML frameworks for informing proactive fire-related policy decisions is tightly interwoven with the quality and quantity of training data that affects reliability of outputs. Limited datasets often influence the methods' ability for generalization, leading to potential overfitting and weak statistical stability. On the contrary, ML methods require larger volumes and high quality of data in order to identify complex patterns, making the selection and pre-processing of the dataset an important determinant of their performance. Moreover, the integration of time variant data (e.g. meteorological data) alongside with static variables can provide more up-to-date fire risk outcomes and enhance preparedness.

In concluding, the aforementioned analysis leads to robust results as to the fire risk assessment in the specific study area, witnessed by the rather converging outcomes of the tested methods. Such an inference forms a solid ground for planning and policy reaction, targeting vulnerability decrease of the high risk parts embedded in the study area. In addition, results demonstrate that such parts seem to be strongly related to the impact of poorly-planned urban sprawl in flammable peri-urban zones, clearly demonstrating the vulnerability of the WUIs and the necessity for dedicated proactive urban planning strategies, especially in those parts. Indicative policy interventions may range from the establishment of low-flammability green zones and firebreaks to land use changes/constraints, risk zoning, awareness raising of local population, preparation of evacuation plans, etc., all contributing to the reduction of fire risk and fuel continuity and assisting firefighting intervention, In addition, fire risk assessment maps could provide good insight for effectively allocating firefighting resources that may enhance response rate of fire forces in cases of fire emergency.

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