Methodologies for Wildland-Urban Interface (WUI) Fire Risk Assessment – Case Study North-Eastern Attica Region

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Abstract. In the light of the Climate Change era, wildfires in forest areas appear to be intensified, placing at risk the urban fabric being in close proximity to wildland fire prone areas. Such a risk causes severe socio-economic and environmental consequences, calling for proactive policy action and rendering Disaster Management planning an urgent need. In support of this urgency, this study aims at assessing fire risk in Wildland-Urban Interfaces (WUIs), i.e. urban and peri-urban areas that are settled in the forests' neighborhood or in close proximity to them. Towards this end, it aims at: establishing a pool of factors/criteria and a pool of methodologies related to WUIs Fire Risk Assessment; and testing/comparing results produced by two methodologies, selected from the above set, namely the Analytical Hierarchy Process (AHP) and the Random Forest algorithm through the Forest-Based Classification tool. Results obtained by the two methodologies demonstrate a rather diversified spatial pattern of forest fire risk, which is further validated by the inspection of the impacts (burned area) of recurrent wildfire incidents, occurring in the study area in the time span 2000-2023; while fire risks in WUIs are sketched in the study area, calling for proactive policy action for ensuring resilience to future forest fire incidents in this quite vulnerable area of Attica Region.

Keywords: Climate Change · Wildland-Urban Interface · Fire Risk Assessment

1 Introduction

In recent decades, wildfires are increasing in frequency and severity, both at the global and the European level, a fact that is tightly associated with Climate Change (CC) repercussions. In addition, climatic models' projections indicate a rising frequency of droughts, hot extrsemes and extended heat waves as well as a declining trend in precipitation rates. That said, climatic conditions that favor fire incidents are expected to be amplified, leading to the culmination of both the number and intensity of fire incidents

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as well as the extension of the fire season. This holds even truer for the Mediterranean territory, namely one of the most vulnerable to CC regions of the world [1], marked by extensive heat waves and droughts [2]. CC implications in the Mediterranean are thus leading to an increasing fire risk and incalculable consequences for both the natural and human ecosystems, a fact that is further exacerbated due to the intense urbanization and urban sprawl occurring in this region [1–4]. Rising of fire risk has, in turn, led to the upgrading of firefighting resources, intense production of fire risk-related information and efforts for awareness raising in Southern European countries, like Portugal, Spain, Italy and Greece. In addition, frequency and intensity of fire incidents advocate the need for more proactive action in order for the recurring wildfire events to be prevented and/or managed; and their adverse impacts to be mitigated [5].

In the Mediterranean region, *Wildland-Urban Interfaces* (WUIs) are nowadays gaining scientific attention with respect to fire risk assessment. Such interfaces are defined as the zones, within which the urban fabric comes into close contact with fire prone vegetation areas. This continuously expanding urban sprawl trend near forested areas is mainly the outcome of population growth; and is remarkably noticeable along the Mediterranean urban coast due to the flourishing of the tourism activity and the poorly planned urban growth. Such an urbanization pattern further exaggerates the consequences of fire incidents of respective urban settlements [3], provided that WUI are considerably vulnerable to fire risk due to their proximity to flammable wildland areas, with fire incidents threatening people's life and property, urban infrastructure and integrity of the natural ecosystems [6, 7].

In recent years, many wildfires are related to WUIs fire risk. In the Mediterranean Region in particular, there are several worth mentioning examples, like the one of Portugal in June 2017, where an extreme fire disaster resulted in very high losses in terms of human lives, structures and forest areas [6]; or that of Sardinia, Italy, where severe and quite extended losses of natural ecosystems occurred in the time span 2005-2019 due to a huge number of fire outbreaks, the majority of which were due to human negligence [7]. The scale of losses in WUIs in the Mediterranean due to forest fire incidents is enormous at all levels, being both environmental (loss of biodiversity and natural ecosystems) and socioeconomic (human live loss, destruction of urban infrastructure, economic losses, etc.). In addition, the proportion of human-caused wildfires due to either negligence or intention in WUIs is quite high in the Mediterranean Region, compared to the rest regions of the world.

Greece has also suffered significant impacts from major fire incidents during the recent past. These have caused remarkable damages to extensive forest areas, but also to urban settlements lying in their vicinity. The most recent and disastrous ones were in 2021 and 2023. In 2021, Evia Island had suffered a devastating wildfire that was perceived as the largest forest fire in the history of Greece. This fire burned more than 400 km^2 forest areas and caused severe damages to the surrounding settlements [8]. In July 2023, another wildfire broke out on the island of Rhodes – Dodecanese Region in Southeastern Greece – resulting in extensive forest damages and evacuations of residents and tourists from the neighboring urban constellations [9]. In August 2023, the megafire in the Evros region – north-eastern part of Greece – destroyed 58% of the National Forest Park of Dadia-Lefkimmi-Soufli, i.e. a forest area protected since 1980 due to

its exceptional biodiversity and the endangered species inhabiting in this forest; while placing at fire risk the adjacent to the burned forest area settlements and also burning most periurban land around the city of Alexandroupolis [9]. Specifically in the Region of Attica, where the study area of the present work belongs, forest fires occurring since 2017 have, according to the European Forest Fire Information System (EFFIS), burned 37% of the region's forest areas, resulting in a huge environmental disaster, noticed not only in terms of forests and vegetation loss, but also in terms of deterioration of the quality of life of local population and the integrity of built infrastructure [10]. Among them falls the deadly wildfire in Mati in July 2018 – a distinct example of forest fire in a WUI – marked as the deadliest disaster event in the recent history of Greece [3].

Taking into consideration the severity and frequency of forest fire events, recent studies indicate the urgent need for integrating proactive strategies alongside with early warning systems into Disaster Management Plans. Preparedness, mitigation and adaptation strategies are principal parts in Disaster Management, highlighting the importance of wildfire risk assessment in *urban and peri-urban areas* [5]. Furthermore, the realization of the factors that influence the ignition and spread of a fire as well as the exploration of methodologies through which fire risk can be assessed is a crucial part of disaster management [11].

That said, the *goal* of this work is to assess the risk of a wildfire in forest areas in close proximity to urban ones (i.e. WUIs). For that purpose, it aims at establishing a pool of factors (or otherwise criteria) and methodologies that can support *fire risk assessment* in *Wildland-Urban Interfaces*. This is accomplished by an extensive literature review, investigating: i) the abundance of factors that are associated with wildfire incidents; and ii) the methodologies that are implemented in different areas, with a specific focus on cases in the Mediterranean region. This knowledge is used for conducting fire risk assessment in a specific study area, by properly selecting the most relevant case-specific factors/criteria. These are used as input to two selected methodologies, namely the Analytical Hierarchy Process (AHP) and the Random Forest algorithm through the Forest-Based Classification tool in order for: forest fire risk assessment, provided by the two methodologies, to be assessed, mapped and compared as to the outcomes produced, user-friendliness and usability; and the WUIs that are at fire risk to be sketched. GIS technologies also form an integral part in the applied part of this work.

The structure of the paper has as follows: Section 2 presents the steps of the methodological framework and elaborates on literature-driven fire-related factors and methodologies used for fire risk assessment. Section 3 presents the study area and its attributes; and attempts to assess and map the risk to fire of this area, based on the use of two methodological approaches and relevant factors out of the literature-based pool established. Finally, in Sect. 4 critical discussion and conclusions on the results obtained by the two methodologies are provided, commenting on the specific attributes of each one and their outcomes in relation to fire risk assessment in the study area in general and the WUIs in particular.

2 Materials and Methods

2.1 The Methodological Approach

The methodological approach of this study consists of the following three stages (Fig. 1):

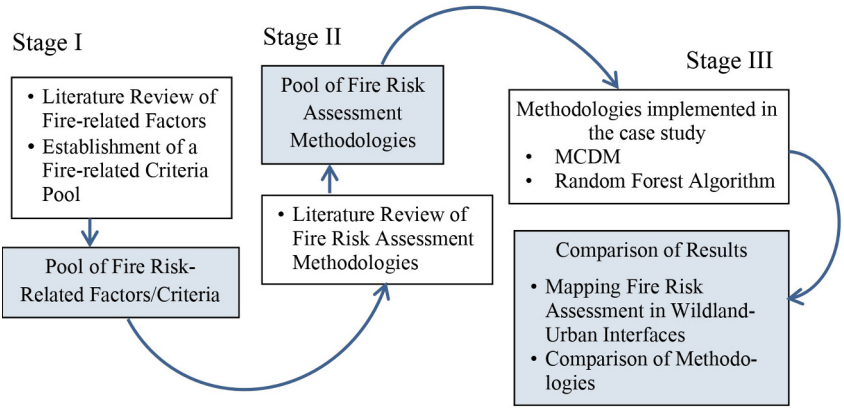

Fig. 1. Stages of the Methodological Framework.

- Stage I: Compilation of relevant literature on the factors/criteria directly related to fire phenomena and the area characteristics, such as topography, environment, etc.; and establishment of a fire risk-related *factors/criteria pool* that is adapted to both the study area at hand and the specific attributes of countries in the Mediterranean Region.
- Stage II: Compilation of literature on fire risk assessment methodologies and mapping of their attributes. This search gathered a plethora of methodologies, some of which are rather conventional, while others make extensive use of state-of-the-art technologies.
- Stage III: Use of two of the above-mentioned methodologies for implementation in the study area of this work, using properly selected factors/criteria from the established pool. The purpose of this implementation is to comparatively analyze results produced by the two methodologies and make inferences as to their performance, user-friendliness and effectiveness in Fire Risk Assessment and mapping, as a proactive action for feeding disaster management strategies in WUIs.

2.2 Establishing a Pool of Fire Risk Assessment Criteria

The identification of fire risk-related factors or criteria is a critical task of the relative assessment process and is strongly depended on the specific attributes of the area at hand (e.g., wind, humidity). In addition, the study of the interrelationships among the factors influencing fire occurrence is an intricate issue and demarcates fire ignition conditions [11].That said, the identification of the contributing factors and the appropriate choice of relevant criteria is expected to make a great contribution to fire risk assessment, not

only by improving results of the fire risk assessment methodology, but also by ensuring a successful outcome [12].

In their fire risk assessment research work, Aksoy et al. [13] have analyzed a large number of studies related to this research topic and have created an extensive list of factors/criteria that can be used in fire risk assessment and can be categorized according to their field of relevance. As such can be mentioned elevation and slope, falling into the topographic attributes of the area at hand; temperature and wind speed, introducing climatic characteristics; factors related to spatial structure, like distance from settlements; network configuration, e.g. road network; agricultural activities; and water resources. In addition, the work of Aksoy et al. [13] contains criteria relating to vegetation and soil moisture as well as fire-fighting resources. The diversity of criteria demonstrates that, depending on the study area and its particularities, scientists are prompted to select the appropriate ones for assessing fire-related dimensions, such as risk and vulnerability [12, 13]. The most common, literature-based factors/criteria in fire-related studies are shortly discussed in the following.

Topographical Factor/Criterion. Topography is a factor related to an area's morphology and topographic characteristics. Elevation, Slope, Aspect and Topographic Wetness Index (TWI) are key criteria for reflecting the topographic dimension, with each one of them being directly related to and influencing the general behavior of a forest fire. The progress of a forest fire affects directly the disaster management process and the conditions of fire suppression [12, 14]. Elevation is an important criterion since it relates to the prevailing climatic conditions, such as temperature, humidity and wind speed; and can directly influence the ignition and behavior of the fire. Similarly, slope is related to the spread pattern of fire, with steep slopes impeding firefighting efforts and favoring the speed of fire spreading. Aspect is related to the percentage of sunlight received by an area, making south-southwest aspects more prone to fire events. Finally, TWI is related to the soil moisture, being an important criterion for fire ignition and spread [14–16].

Environmental Factor/Criterion. Forest fire risk research has demonstrated that the type of forest and vegetation are significantly influencing fire ignition and progression. While vegetation is generally flammable, criteria related to Vegetation Density and Moisture levels are greatly impacting the way fires behave [13]. Additionally, the type of leaves plays a crucial role in determining how vegetation responds to fire, so criteria like Forest Type, Dominant Leaf Type and Plant Type are important dimensions in fire risk assessment. Specifically, coniferous trees are more susceptible to fire due to their leaf structure and the presence of highly flammable pine needles. These pine needles form a litter layer around the tree base, which provides another criterion, referred to as Stand crown closure. In contrast, broad-leaved trees, with their moisture-rich foliage, have a different ignition rate and are less prone to fire risk [13–15]. The Normalized Difference Vegetation Index (NDVI), as a means for assessing the criterion directly related to vegetation and fuel, provides quite important information on the vegetation conditions. NDVI indicates the state of vegetation's health, where high values of NDVI indicate healthy vegetation, low values indicate dry vegetation with higher fire risk rates, values near zero indicate the absence of vegetation, while negative values indicate water areas [16, 17].

Climate Factor/Criterion. The decisive influence of weather conditions on the occurrence of a fire has drawn the attention of scientists to the study of fire weather circumstances and the way these contribute to fire risk [4]. Long heat waves and high temperatures affect the moisture content of vegetation, rendering it dry and more flammable, thus leaving forests more vulnerable and prone to fire [16]. As far as precipitation is concerned, this is directly related to the soil moisture and relative humidity of an area. A decrease in the frequency and amount of precipitation, combined with high temperatures, causes a decrease in the relative humidity of an area, thus increasing the risk of fire and creating conducive conditions for its progression [14]. High wind speeds also affect the conditions of fire spread and the speed at which it progresses, impeding its suppression from fire services. Therefore, climatic criteria, such as temperature, humidity and wind speed are critical in fire risk assessment, demarcating the conditions for fire ignition and expansion [14, 15, 17].

Human Factor/Criterion. Literature review witnesses that the majority of forest fires are caused by human negligence. Thus, criteria related to population, activities and attributes of the urban environment are of particular importance. Areas with increased population density and settlements near forested areas (WUIs) increase the risk of ignition due to the intensity of population activities, rendering criteria of population density and forests' distance from settlements very important. Thus, the criteria of distance from road network as well as agricultural and tourist activities respectively delineate areas with an increased likelihood of fire ignition, as they appear to be in proximity with human activities. Similarly, the proximity to water resources, e.g. a lake or a river neighboring forest places, where recreation activities take place, are more vulnerable to fire events [14, 17].

2.3 Exploring Methodologies for Fire Risk Assessment

Methodologies for forest fire risk assessment are rapidly developing due to the imperative need of fire occurrence estimation [5]. In fact, fire risk assessment has recently raised to a topic of great concern in the research and policy community. These methodologies can be classified into three general categories, namely those based on the experience of researchers, those using statistical methods and those using machine learning tools [11, 18].

In the field of Geosciences and Geospatial Data, Machine Learning and Deep Learning are gaining momentum and are rapidly growing due to their prediction potential and promising results [11, 19]. Machine learning, as part of the Artificial Intelligence, offers today several algorithms for relevant use, taking advantage of the variety of data and the extensive use of human-centric parameters. The choice of a specific algorithm depends on the research question and the desired outcome [13]. Their efficiency is directly related to the quantity and quality of the data used [19]. A great advantage of methodologies, using machine learning methods, is the automation of respective processes, thanks to the evolution of technology and computing power [11, 20], thus eliminating the human factor and the possible bias as to the studied object [18].

According to an extensive literature review on the application of machine learning methodologies in studies related to fire occurrence and management [19, 21], respective

methodologies can be classified into four main categories, namely: Supervised Learning, Unsupervised Learning, Semi-supervised Learning, and Reinforcement Learning [19, 21]. In Jain's et al. [19] review, methodologies are demonstrated in a very informative diagram, depicting the most commonly used algorithms and their potential fields of application [19]. In general, Supervised Learning algorithms are used for classification and regression; Unsupervised Learning algorithms are primarily used for clustering, density estimation and association; while Semi-supervised Learning is a combination of the above [21].

The detailed presentation of the methodologies goes beyond the scope of the present study. However, it should be noted that the combination of Machine learning algorithms with Geographic Information Systems (GIS) is an interesting field of evolving methodologies and interaction among technologies, taking advantage of the capabilities of each tool in order for the best possible outcome to be achieved [13, 20]. Among the most commonly used methods are Decision Trees, namely machine learning algorithms used for both classification and regression analysis purposes.The most commonly used algorithm is the *'Random Forest'*, which consists of multiple Decision Trees and its basic idea is that at each node of each tree a random selection of features is made [19]. Table 1 provides a synoptic review of the methodologies used for Fire Risk Assessment in descending order of user-friendliness.

Furthermore, the majority of studies appearing in the literature uses Geographic Information Systems (GIS) and Remote Sensing for fire risk assessment. The implementation of methodologies varies. Some cases use geostatistical analyses to calculate risk, taking into consideration the relationships among criteria and the contribution of criteria to the fire occurrence assessment; while others digitize, analyze and categorize data through satellite imagery [18].

The use of spatial information technologies, tools and software is extended for risk assessment and mapping. Thus, in conjunction with GIS tools, the use of Multi-Decision-Making Methods (MCDM) for risk assessment and mapping is noticeable. An example is the Analytic Hierarchy Process (AHP) [14, 15, 22, 23], which uses a variety of criteria and subcriteria and assigns weights to them according to their importance to a potential fire event [13, 15, 18]. Statistical methods, such as linear and logistic regression analysis, are also used to analyze the relationships among fire occurrence factors.

Based on the literature review as to the factors/criteria as well as the currently available methodologies for fire risk assessment/mapping, two methodologies are selected and applied in order for fire risk assessment to be conducted in the study area; and results obtained by each methodology to be compared. The first choice is *Analytic Hierarchy Process* (AHP), namely a Multi-Decision-Making Method (MCDM) for analyzing scenarios using GIS technologies [14]. The second is the *Random Forest Algorithm*, implemented by use of the Forest-Based Classification and Regression tool in ArcGIS Pro software [24]. Selection criteria of the two methodologies are the level of their user-friendliness and the moderate level of specialization required for their application, both providing the chance of being used by less-experienced staff at the community level for articulating local disaster management plans. The scope of their practical implementation is to assess effectiveness of results obtained by the distinct philosophies for fire risk assessment these reflect, with the AHP being based on the researcher's experience and

the evaluation problem at hand; and the Forest-Based Classification Tool on automated procedures for deriving assessment outcomes.

Table 1. Classification of methodologies for Fire Risk Assessment, Source: Own Elaboration.

Category	Methodology Examples	Examples of Tools/Techniques	Advantages	User-Friendliness
Experience-based	Expert's Judgment and Evaluation	Based on the researcher's expertise	Flexible and adaptable Comparison of a variety of criteria and subcriteria	Most user-friendly for non-experts No need of technical tools or software
MultiCriteria Decision Making (MCDM)	Analytic Hierarchy Process (AHP)	GIS Comparison of a variety of criteria and subcriteria	Systematic approach combining qualitative and quantitative data	User-friendly for non-experts Use of expert's judgment and systematic methods
Statistical Methods	Linear and Logistic Regression	Regression models Statistical software (e.g., R, SPSS)	Quantitative measures	Moderately user-friendly Requires basic statistical background, familiarity with statistical software and model interpretation
Machine Learning Methods	Supervised Learning, Unsupervised Learning, Semi-supervised Learning, Reinforcement Learning	Decision Trees, Random Forest (Supervised) Clustering, Density Estimation (Unsupervised), Various ML algorithms	Reduction of human bias and subjectivity Automation and capability of handling complex, high-dimensional data	Least user-friendly for non-experts Requires expertise in data science, programming, and algorithm selection It demands technical skills to train, evaluate, and interpret models

(*continued*)

Table 1. (*continued*)

Category	Methodology Examples	Examples of Tools/Techniques	Advantages	User-Friendliness
Geospatial Analysis	GIS and Remote Sensing	GIS Remote Sensing data	Spatial interpretation Visual representation at various scales	Challenging for non-experts Need of technical expertise, GIS software and spatial analysis techniques
Hybrid Methods	GIS + Machine Learning Integration	GIS tools and spatial data ML algorithms	Combination of spatial data with ML models Accuracy and predictive power Large-scale projects	Challenging for non-experts Integrating GIS and ML requires expertise User-friendly interfaces

3 Implementation of the Methodological Framework - Results

3.1 The Study Area

The study area (Fig. 2) comprises six Municipalities (Municipality of Oropos, Marathonas, Rafina-Pikermi, Pallini, Penteli and Dionisos), all closely related to the recurrent wildfires occurring in Northeastern and Eastern Attica Region in the time span 2000-2023. Three of these municipalities are located in the eastern seaside area of the Attica Region, while the study area borders the Mountains of Penteli and Parnitha that prevail in the Region's scenery. All six municipalities cover an area of 712.82 km^2; while their population, according to the 2021 Census, amounts to 222,914 inhabitants [25]. The climate of the region is generally characterized as maritime, with dry, very warm and extensive summer [26].

Given that the eastern part of the study area is located in the coastal part of the Attica Region, much of the area under consideration hosts tourism activities, with seasonal population being increased during the summer time (May-August), a period that coincides with the main fire season. Additionally, agricultural activities are taking place in the area, being the main occupation of the permanent population. Studying recent forest fire incidents, occurring in 2017, 2018 and 2024, as well as historical fire events, occurring in 2005 and 2009, it is inferred that the study region is plagued by recurrent wildfire events, with extensive repercussions on both the natural and the socioeconomic environment. These imply that both population and the area at hand are exposed to extensive fire risk during the fire season. The municipalities located in the inner part of the study region are directly related to Penteli Mountain and represent peri-urban areas close to forests, a fact that fully exposes urban settlements to fire events. A characteristic example of this state is the Varnavas area, a part of the Municipality of Marathonas. The wildfire incident on August 2024, which reached the outskirts of the urban space of metropolitan

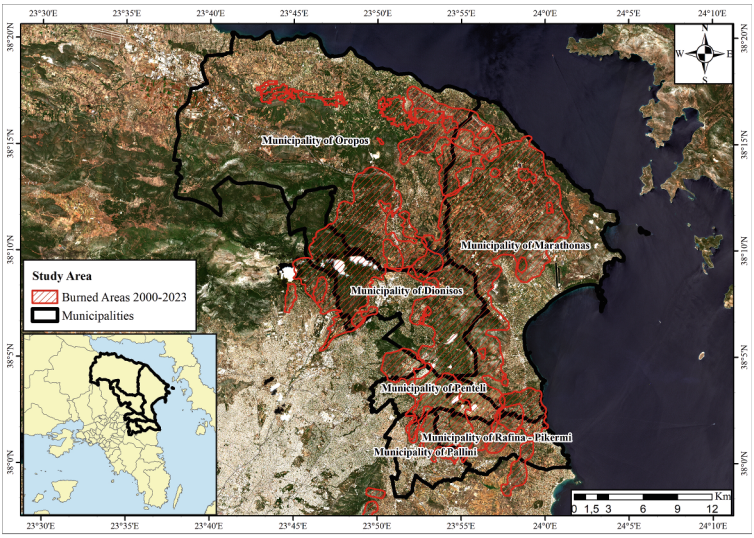

Fig. 2. Location of the study region, boundaries of municipalities (black line) and burned area through recurrent fire incidents (shaded area in red lines). Source: Own elaboration.

Athens, placed Varnavas area in a highly risky position [27]. The recurrence of fire events stresses the vulnerability of this area, while rendering fire risk assessment an essential task that, in addition, needs to be directly embedded in both the general (at the Region's level) and the local disaster management plans (at the municipalities' level).

3.2 Assessing Risk of Fire in the Study Area

The selection of data sets for fire risk assessment is driven by the need for a holistic approach. Thus, it takes into consideration all fire-related criteria/subcriteria and all dimensions of the study area. Topography-related subcriteria (Elevation, Slope, Aspect) are extracted using the Digital Surface Model (DSM), obtained from the Copernicus program. Vegetation and Land Cover subcriteria [Dominant Leaf Type (DLT), Tree Cover Density (TCD), NDVI index and Urban Atlas] were obtained from Copernicus program as well, along with Sentinel-2 Satellite Images for the extraction of NDVI index. DLT, TCD and Urban Atlas data refer to 2018, since this is the most recent data in the program. Meteorological Data (Temperature, Wind Speed, Humidity and Precipitation) were downloaded from E-OBS, Copernicus program, collecting daily gridded meteorological data, referred to the time period 2000-2023. The same holds for the Burned Areas for the time period 2000-2023 [27]. Data related to 2021 Population-Housing Census were acquired from the Hellenic Statistical Authority, along with Settlements and Greek Municipalities' Shapefiles [25]. Road and Hydrographic Network are downloaded from Geofabrik's website [28]. The implementation of the selected methodologies and the creation of the fire risk maps are based on the ArcGIS software, specifically on ArcGIS 10.8.2 and ArcGIS Pro 3.3.

Analytical Hierarchy Process (AHP). The AHP, pioneered by Saaty [29], is one of the most renowned Multi-Decision-Making Methods (MCDM) and serves as a systematic framework for structuring and analyzing complex decision-making scenarios. AHP is extensively utilized across various disciplines and topics; and is capable of effectively incorporating both qualitative and quantitative data. The process simplifies decision-making by breaking down a problem into a hierarchy that leads to a better understanding and evaluation of potential alternatives, using multiple criteria and subcriteria that facilitate a more comprehensive and nuanced analysis [14, 23, 30]. On the first stage, the problem is analyzed and relevant criteria and subcriteria are selected. Each subcriterion is scored on a unified scale (1 to 5 or 1 to 10) [14, 15, 22, 31]. Secondly, a Pairwise Comparison of criteria and subcriteria is taking place [30]. Next, the weights of each criterion and subcriterion are calculated in order for their contribution to the final decision to be determined [32]. Finally, the consistency of comparisons is carried out by use of the Consistency Ratio (CR). The CR value should be no greater than 0.10, otherwise the demanded consistency is not met, leading to the revision of comparisons. Calculation of CR (Equation 1) presupposes estimation of the Consistency Index (CI) (Equation 2), where λmax is defined as the maximum eigenvalue, n is the number of criteria/subcriteria used in the analysis and RI is the Random Consistency Index [32].

$$CR = \frac{CI}{RI} < 0.1 \sim 10\% \tag{1}$$

$$CI = \frac{\lambda max - n}{n - 1} \tag{2}$$

Table 2. Selected criteria for assessing risk to fire in the study region.

	Low Risk									**High Risk**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Elevation (m)	0-100		100-200		200-400		400-800			>800
Slope (%)	0-5			5-15		15-25		25-35		>35
Aspect	N	NE, NW	E		Flat	SE, W		S		SW
Temperature (°C)	25.5-26	26-26.5	26.5-27	27-27.5	27.5-28	28-28.5	28.5- 29	29-29.5	29.5-30	>30
Wind Speed (m/s)	<2.5	2.5-3	3-3.5	3.5-4	4-4.5	4.5-5	5-5.5	5.5-6	6-6.5	>6.5
Humidity (%)	>80	75-80	70-75	65-70	60-65	55-60	50-55	45-50	40-45	<40
Precipitation (mm/y)	>200	120-200		80-120		30-80		10-30		<10
DLT	No Tree				Broad Leaved					Coniferous
TCD	0-10	11-20	21-30	31-40	41-50	51-60	61-70	71-80	81-90	91-100
NDVI	<0.1		0.1-0.3		0.3-0.5		0.5-0.7		0.7-0.9	>0.9
Population Density (Nr)	0-1000		1000-5000			5000-10000		10000-15000		>15000
Distance from Settlements (m)	>3000		2000-3000			1000-2000		500-1000		<500
Distance from Road Network (m)	>2000		1000-2000			500-1000		250-500		<250
Distance from Recreational Waters (m)	>2000		1000-2000			500-1000		250-500		<250
Land Use	Water Wetlands Open Spaces		Urban Fabric				Agricultural Areas			Forests and Vegetation Areas

The particular criteria and subcriteria for the AHP that are used as fire risk variables reflect the peculiarities of the study area and are shown in Table 2. The calibrated scores in Table 2 show the rating of the fire risk for the selected criteria and subcriteria. Furthermore, in Table 3 the values of Consistency Ratio (CR) are indicated as well as the weights of the criteria and subcriteria.

Forest-based classification. Forest-Based Classification and Regression tool is included in the Modeling Spatial Relationships toolset in ArcGIS PRO software and uses the Random Forest algorithm, developed by Leo Breiman and Adele Cutler [33]. Through model creation and training using a training dataset, it aims at predicting unknown values in a dataset using the same explanatory variables as the training dataset. The model creates a forest, which consists of a number of decision trees, each of which is generated from a random subset of the training dataset and provides a prediction for the research subject. Each prediction contributes to the final one, which is derived from all the decision trees created, i.e. the entire forest. The possibility of using the tool with a smaller variety of variables, as well as its intuitive nature are important advantages in selecting this tool [24]. Table 4 indicates the Importance Values of the Subcriteria, as these occurred from Forest-Based Classification tool and are used for Fire Risk assessment.

Table 3. AHP's criteria/subcriteria weights

Factor/Criterion	CR	Weight	Subcriterion	CR	Weight
Topography	0.0515247	0.068	Elevation	0.0477254	0.106
			Slope		0.633
			Aspect		0.261
Climate		0.152	Temperature	0.0650317	0.272
			Wind Speed		0.540
			Humidity		0.131
			Precipitation		0.057
Environment		0.456	DLT	0.0201833	0.123
			TCD		0.557
			NDVI		0.320
Urban Space		0.324	Population Density	0.0812568	0.289
			Distance From Settlements		0.110
			Distance From Road Network		0.287
			Distance From Recreational Waters		0.047
			Land Use		0.267

Table 4. Importance values (weights) of the subcriteria according Forest-Based Classification

Subcriterion	Importance Value	Subcriterion	Importance Value
NDVI	0.0867	Distance from Road Network	0.0775
Precipitation	0.0865	Distance from Settlements	0.0771
Elevation	0.0841	Temperature	0.0742
Distance from recreational waters	0,0828	Humidity	0.0716
Population density	0.0811	TCD	0.0371
Slope	0.0795	Land Use	0.0039
Wind Speed	0.0777	DLT	0.0027
Aspect	0.0775		

3.3 Empirical Results

After the appropriate data preparation, the two methodologies were implemented in order for the final Forest Fire Risk Assessment maps to be derived. Following the calibration of the subcriteria in a unified scale [fire risk scores 1 to 10 as shown in Table 2], the subcriteria maps were generated (Fig. 3). The final maps were produced using the associated weights assigned to the Criteria/Subcriteria, which are shown in Table 3 for AHP and Table 4 for Forest-Based Classification respectively. Final Forest Fire Risk Assessment maps are demonstrated in Figures 4 and 5, in association with Burned Areas and Settlements; and depict the pattern of Fire Risk in the study area.

Regarding the Fire Risk map derived from AHP (Fig. 4a), the fire risk values range from 1.76 to 7.64. Most high fire risk values (brown color) appear in the Western – North-Western part of the study area (Municipalities of Oropos and Dionisos), with intermediate risk values (yellow color) occurring in the Southern part (Municipalities of Penteli and Pallini). In contrast, the coastal part of the study area (Municipality of Marathonas and Rafina-Pikermi) shows moderately low risk values (green color). Very low values display limited occurrences within the study area (blue color).

As for the fire risk map derived from Forest-Based Classification (Fig. 4b), the fire risk values range from 2.65 to 6.56. The different fire risk pattern is apparent between the two maps. In Fig. 4b, the presence of increased values (brown color) is more extensive throughout the study area, with a more pronounced occurrence in the Southern part of the area (Municipalities of Penteli and Pallini). Intermediate fire risk values (yellow color) appear as a continuation of the higher values, with moderately low fire risk values (green color) being relatively limited in the study area. A distinct difference with Fig. 4a is the appearance of several points with low fire risk values (blue color). Results, estimated by the two methodologies, display a small difference in the range of fire risk values, with the Forest-Based Classification tool estimating values slightly lower than AHP.

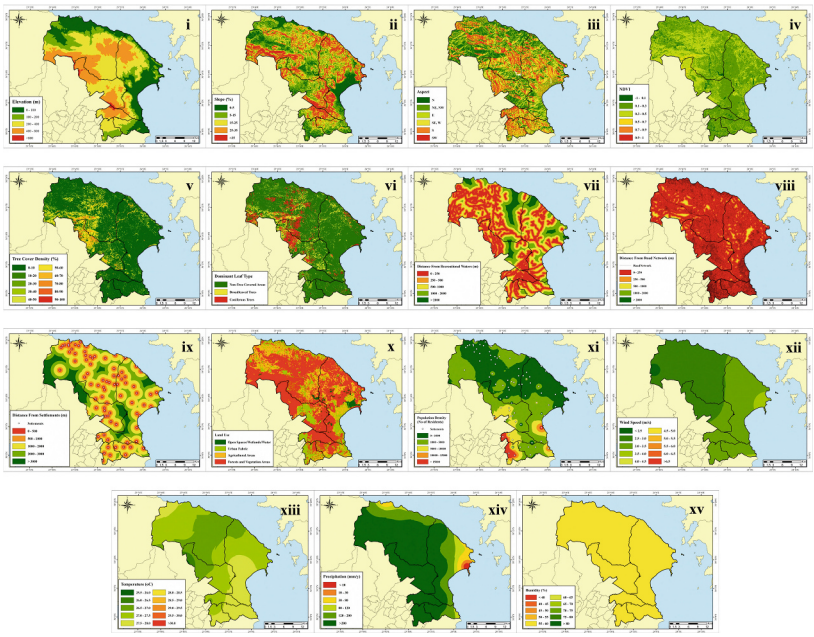

Fig. 3. Maps of the criteria used for the two methodologies. i) Elevation, ii) Slope, iii) Aspect, iv) NDVI, v) TCD, vi) DLT, vii) Distance from Recreational Waters, viii) Distance from Roads, ix) Distance from Settlements, x) Land Use, xi) Population Density, xii) Wind Speed, xiii) Temperature, xiv) Precipitation and xv) Humidity.

However, the difference in the fire risk pattern assessed by them in the study area is rather noticeable.

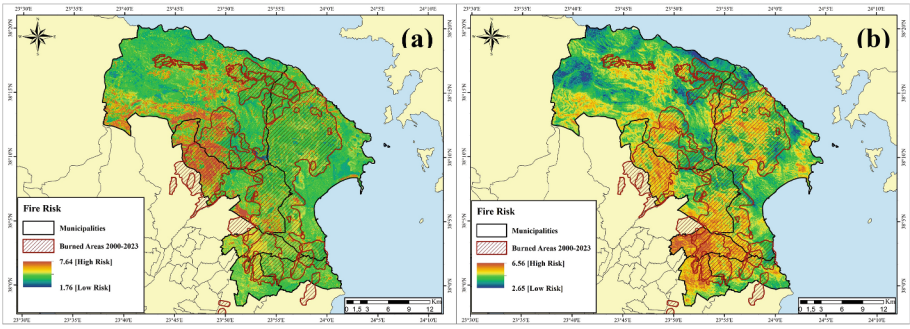

Fig. 4. Forest Fire Risk Assessment Maps and Burned Areas 2000-2023 – a) AHP methodology and b) Forest-Based Classification Tool, Source: Own elaboration.

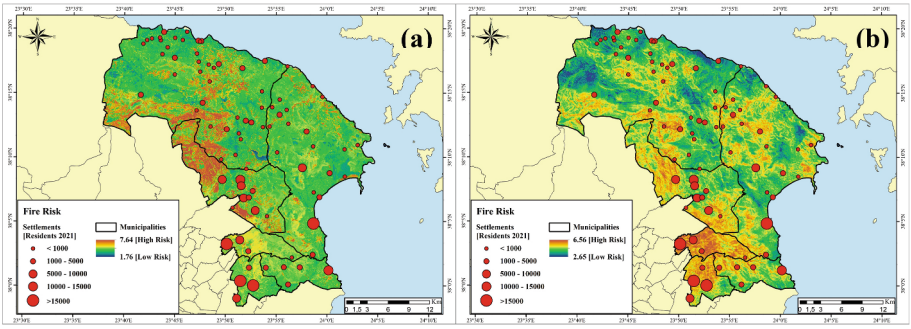

Fig. 5. Forest Fire Risk Assessment Maps and Settlements at risk – a) AHP methodology and b) Forest-Based Classification Tool, Source: Own elaboration.

4 Discussion and Conclusions

In the last few years, the increasing vulnerability of WUIs, affected by the rising number of wildfires has attracted the research interest in order for data-enabled policy response, targeting mitigation and adaptation of WUIs to the escalating fire incidents that are due to climate change, to be articulated [2, 3]. In this respect, the focus of this work is on highlighting the factors that affect wildfire occurrences in WUIs and are considered in fire risk assessment studies; and the methodologies utilized for this purpose. That said, a range of placed-specific factors/criteria (see Table 2) and two methodologies, namely the AHP and the Random Forest algorithm through the Forest-Based Classification tool are selected for implementation in a specific case study. The scope of this study is to assess the risk to fire in the study region in general and WUIs in particular; and compare the results produced by each methodology. Both methodologies are quite user-friendly. However, certain expertise in the subject is definitely needed for their best implementation. More precisely, AHP relies mainly on the researcher's experience and literature-enabled decisions; while the Forest-Based Classification tool is rather grounded in state-of-the-art technology and more automatized procedures.

Worth noticing is also the diverging outcome these methodologies produce with regard to both the values and the spatial pattern of forest fire risk in the study area. As far as the values are concerned, those calculated by the AHP appear to be slightly increased, compared to the ones calculated by the Forest-Based Classification tool. This difference is attributed to the researcher's estimation, who appears to give slightly higher risk values, compared to an automated procedure. However, this difference is not a significant one. Speaking of the spatial pattern of the forest fire risk, a notable divergence is observed in the results produced by the two methodologies, as shown in Fig. 4a and 4b. Comparison of the spatial pattern of forest fire risk produced by the two methodologies and the one of the burned areas due to the recurrent fire incidents of the last years raises some noticeable points. More specifically, AHP results (Fig. 4a) indicate a lower forest fire risk in the coastal or the near to the coast part of the study area, compared to the one produced by the Forest-Based Classification (Fig. 4b). The latter seems to better fit to the repeatedly burned coastal parts of the study area in the past years in contrast to the AHP results that seem to underestimate fire risk in this part. Regarding the fire risk assessment in

WUIs, the Forest-Based model (Fig. 5b) also shows a better matching between higher fire risk values and WUI areas, as it is shown for example in the southern part of the study area, compared to the AHP (Fig. 5a), in which the coastal side displays a lower fire risk despite the increased population and the number of settlements.

In terms of the accuracy and consistency of the tested methodologies, CR value in AHP (less than 0.10) demonstrates that the pairwise comparison among the subcriteria/criteria is valid and the procedure displays the consistency needed in order to proceed and create the final map. In the Forest-Based Classification model, the values of F1-score (0.90 on the training data and 0.83 on the validation dataset) indicate that the model is capable of identifying fire prone and non-fire prone areas in an effective way. The small difference between the validation accuracy and the training set suggests a possible over-fitting. However, the model appears to be robust and performs successfully.

The comparison of the two methodologies unveils that the Forest-Based Classification model provides the opportunity to optimize the model through the output indexes that accompany the final results; whereas in AHP it is in the researcher's convenience and decision to modify the subcriteria/criteria or the weights in case that the outcome is not satisfactory. Finally, it should be noted that data quality and data availability at different time scales are quite important in further improving the outcome of this research. This could allow for the: implementation of the methodologies both prior to and after major wildfire events; investigation of the accuracy of the outcomes with respect to future events and areas at risk; and capturing of particularities within WUIs. Apart from data issues, testing the aforementioned methodologies in a further expanded forest area in the neighboring of the studied one or in other case studies could enhance knowledge as to their performance. This holds true especially for the Forest-Based Classification model. Moreover, enriching the criteria pool could support replicability of these methodologies in other regions as well and comparability of produced results. Lastly, as technology is an integral part of current research on these topics and is advancing at a rapid pace, it may be beneficial to test and compare state-of-the-art methodologies using AI with more conventional ones in order for the AI advantages and the efficiency of their results to be investigated.

5 Disclosure of Interests.

The authors have no competing interests to declare that are relevant to the content of this article.

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