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ORIGINAL PAPER

GIS-based forest fire risk determination for Milas district, Turkey

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Abstract

Forest fires are highly destructive phenomena in both ecological and economic terms. Therefore, it is significant to develop measures to detect and mitigate them. In this study, the forest fire risk map of the Milas district of Turkey was studied using geographical information systems and remote sensing methods. In the first part of the study, the forest fire risk map of the area was developed via a weighted overlay technique with analysis of stand characteristics, topographic features, distance from intermittent streams and built-up environment. According to the resulting forest fire risk map, extremely low-, low-, medium-, high- and extremely high-risk classes covered 0%, 0.5%, 65%, 30% and 0.5% of the forested areas in Milas district of Turkey, respectively. In the second part, the location of a major forest fire, which took place in 2007 in the study area, was determined using the normalized difference vegetation index, the normalized burn ratio, and the burn area index. When compared with the forest fire risk map, it was revealed that 45% of the burned areas in 2007 fell into the high-risk class, while 51% of it was from the extremely high-risk zones. Moreover, the forest risk map was compared with eleven forest fire cases between 2013 and 2019. The results show that eight of these fires took place in high-risk territories. According to these results, it was concluded that the created risk map coincides with the fire incidents.

Keywords Burn area index · Forest fire · GIS · Normalized burn ratio index · Risk assessment

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1 Introduction

Large fire cases release huge amounts of gas and particulate matter into the atmosphere, which increase the direct and indirect impact of global climate change and result in serious problems for public health and even security (Patz et al. 2014; Wang et al. 2019). Wildfires around urban areas threaten residential areas as they may destroy the built-up environment and cause injury and death (Cosgun et al. 2019; Modugno et al. 2016). Based on the Global Fire Monitoring Center Report, wildfires killed 297 firefighters and civilians between 2008 and 2015 worldwide (Doerr and Santín 2016). Forest fires also destroy precious forest ecosystems, since they damage the vegetation and increase soil erosion and flood risks (Nasi et al. 2002; Verma and Jayakumar 2012). In Greece, the huge forest fire in July 1997 burned almost 1100 hectares, roughly two-thirds of the forest area, which had been the largest source of oxygen for the city of Thessaloniki (Siachalou et al. 2009).

The forest fire that took place in Chile in 2017 destroyed forest plantation and shrubland ecosystems. The resulting air pollution also influenced almost 74% of the Chilean population (de la Barrera et al. 2018). During a series of mega forest fires in eastern Australia, between September 2019 and January 2020, nearly 5.8 million hectares of forests burned (Boer et al. 2020; Nolan et al. 2020). The smoke of the fire in the Amazons on August 19, 2019, turned the city of São Paulo, 2000 km away from the centre of the fire, into darkness at 3 pm (Bencherif et al., 2020). Over the last two decades, 63,724 forest fires, of which 90% were human-induced, were recorded in Turkey (Çolak and Sunar 2020).

Considering the devastating consequences of the forest fires, a good number of research studies have been conducted to help prevent and manage forest fire risks. As highlighted in these studies, it is necessary to determine high fire risk locations before developing preventive measures. In this regard, a forest fire risk map can be prepared via the analysis and evaluation of different natural and cultural factors (Akinola and Adegoke 2019; Chuvieco 2009; Çolak and Sunar 2020; Ghorbanzadeh et al. 2019a; Ljubomir et al. 2019; Naderpour et al. 2019; Nami et al. 2018). Forest fire risk maps are a valuable basis for locating firefighting resources in suitable and easily accessible spots (Romero-Calcerrada et al. 2008).

There are multiple factors affecting the risk of fire outbreaks, and these must be considered, based on the nature of the study area. They can be categorized into two groups: dynamic and non-dynamic factors. Dynamic factors are temporal and may change seasonally, daily or even hourly. Factors such as temperature, precipitation, radiation and seasonal travel rates are in this category (Amiro et al. 2004; Bar Massada et al. 2009; Busico et al. 2019; Holsinger et al. 2016; Nuthammachot and Stratoulias 2019). In contrast, non-dynamic factors, such as topography, forest accessibility and stand characteristics, do not change, or their change is only significant over a longer time span (Adab et al. 2013; Akinola and Adegoke 2019; Busico et al. 2019; Mota et al. 2019). Therefore, two types of forest fire risk maps (dynamic and non-dynamic) can be produced, based on the nature of the variables. The dynamic risk maps are useful for quickly responding to instant or changeable events, such as daily fire warnings. The non-dynamic maps are helpful to develop long-term preventive measures and strategies, such as the locating of fire watchtowers (Bao et al. 2015) and firefighting stations, constructing water storage facilities, planning forest roads, determining recreational sites (Molina and y Silva 2019) and implementing public training programmes (Gençay and Mercimek 2019). As they are more stable, non-dynamic factors are evaluated within the scope of this study.

The forest fire risk assessment studies in the literature primarily concentrate on inappropriate weather conditions, which may favour fire ignition and propagation (Akay and Şahin 2018; Çolak and Sunar 2020; Fatma and Vedat 2018; Finney 2005; Mota et al. 2019; Nuthammachot and Stratoulias 2019), as well as a variety of other natural factors, such as topography, plant and soil moisture, stand types, canopy density, and factors relating to human behaviour, such as proximity to settlement areas and roads, demographic characteristics and so on, which have been adopted for the development of either fire risk index (FRI) (Çolak and Sunar 2020; Naderpour et al. 2019; Sivrikaya et al. 2014) or fire danger index (FDI) (Castro and Chuvieco 1998; Chuvieco and Salas 1996).

In studies dealing with environmental factors, it may be necessary to work with variety of data layers. GIS and RS are important tools in many current issues that require the analysis of a large number of spatial data, such as soil organic carbon research (Pekkan et al., 2021), ecological footprint research (Cetin et al., 2021a, b) and urban development process research (Cetin et al., 2021a, b). In addition to the variety of data layers, different methods embracing geographical information systems (GIS) and remote sensing (RS) capabilities have also been utilized by the researchers for the realization of spatial analyses and production of forest fire risk/danger maps (Akay and Erdoğan 2017; Chuvieco and Salas 1996; Romero-Calcerrada et al. 2008). For example, Massada et al. (2009) studied fuel and topography, weather and structure data as main inputs to analyse the FRI. Chuvieco and Salas. (1996) considered fuel type, temperature, humidity, compactness, plant moisture, topography and human activity to estimate the FDI. Siachalou et al. (2009) integrated five factors, vegetation, slope, aspect, roads and settlements, to generate a fire risk map showing high-risk zones in areas with high slope, a south-facing aspect and low moisture. Akbulak et al. (2018) considered both human and natural factors, such as slope, elevation, aspect, vegetation type, canopy density, distance from roads, settlements, agricultural areas and population density based on the Canadian forest fire weather index (FWI) (Wotton et al. 2005). Vadrevu et al. (2010) studied tropic forest fires in India and developed a fire hotspot map using the GIS and analytical hierarchy process (AHP).

The risk and danger indexes and maps in the majority of these studies are based on different risk level classes, which identify the severity of forest fire risk. In a number of studies (Akay and Erdoğan 2017; Akbulak et al. 2018), a 4-level (medium, high, very high, extreme) fire risk classification was also adopted. A. G. McArthur, who developed the McArthur Forest Fire Danger Index (FFDI) (McArthur 1967), is one of the leading scientists working on forest fires. In their study, published by Luke and McArthur in 1978, they defined FFDI in five classes (Luke and McArthur 1978). Accordingly, in many studies including forest fire risk and danger, the classifications were evaluated in five groups. In this sense, Akay and Sahin (Akay and Şahin 2018) used a 5-level (very low, low, medium, high, very high) fire risk classification in their study.

From this perspective, the main goal of this study is to determine the forest fire risks in the Milas district of Muğla province, Turkey, which is both a popular tourist destination and a delicate landscape, in terms of natural characteristics and values. To fulfil this aim, a weighted overlay analysis was performed with GIS capabilities and a non-dynamic forest fire risk map was proposed.

2 Material and methods

2.1 Study area

The Milas district of the Muğla province, Turkey, was selected as the study area due to the high number of forest fires in the region, as reported by the General Directorate of Forestry (OGM 2018) (Fig. 1). Milas is the second largest district of the Muğla province and is located in southwest Anatolia, between 27° 30'–28° 30 ' east longitude and 37° 00'–37° 30' north latitude. The total area of the district is 2067 km^2. Milas lies within the Mediterranean climate zone where summers are hot and dry, and winters are mild and rainy. In summer, the average temperature is between 32 °C and 34 °C and sometimes even exceeds 40 °C. Milas is mostly open to northern and southern winds. According to statistics derived from the General Directorate of Forestry (OGM 2018), 66% of the Muğla province is covered by forests and the forests in Muğla province constitute 4% of the forests in Turkey. This rate refers to a total forest area of 829,309 hectares and ranks the province in fourth place in terms of forested area size. The dominant stand type in the Milas forests is Turkish pine (*Pinus brutia*). There are other species, such as the European Black Pine (*Pinus nigra*), Stone pine *(Pinus pinea*), and deciduous plants in smaller proportions.

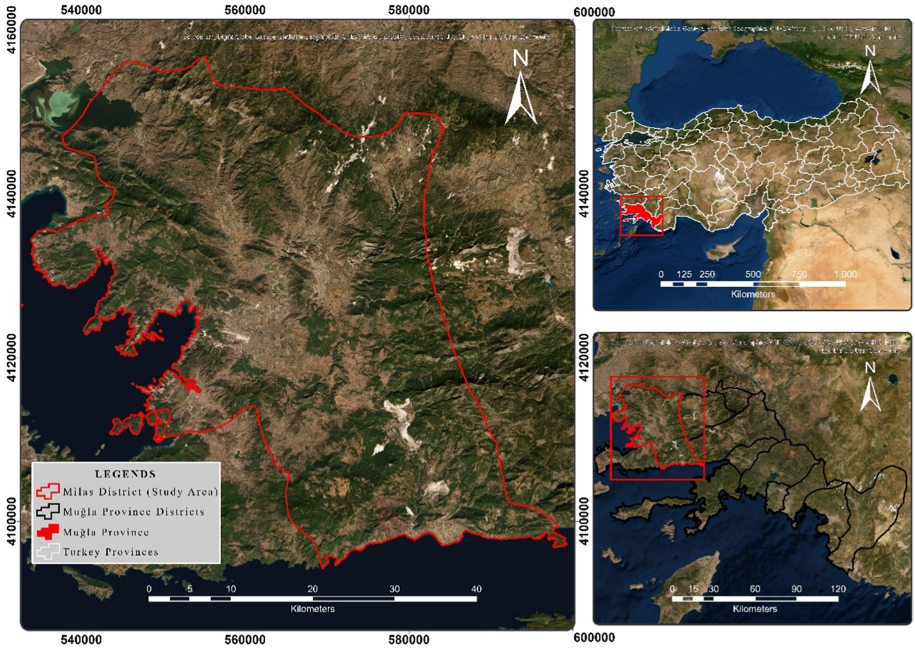


Fig. 1 Location of the study area, Milas district, Muğla/Turkey

2.2 Research variables

2.2.1 Stand characteristics

The quality of the fuel, more specifically the characteristics of biomass, depends on the stand types. Therefore, stand type is a significant variable that affects ignition and also the behaviour of fire propagation. For example, needle leaved trees, such as conifers and dried leaved plants, have a greater potential to burn, whereas wet broad leaved species, such as beech, do not catch fire easily (Karabulut et al. 2013).

A ground fire could easily turn into a top layer fire where the fuel type is highly inflammable (Akkaş et al. 2008). According to the literature, a significant proportion of forest fires occur in young stand regions (Akkaş et al. 2008). Generally, older trees are large in size and possess a porous structure where they can retain greater amounts of moisture. As the moisture increases, the burning effect decreases (Hood 2010). Therefore, more energy is needed to burn old trees, so they are less likely to catch fire.

An extremely dense canopy corresponds to a higher moisture content of fuel beneath the canopy, which decreases the risk of fire. On the other hand, where the canopy density is severely low, the level of produced heat is hardly enough to burn any adjacent fuel (Ray et al. 2005). However, a sparse canopy allows the wind to flow more easily, resulting in an increased fire spread rate.

2.2.2 Topographic factors

Terrain elevation affects temperature and moisture. The wind effect also varies at different elevations (Holsinger et al. 2016; Sullivan et al. 2014). Vegetation type, fuel moisture, and air humidity vary at different elevations (Castro and Chuvieco 1998). It is reported that humidity and temperature effects become more significant at higher altitudes (Hernandez-Leal et al. 2006). In contrast, it is also reported that forest fires may be less severe at higher elevations due to increased precipitation (Adab et al. 2013).

Terrain slope is a significant factor in the fire spread rate and pattern (Butler et al. 2007; Xavier Viegas 2004). The fire propagation rate increases with an increase in slope. The effect of slope varies in accordance with the direction of fire spread direction, downhill or uphill. In an experimental study, Wagner (Van Wagner 1988) conclude that a downhill fire spread rate against the slope follows a parabolic pattern where it decreases when the slope increases from zero to 22° and then increases to the initial flat level rate when the slope increases to 45°. This phenomenon is explained by the effect of fire head radiation and falling burned debris. However, for uphill fire propagation, there is consensus in the literature that a steeper slope corresponds to a faster fire spread rate (Dupuy 1995; Viegas 2004).

Another significant topographical factor is aspect, where south-facing land receives more radiation, and therefore is drier and more prone to fire ignition compared to north-facing land (Noonan 2003).

2.2.3 Human intervention

The distance between settlements and forests is a determining risk factor, because human activities, such as camping, hunting and recreation in or near forests, mainly take place when the forests are close to the settlement areas (Fatma and Vedat 2018).

The impact of human activity starting a fire can be quantified in terms of proximity to/distance from roads and settlements (Rogan et al. 2006). Forest areas in the vicinity of roads are more prone to fire risk, because roads allow local people, shepherds and tourists to reach forests more easily (Jaiswal et al. 2002).

Another significant factor causing forest fire risk is the existence of human settlements nearby or close to forested areas (Ghorbanzadeh et al. 2019b). There are higher risks of fire in forested regions that are close to the settlements and houses (Jaiswal et al. 2002). Carelessly thrown unextinguished cigarette butts and campfires are amongst the sources of fire risk.

Intermittent streams also play an important role in the start and spread of a fire, especially in dry seasons, as they may contain dry fuel (leaves, branches, roots, barks, seeds and suchlike) or other flammable materials (Townsend and Douglas 2000), such as human produced garbage. Intermittent streams are also places through which the wind blows faster compared to dense forest areas, and therefore, a fire can spread extremely quickly causing more damage.

2.3 Data sources

The main materials used in this study include a combination of vector and raster data covering the Milas district. A 1/25000 scale stand map, covering the 2003–2013 period and detailing road networks and settlement areas, was obtained in vector format from the Regional Directorate of Muğla Forestry and was used to determine and reclassify the types of stand, stand age and canopy density.

Raster data, with Landsat 5 images of the study area, were obtained from USGS Earth Explorer. A digital elevation model (DEM) of the study area was provided from ASTER available on the EARTH DATA platform of NASA and used to produce elevation, slope and aspect layers (Table 1). Two Landsat 5 images (dated 12.06.2007 and 15.08.2007) (Table 1) were utilized to calculate NDVI, NBR and BAI indexes for the detection of the burned forests in Güvercinlik, Milas, in 2007. The forest fire risk map of the Milas district

Table 1 Satellite imagery data sources

Acquisition date	Product id	Satellite, sensor	Spatial resolution (m)
06.12.2007	LT05_L1TP_180034_20070612_20180126_01_T1	Landsat 5, TM	30
15.08.2007	LT05_L1TP_180034_20070815_20180123_01_T1	Landsat 5, TM	30
01.03.2000, and 30.11.2013	ASTGTMV003_N38E028 ASTGTMV003_N38E027 ASTGTMV003_N37E028 ASTGTMV003_N37E027	ASTER, V003	30

was compared both with the resulting map (Güvercinlik fire map) and the locations of eleven large fire cases, which occurred between 2013 and 2019. The data related to the fire locations were provided by the General Directorate of Forestry (Milas, Turkey), and the exact locations of these fires were detected using Google Earth images.

2.4 Weighted overlay analysis

The main method adopted for the development of the forest fire risk map of the study area is weighted overlay analysis, conducted in a GIS environment. Weighted overlay analysis has been used by researchers for different spatial analysis applications. This method is mainly preferred when the cumulative interaction of different variables with their relative importance is of interest (Jabbar et al. 2019; Mandal and Mondal 2019; Yathish et al. 2019). A work flowchart for forest fire risk map development is provided in Fig. 2.

As can be seen in the figure, different factor layers were weighted and overlaid. To fulfil this aim, each factor layer was reclassified based on information in the literature (Çolak and Sunar 2020; Nolan et al. 2020; Yathish et al. 2019) and the speculations of experts in the field of forestry and forest fire management. Since multiple factors do not have equal significance on fire risk, weight factors, which were determined using the AHP, were allocated to each category (Table 2). The same process was also applied for sub-categories. A ten-score scale was used for quantifying risk factors where ‘ten’ was the highest risk class and ‘one’ referred to the lowest risk. Equation one shows the calculation procedure (Eq. 1):

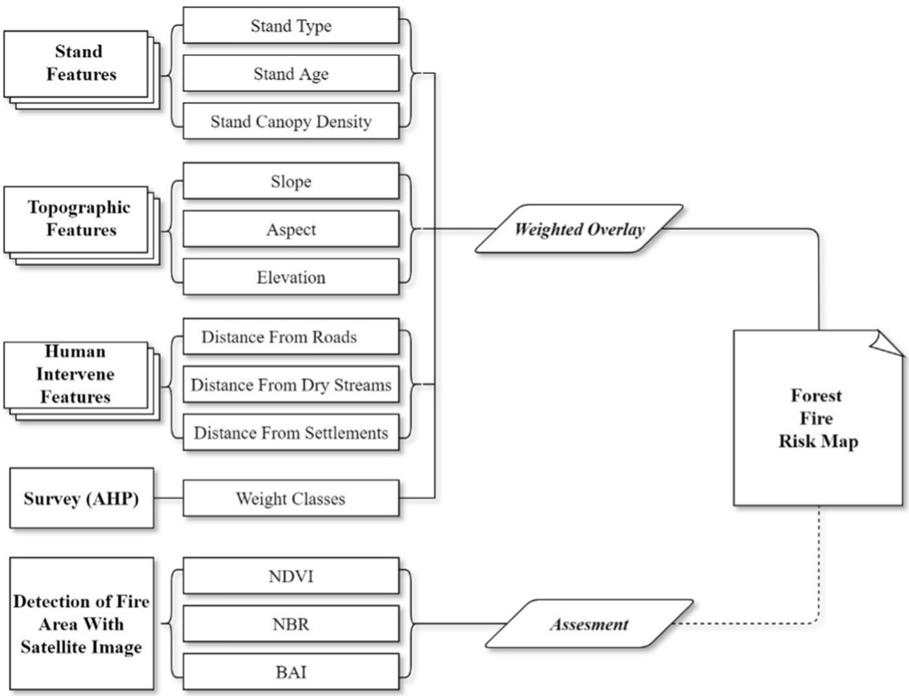


Fig. 2 Flowchart for fire risk map development and assessment

Table 2 Risk scores and weight percentage for risk variables

Main categories	Weight(φ_i)	Subcategories	Weight (ω_j)	Subcategory classes	Risk score ($P_{\pi j}$)
Stand characteristics	42.85%	Stand type	60.80%	Pinus brutia	10
				Pinus nigra	7
				Pinus pinea	9
				Deciduous plants	4
		Stand age	27.20%	I	5
				II	9
				III	8
				IV	7
				V	6
				VI	5
				Unspecified (damaged stand)	4
		Stand canopy density	12.00%	1–10%	5
				10–40%	8
				40–70%	10
				> 70%	7
Topographical characteristics	14.30%	Slope	6.66%	> 35 degree	6
				35–15 degree	5
				15–10 degree	4
				10–5 degree	3
				0–5 degree	2

Table 2 (continued)

Main categories	Weight(φ_i)	Subcategories	Weight (ω_j)	Subcategory classes	Risk score ($P_{\pi j}$)
		Aspect	46.66%	South	10
				Southwest	8
				Southeast	8
				Northwest	3
				Northeast	3
				North	2
				East	4
				West	4
				Flat	5
		Elevation	46.66%	0–200 m	10
				200–400 m	9
				400–600 m	8
				600–800 m	7
				800–1000 m	6
				1000–1200 m	5
				1200–1400 m	4
Human intervention	42.85%	Distance from roads	28.95%	0–50 m	10
				50–100 m	9
				100–200 m	8
				200–300 m	7

Table 2 (continued)

Main categories	Weight(φ_i)	Subcategories	Weight (ω_j)	Subcategory classes	Risk score ($P_{\pi j}$)
				300–400 m	6
				400–12,500 m	5
		Distance from intermittent streams	6.42%	0–50 m	8
				50–100 m	7
				100–200 m	5
				200–300 m	3
				300–400 m	2
				400–7000 m	1
		Distance from settlements	64.63%	0–50 m	10
				50–100 m	9
				100–200 m	8
				200–300 m	7
				300–400 m	6
				400–500 m	5
				500–1000 m	4
				1000–1500 m	3
				1500–30,000 m	3

$$Riskscore = \frac{\sum_{i=1}^{n_c} \sum_{j=1}^{n_{sc}} \varphi_i \omega_j P_{ij}}{n_c} \tag{1}$$

where $P_{\pi j}$ is the factor score, ω_j is sub-categories weight factor, φ_i is the main categories weight factor, n_{sc} is the number of sub-categories under that category, and n_c is the number of main categories, which is three in this study.

The AHP was implemented for the determination of the weights shown in Table 2. The AHP is a decision-making approach, which was first introduced by Thomas L. Saaty (Saaty 1990). It is a process based on the quantification of binary choices according to an allocated degree of significance, which provides a scored list of choices. The method basically originated from Eigenvalue problems. In this process, the results of pairwise comparison of variables are inserted into a matrix. In the AHP, a certain degree of inconsistency is still acceptable (Shim 1989). In this study, score ranges of 0–2, 2–4, 4–6, 6–8 and 8–10 are classified as extremely low risk (VLR), low risk (LR), medium risk (MR), high risk (HR) and extremely high risk (VHR), respectively.

ArcGIS Desktop software was used to analyse the data and to obtain maps.

2.5 Burned area detection and fire risk map assessment

In addition to determining the forest fire risk map of the Milas district, a major fire in the study area in 2007, and eleven other forest fires between 2013 and 2019, were detected. The location of these past eleven fires was overlaid with the forest fire risk map to evaluate the risk potential and categories of the previously burned areas. Since point values are inadequate in defining the exact locations of the forest fires, as well as the total boundaries of the burned land, a number of indexes, based on remotely sensed data, including NDVI, NBR and BAI methods, were utilized to determine the forest areas burned and damaged vegetation during the Güvercinlik fire in July 2007. This forest fire deeply affected the local people who were followed by the media for months.

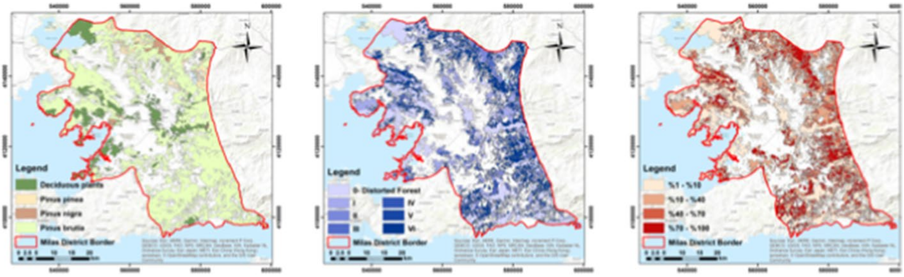
The NDVI method basically shows the vegetation health based on differences between the near infrared (NIR) band, which is strongly reflected by vegetation, and the red band, which is absorbed by vegetation (Eq. 2). NBR calculation is similar to NDVI, but uses short wave infrared (SWIR) instead of the red band. It is reported that the NBR method is a more sensitive index compared to NDVI for fire severity quantification (Escuin et al. 2008). The BAI method, which also uses NIR and red bands, relies on the designation of a 'conversion point' depending on the radiative characteristics of charcoal-char (Martín et al. 2005) (Eq. 4). The BAI method is considered a more sensitive index when compared to NDVI and NBR (Chuvieco et al. 2002). These three indexes have been used by researchers for burned area and fire severity detection studies.

For the NDVI and NBR methods, band ratios were used, as in the following equations (Eqs. 2–4), respectively:

$$\text{NDVI} = (\text{NIR}-\text{R})/(\text{NIR} + \text{R}) \tag{2}$$

$$\text{NBR} = (\text{NIR}-\text{SWIR})/(\text{NIR} + \text{SWIR}) \tag{3}$$

For the BAI, digital numbers (i.e. pixel value) of red and near infrared (NIR) bands need to be calibrated for the top of atmosphere (TOA) reflectance to calculate BAI according to



(a) Reclassified stand type map (b) Reclassified stand age map (c) Reclassified canopy density map

Fig. 3 Reclassified stand characteristics maps

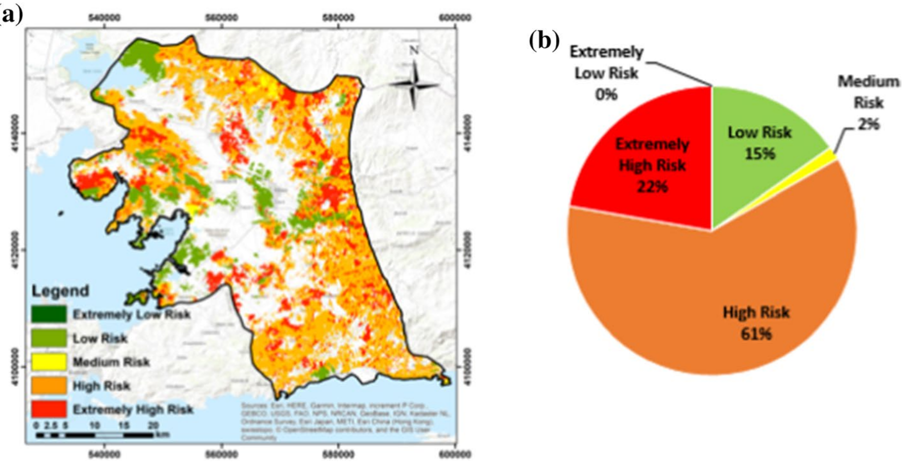


Fig. 4 Forest fire risk map based on stand characteristics (**a**), risk class distribution (**b**)

(Chander and Markham 2003). After this, BAI was calculated based on the work of (Chuvieco et al. 2002) using Eq. 4 as follows:

$$BAI = 1/\left(\left(\rho_{cr} - \rho_r\right)^2 + \left(\rho_{cnir} - \rho_{nir}\right)^2\right) \tag{4}$$

3 Results and discussion

3.1 Fire risk map based on stand characteristics

Stand characteristics, including stand type, age and canopy density, were reclassified and are mapped as shown in Fig. 3. The weight factors (Table 2) were set to 60.8%, 27.2% and 12.0% for stand type, age and canopy density, respectively. The weighted overlay of these sub-categories resulted in a fire risk map based on stand characteristics (Fig. 4). The estimated risk scores ranged between 3.79 and 9.52. Since the area is mainly covered with

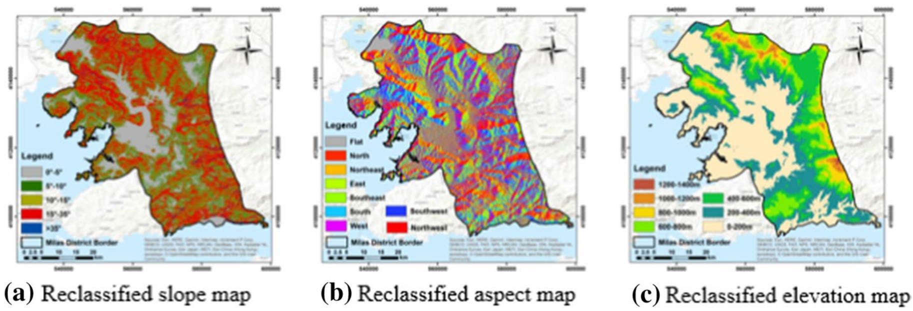


Fig. 5 Reclassified topographic characteristics maps

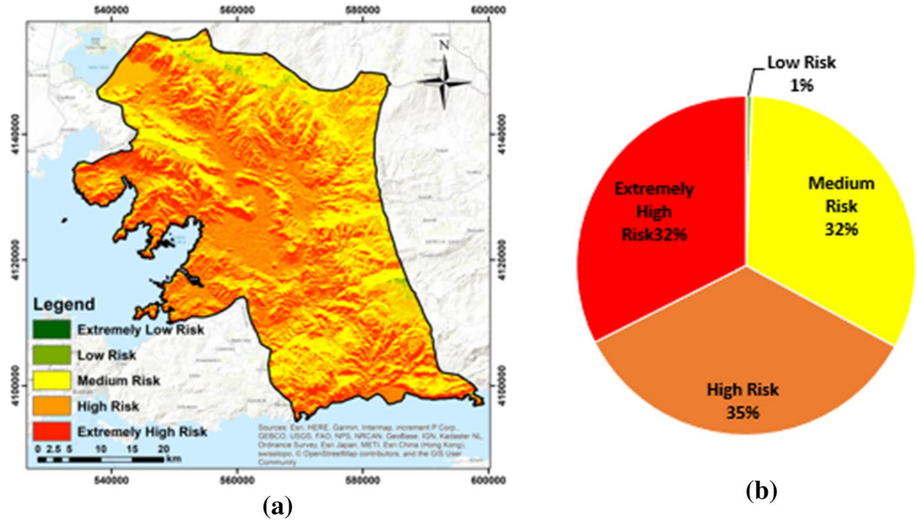
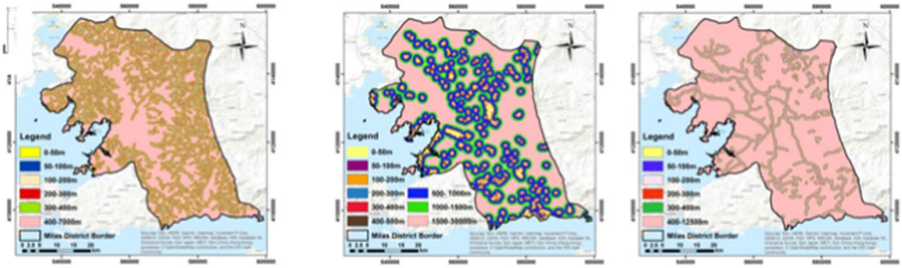


Fig. 6 Forest fire risk map based on topographic characteristics (**a**) and risk class distribution (**b**)

stand types of easily ignitable properties (Fig. 3), almost 83% of the district was found to comprise areas of high- and extremely high-risk classes (Fig. 4). The distribution of the high, extremely high, low and medium risk classes was detected as 61%, 22%, 15% and 2%, respectively.

3.2 Fire risk map based on topographic characteristics

The topographic characteristics within the study area are reclassified in line with the weighted overlay objectives (Fig. 5). The resulting map shows that the study area has considerably high risks for forest fires in terms of elevation, especially at elevations lower than 200 m, because the highest weight is allocated for less than the 200 m class, and the majority of the region possesses an elevation below 200 (Fig. 5c). The aspect map, on the other hand, reveals that the topography is mainly southeast, south and southwest facing. The reclassified slope characteristics map shows that sharp slopes above 35° are extremely



(a) Reclassified intermittent streams map **(b)** Reclassified settlement areas map **(c)** Reclassified distance from roads map

Fig. 7 Reclassified human intervention maps

rare, while slopes between 15° and 35° are very dense in the area. However, the latter is observed mostly at higher elevations.

The fire risk map based on topographic characteristics is illustrated in Fig. 6. According to Fig. 6, the Milas district is a highly risky region in terms of forest fires when the topographic characteristics are considered. The area distribution of risk classes in the study area is shown in the pie chart in Fig. 6. Figure 6b shows that almost 67% of the district falls into the high- and extremely high-risk classes with a fire risk score ranging of between 6 and 10.

3.3 Fire risk map based on human intervention

In previous studies, authors have highlighted that intentional or unintentional human intervention was the main reason for forest fires (Caldararo 2002; Ganteaume et al. 2013; Mollicone et al. 2006; Sanford et al. 1985). Examples of unintentional actions include throwing glassware or high radiation absorbing black objects into forests. Human intervention is directly related to accessibility to forests and population density. Depending on the distance from roads and intermittent streams, the entire study area was grouped into six different classes (Fig. 7) and weight factors were set to 6.42%, 28.95% and 64.63%, respectively, for the distance from intermittent streams, distance from roads and distance from settlements.

The forest fire risk map, based on human intervention, is shown in Fig. 8. As can be seen in the figure, areas with medium fire risk are homogeneously distributed all over the Milas district. Areas with an extremely high-risk potential (8–10 scores) comprise only 3% of the total forest areas and 8% of the total area fall into the high-risk class. Sixty-six percentage of the forested lands are at low-risk and no extremely low-risk areas are detected in terms of human intervention.

3.4 Final forest fire risk map

The final forest fire risk map for the Milas district was produced via a weighted overlay of three forest fire risk maps, based on stand characteristics, topographic characteristics and human intervention, respectively, as shown in Figs. 4, 6 and 8.

According to the final forest fire risk map, it can be seen that 35,050.72 hectares of forested land, corresponding to 30% of the total 114,920 hectares of forested area in the Milas

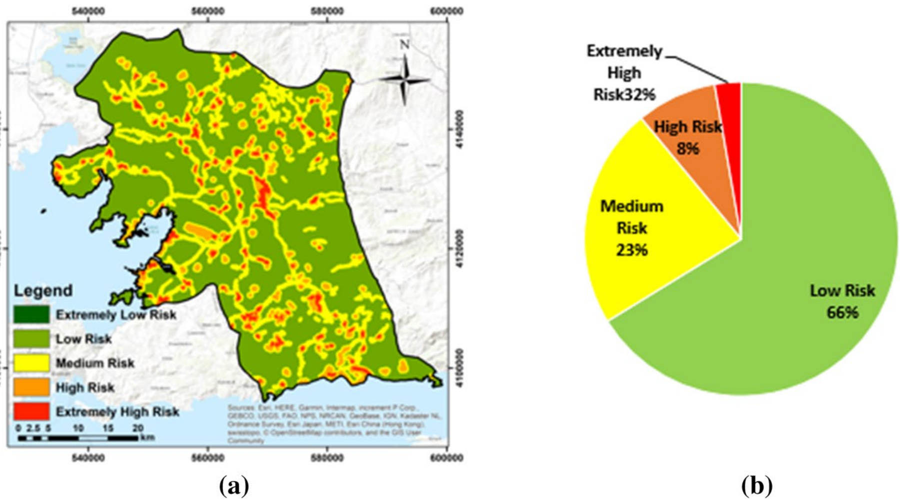


Fig. 8 Forest fire risk map based on human interference (**a**) and risk class distribution (**b**)

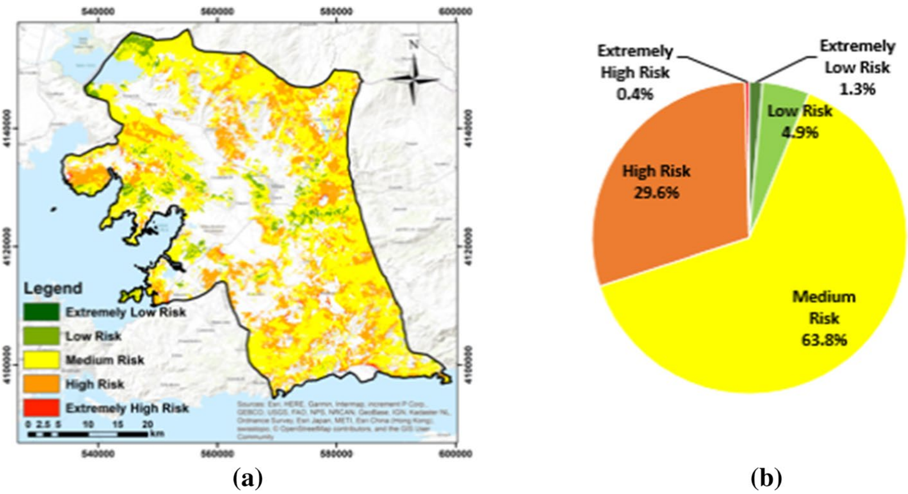


Fig. 9 Final forest fire risk map (**a**) and risk class distribution (**b**)

district, falls into the high- and extremely high-risk classes (Fig. 9). The other risk classes are found to be 63.8% (medium risk), 4.8% (low risk), and 1.3% (extremely low risk).

3.5 Assessment of risk maps in comparison with past fire data

As can be seen in Table 3, topographic characteristics alone are not sufficient for fire risk assessment, because seven of the eleven forest fires took place in medium-risk class zones. There are just three cases (number 1, number 5, number 9) in the extremely high-risk class.

Table 3 Risk scores for the past eleven large fires during the period 2013–2019

No.	Coordinates	Risk score (Max 10) Topography	Risk score (Max 10) Stand	Risk score (Max 10) Human	Risk score (Max 10) Final map
1	573,076.625 4,132,390.385 m: Akgedik Barajı	8.5	7.7	3.32	5.94
2	547,211.179 4,123,544.705 m: Kıyıkışlacık	6.34	9.52	4.8	7.32
3	549,289.618 4,115,358.292 m: Boğaziçi	5.8	7.44	6.9	7.12
4	565,108.858 4,108,365.237 m: Kısırlar	5.8	9.25	4.67	6.82
5	567,601.295 4,106,975.955 m: Demirciler	9.2	7.4	5.03	6.78
6	565,213.143 4,106,169.327 m: Demirciler	5.9	8.4	3.77	6.07
7	567,481.477 4,104,171.308 m: Fesleğen	5.8	8.44	3.58	5.98
8	569,162.259 4,103,807.003 m: Fesleğen	5.4	9.52	3.58	6.39
9	569,667.017 4,102,961.884 m: Fesleğen	8.2	7.16	4.16	6.06
10	568,216.866 4,102,566.795 m: Demirciler	4.9	7.44	2.94	5.16
11	576,096.325 4,102,965.774 m: Akçakaya	5.5	7.17	7.55	7.09

[a]The scores represent risk classes of extremely low risk (0–2), low risk (2–4), medium risk (4–6), high risk (6–8) and extremely high risk (8–10)

As to the human intervention factor, Table 3 reveals that the majority of forest fires took place in medium-risk areas. However, when the risk values in the table are analysed, it can be concluded that human-induced risk factors are relatively low.

Considering the eleven forest fires risk scores for stand characteristics, it is possible to explain that the forest fires burned the stand types in the high- and extremely high-risk classes. One reason for this is the high-risk score of Pinus brutia (10), which is the most common stand type throughout the study area.

Similarly, regarding the final risk map, Table 3 illustrates that eight of the eleven fire cases took place in high-risk zones. This number of correct matches actually supports the consistency of the produced forest fire risk map. However, there is no doubt that the point data are sufficient to make a full comparison and to justify the success of the risk map because, for large fires which cover a wide area, the starting point is not clear. Therefore, the consistency of the map is also evaluated via comparison of the forested land burned in Güvercinlik, Milas district, in 2007.

The burned area in 2007, in the Güvercinlik fire, was determined using NDVI, NBR and BAI indexes, as shown in Fig. 10. The results show that all three indexes were able to detect the burned area. The difference in index values, both before and after the fire, provides a high distinction between the burned and unburned areas. The burned area is determined as 271, 277 and 332 hectares using the BAI, NDVI and NBR indexes, respectively.

The forest fire risk map of the Milas district is overlaid with both the territories of the burned area in the Güvercinlik fire (Fig. 11) and the locations of the eleven forest fires in the study area, between 2013 and 2019 (Table 3).

To fulfil this aim, the forest fire risk map (Figure 9) is clipped according to the burned areas in Güvercinlik (Fig. 11). The results reveal that 51% of the burned areas were from the extremely high-risk class and 45% of the area fell into the high-risk zones.

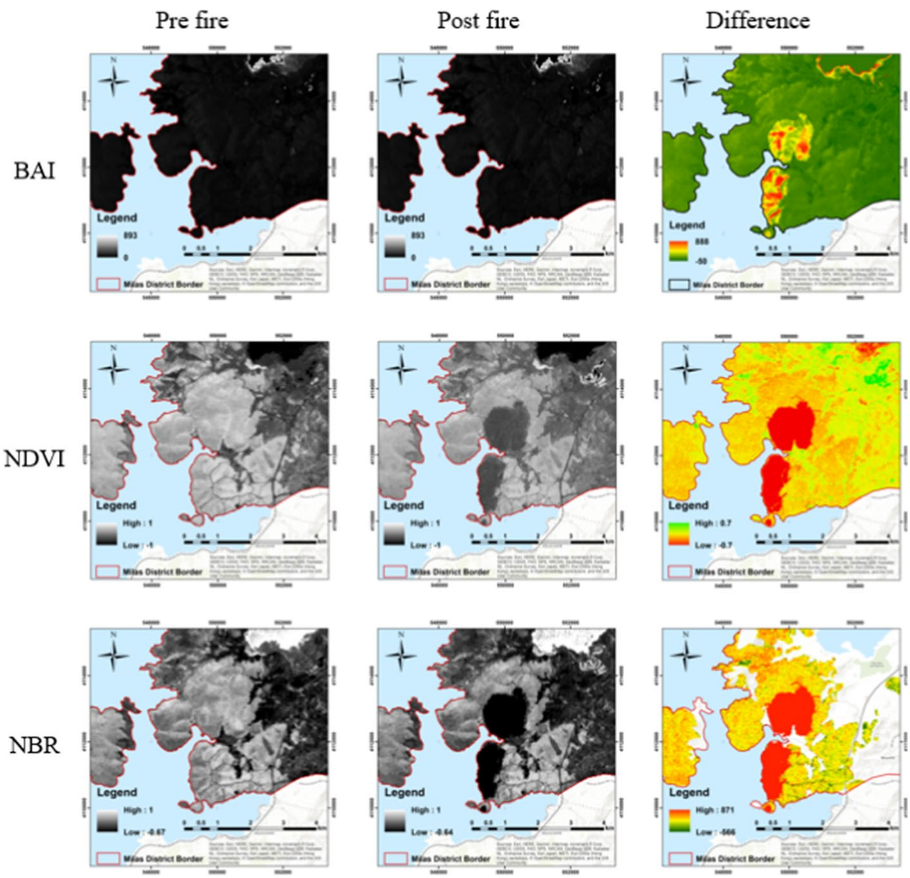
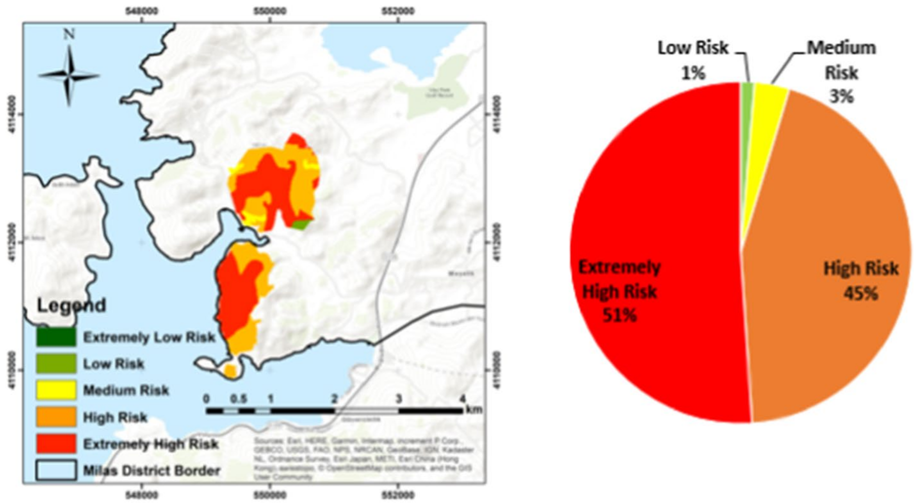


Fig. 10 Burned area detection using the BAI, NDVI and NBR indexes for the Güvercinlik fire, Milas, Turkey, 2007

4 Conclusions

Forest fires can cause irreversible effects on forest resources, have major economic consequences and threaten human life. In this context, it is extremely important to take the necessary precautions to identify fire hazards and risks in forest areas and to mitigate damage. Based on the study of Giannakopoulos et al. on global warming effects during 2031–2060, Turkey may be one of the most affected countries for this period in terms of the increase in the number of summer days (Giannakopoulos et al. 2009). In this context, it is important to identify the factors that cause fires and to obtain the necessary data for risk management.

In this study, the GIS-based weighted overlay method is performed to produce a forest fire risk map in the study area regarding stand characteristics (stand type, stand age, stand density), topographic features (slope, aspect, elevation) and human intervention factors (distance from roads, distance from settlements, distance from intermittent streams). As the necessary layers in a weighted overlay process, as well as their assessment in terms of the weights and influence factors, may vary depending on the geographic context, local, regional and national policies and strategies, related legislation



(a) **(b)**

Fig. 11 The estimated forest fire risk classes for the Güvercinlik mega fire area, Milas, Turkey, 2007(**a**), Risk class distribution (**b**)

and so on, the obtained forest risk map is specific to the study area and the estimated risk scores cannot be used as a scheme directly for other similar studies without considering and evaluating the unique characteristics and variables of the region. The study research shows that forest fire risks can be mapped based on non-dynamic factors. In addition, possible future studies may include additional dynamic fire risk factors, such as climate parameters, for the development of fire risk maps.

The forest fire risk produced for the Milas district is supposed to be a valuable basis and input for further planning processes within the province. One recent precaution to mitigate and prevent forest fires is the plantation of fire resistant tree species. To fulfil this aim, the determination of risky areas, in terms of forest fires, is of significance in order that a proper plantation plan is implemented.

Responsible organizations and firefighters need to consider potential forest fire hazards to identify local forest fire threats and to assess risks for communities. Moreover, forest fire risk maps are important for training the public and local people, raising awareness, and increasing community participation in forest fire mitigation and preventative action. Forest fire risk maps can also facilitate pre-attack planning, detection of areas to be treated in terms of forest fire risk reduction, application of fuel treatment applications, locating fire towers and water tank construction.

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Authors' Contributions Mehmet designed the study and performed the experiments; Ozge, Mehtap, ilker performed the experiments, analysed the data, and wrote the manuscript; and Suhrabuddin, Masoud, Saye performed the experiments, analysed the data, and wrote the manuscript.

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Code availability No extra code has been created.

Declarations

Conflicts of interest There are no conflicts of interest to be declared.

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