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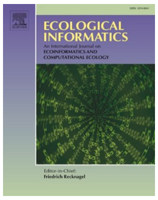

Forest fire risk mapping with Landsat 8 OLI images: Evaluation of the potential use of vegetation indices

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ABSTRACT

Fire is one of the most important natural catastrophes threatening the forest ecosystem. The severity and frequency of forest fires are increasing daily due to the increase in population in vulnerable areas and the effects of global climate change. Creating fire risk maps and using them to take the required protective actions to prevent fires will decrease the adverse effects of forest fires. This study focused on producing and comparing fire risk maps based on four vegetation indices, the Normalized Burn Ratio (NBR) index, Normalized Burn Ratio Thermal (NBRT) index, Normalized Difference Vegetation Index (NDVI), and Normalized Difference Water Index (NDWI) and data gathered with the use of remote sensing devices. The Muğla Regional Directorate of Forestry, which is in the Mediterranean climate zone and has experienced mega-fires, was selected as the case study area. Fire risk maps were prepared for the four vegetation indices from Landsat 8 OLI satellite images. Receiver operating characteristic curves and 195 fire ignition points that occurred in 2021 from July 5 to the end of the year were used to assess the accuracy of fire risk maps. Most fire ignition locations (>90%) were in high- and extremely high-risk fire areas on the maps prepared according to the NBR, NDWI, and NDVI. The fact that almost all of the fires occurred in high-risk areas revealed that the study area was sensitive to fire and that the vegetation indices used to draw up the risk maps were highly accurate in predicting where fires might occur. The accuracy results showed that the area under the curve was 0.842 for the NBR, 0.835 for the NDWI, 0.812 for the NBRT, and 0.810 for the NDVI. The NBR approach was more precise than the other models in providing information for fire risk maps. Risk maps created with the NBR could help decision-makers to take precautions and minimize fire damage.

1. Introduction

Global forest fires have been experienced more frequently and destructively, especially in recent years, due to climate change (Avetisyan et al., 2022; Milanović et al., 2021). According to the fire data of the last ten years, fires described as mega-fires have occurred in Australia, Canada, America, Russia, and Europe. Forest fires have become an important problem in recent years, especially for Mediterranean basin countries and Türkiye (Bilgili et al., 2021a). The long, dry summer periods significantly increase the risk of fire due to their high flammability in coniferous pine forests and maquis areas, which are sensitive to forest fires spreading in large areas.

Fires have played an essential role in altering the forest ecosystem throughout history (Bond et al., 2005; Glasspool et al., 2004). Intensive studies have been conducted to learn about these events, including studies on integrating new technologies in firefighting to reduce fires' ecological and economic effects. Fire-fighting studies generally focus on the stage after the fire has broken out. The accumulation of combustible materials in forests is a factor in these fires, and it has increased for several reasons. Because fire-fighting organizations now engage in intensive efforts to control new fires quickly, people have become complacent about preventing fires ahead of time. There is also a need to understand how fires occur as ecological events within a more extensive system. Another issue is that the silvicultural interventions that reduce combustible materials should be undertaken promptly (Pausas and Keeley, 2021). Fire regimes have started to change worldwide due to these issues and restoration efforts, such as pre-fire maintenance and post-fire forestry approaches (Lemesios, 2022; Moreira et al., 2020).

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The impact of human intervention, along with other environmental factors, has been significant in shaping ecosystems. Along with the changes in fire regimes seen in different parts of the world, significant changes have been observed in the fire regimes of the Mediterranean ecoregion (Keeley et al., 2012). Increasing populations, improper land use, dense human populations at the forest–urban interface, and the consequent construction of buildings have been essential factors in the increase of forest fires during extreme weather conditions (Bowman et al., 2017). Along with the increase in the number of fires, fires have intensified owing to more severe and prolonged heat waves caused by climate change. These conditions have paved the way for fires in the Mediterranean basin to grow and cause great destruction in ecosystems (Kalem et al., 2022; Tavşanoğlu, 2021).

Fire severity, frequency, and fire season all have an immediate impact on ecosystems. As fires have become mega-fires, the destruction they have caused in ecosystems has become much more significant. It is crucial to ascertain the extent of this destruction very quickly and to carry out forestry activities in an uninterrupted and planned manner to restore the ecosystem (Bilgili et al., 2021a; Bilgili et al., 2021b). Understanding the causes of fires and their role in the ecosystem directly affects the scope and success of restoration practices (Moore, 2005). Field studies carried out in a burned area immediately after a fire (Vallejo et al., 2012) and remote sensing (RS) methods used to monitor the burnt areas can enable the effective implementation of post-fire restoration efforts (Cocke et al., 2005) by determining the extent of fire damage and the potential for regeneration. RS is used today to obtain information about areas most affected by fire and most likely to be affected in the future (Chuvieco, 2009; Coşkuner et al., 2021). Additionally, RS improves the effectiveness, speed, and feasibility of identifying and monitoring regions at risk for forest fires (Atun et al., 2020). In particular, calculations of the normalized burn rate provide useful information on the burning degrees of burnt areas (Szpakowski and Jensen, 2019).

Major forest fires in the summer months of 2021 and 2022 had devastating effects in Türkiye, as well as in many other parts of the world and other Mediterranean countries (Kalem et al., 2022; Tavşanoğlu and Pausas, 2022). It is expected that mega forest fires will continue in Türkiye and the Mediterranean Basin in the future due to the existence of uninterrupted forest areas, the increase in the load of combustible materials in the forests, and the more extreme meteorological conditions caused by climate change (Pausas and Keeley, 2021; Tavşanoğlu, 2021). As mega-fires were occurring in Türkiye in 2021 and 2022, it became apparent that different forest ecosystems and types of vegetation had started to be exposed to fire not only at low altitudes of the Mediterranean ecosystems but also in almost all elevation zones (Kalem et al., 2022).

To adapt to the changing conditions during this new era of mega-fires, more is needed to make changes in forestry management only during and after a fire. Developing an objective and standardized rapid risk assessment system for at-risk regions has become necessary. Doing so will make it possible for people to adapt to this situation in terms of human and environmental health. When focusing on the new mega-fire process, we need to be concerned about minimizing the loss of life and property, making more sustainable use of forest assets, and ensuring the safety of wildlife and the continuation of ecosystem functions. In recent times, with the rapid advancement of technology, the detection of forest fires using RS and the identification of areas prone to fire and the assessment of fire damage have witnessed a gradual increase. As a result, there has been a surge in research studies conducted on this subject (Atun et al., 2020; Matin et al., 2017). Geographic information systems (GIS) can be utilized in combination with knowledge-based techniques and analyses based on logistic regression, fuzzy logic, analytic hierarchy process, artificial neural networks, the analytical network process, goal programming, and the random forest method can all be used, and are currently being used, in the generation of fire risk maps (Küçük and Sevinç, 2023; Novo et al., 2020; Sivrikaya and Küçük, 2022).

Mapping forest fire risk is an essential step in fire management in the short term, especially in terms of being prepared for fire during the fire season and directing fire sources from places with low fire risk to areas with higher fire risk. Additionally, in the long term, mapping the probability of fire is an invaluable tool in forest management planning to implement various fire prevention silvicultural measures that increase forest fire resilience.

In recent years, RS has become widespread in relation to high-definition and very high-definition optical remote control monitoring needs, and these strategies provide affordable multi-time and multi-band pictures of the phenomenon under consideration at a given time. Satellite sensors are among the technologies used in forest fire studies (Avetisyan et al., 2022). Fire-related applications of RS technology, pre-fire and post-fire information, fire risk mapping, combustible material mapping, burn severity assessment, and vegetation re-establishment, including post-fire are widely discussed and accepted (Stankova and Nedkov, 2016; Szpakowski and Jensen, 2019). These technologies are both cost-effective and time-saving on both regional and global scales. In addition, the development and use of new technologies and techniques increase the accuracy and efficiency of research.

In addition to providing information at a coarse scale, RS technology has enhanced methods for identifying differences in spectral behavior between burnt regions and other land use/land type categories in the vicinity. Different vegetation indices have been created considering these variances in spectral behavior. For example, one of the few methods for accurately detecting vegetation change is the NDVI index (Lazaj, 2016).

Evaluating the usability of different vegetation indices in estimating the fire risk and revealing which index provides the most effective and accurate information could provide critical support for future functional forest management efforts. To address the emerging concerns, the study focused on evaluating the feasibility of employing vegetation indices to map the fire risk in the Muğla Regional Directorate of Forestry (RDF), where the likelihood of mega-fires is expected to rise soon. By identifying the most precise index and utilizing an innovative approach to mapping, the research endeavors to furnish decision-makers and researchers with valuable insights, enabling them to enhance their efforts toward forest fire management.

2. Materials and methods

2.1. Study area

The Muğla RDF, one of the 30 RDFs in Türkiye, was chosen as the study area. It is located between 26°58′27″ and 29°46′47″ E longitude and 36°16′20″ and 38°07′36″ N latitude (cf. Fig. 1). It is surrounded by the İzmir RDF in the north, the Denizli and Antalya RDFs in the east, the Mediterranean Sea in the south, and the Aegean Sea in the west. The Muğla RDF has 1,155,914 ha of forested area; 65% of this forest area is productive, but the remaining 35% is substantially degraded. The *Pinus brutia* Ten., *Pinus pinea* L., *Pinus nigra* Arnold, *Cedrus libani* A. Rich., *Eucalyptus camaldulensis* Dehn., *Liquidambar orientalis* Mill., and *Quercus* spp. are the most common tree species in the Muğla RDF. Summers are hot and dry in the study region, which has a Mediterranean climate, while winters are moderate and wet. The region is also mountainous, and the Mediterranean climate gives way to a continental climate as one enters the interior and the altitude increases. The mean annual precipitation is 1209 mm, the mean number of rainy days is three days, and the average summertime high temperature is 32 °C, with the mean yearly temperature being 15 °C (GDM, 2022).

Agricultural activities are intense, and agricultural areas are intertwined with forest areas in Muğla province. Because the site is one of the most popular tourist regions of Türkiye, the population is dense, and the transportation network is extensive. The most prevalent tree species in the Muğla RDF is the *Pinus brutia* Ten., one of the most vulnerable species to fire. There is also a dense understory and much litter in the

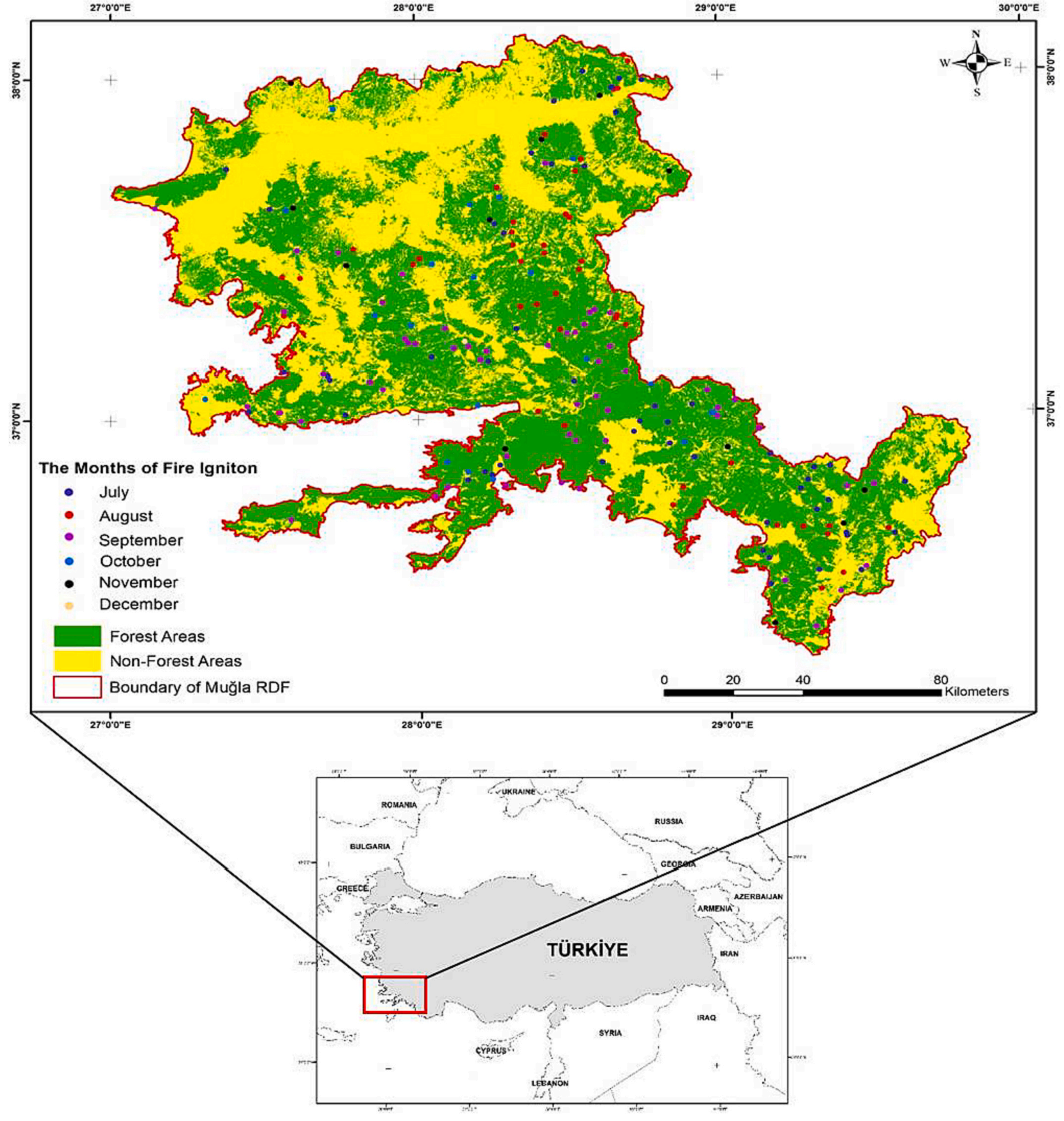

Fig. 1. The study area in Muğla, Türkiye; forest and non-forest areas, and the months of fire ignition points.

forests. In addition, the Muğla RDF is the most sensitive of all regions in Türkiye to forest fires. It was chosen as the study area because it embodies all forest fire risk factors. To provide a current overview of the fire situation, we can say that 3312 forest fires occurred in this region between 2012 and 2021, resulting in the burning of 57,241 ha. In 2021 from July 5 to the end of the year, 195 forest fires occurred, and 51,024 ha were burned. In addition, when forest fires in 2021 were classified according to size, nine were found to be mega-fires, defined as fires that burn >500 ha; these nine fires burned 49,748 ha of the forest area (GDF, 2022).

2.2. Data

Landsat 8 OLI satellite images were downloaded from the dedicated web page of the US Geological Survey (U.S. Geological Survey, 2022 - https://earthexplorer.usgs.gov/). In this study, three Landsat 8 images acquired in June and July 2021 were used to estimate the fire risk. Information on these images is given in Table 1. In this study, six spectral bands were used. The spectral bands of each image were merged to create a single image, and this image was extracted for the areas to be studied. Atmospheric correction is required to minimize the negative impact of topographic factors, shadow effects, and atmospheric effects

Table 1
Parameters of Landsat 8 satellite images.

Sensor	Path/Row	Acquisition Date	Cloud Cover (%)	Band Name	Central Wavelength (μm)	Spatial Resolution (m)
Landsat 8 OLI	180/34	July 4, 2021	2.09	Blue	0.45–0.51	30
	179/34	June 27, 2021	0.19	Green	0.53–0.59	
	179/35	June 27, 2021	2.30	Red	0.64–0.67	
				NIR	0.85–0.88	
				SWIR 1	1.57–1.65	
				SWIR 2	2.11–2.29	

in satellite images (Al-hasn and Almuhammad, 2022; Atun et al., 2020; Kalkan and Maktav, 2018). For this reason, the first action taken was to perform atmospheric correction on the images in QGIS.

Fires that occurred later than the satellite image dates were used to test the accuracy of the developed model. For this reason, 195 historical fire ignition points with a burnt area >2 ha in Muğla RDF in 2021 from July 5 to the end of the year were used to assess the accuracy of fire risk maps. The General Directorate of Forestry (GDF) obtained the fire ignition points. Most of these fires occurred in August, totaling 59 fire incidents. In July, six fires exceeding an area of 20 ha and three mega fires surpassing 500 ha in size were recorded. Similarly, during the subsequent month of August, fifteen fires and six mega fires were reported. The distribution of fires that occurred in the study area in 2021 from July 5 to the end of the year by month is given in Fig. 2. The accuracy of the fire risk maps derived from the vegetation indices was evaluated using these fire ignition points. The data averages for Turkish fires in 2021 were considerably higher than those for the ten years before 2021 (GDF, 2022).

2.3. Vegetation indices and fire risk mapping

A single spectral index is not sufficient for generating a fire risk map (Chen et al., 2011). To determine which vegetation indices were the most accurate and, therefore, would be the most valuable for mapping forest fire risks, the performances of different vegetation indices needed to be evaluated and compared. Some information on vegetation indices, widely used in monitoring forest fire risks and severity, was gathered by perusing the relevant literature (Gao, 1996; García and Caselles, 1991; Smith et al., 2007; Tucker, 1979). This study used four different vegetation indices (Table 2). Vegetation indices were calculated using a Raster Calculator tool according to the relevant formulas and used to produce the fire risk maps. The vegetation index values were divided into four classes with different susceptibility classes, namely low, medium, high, and extreme, using Jenks' natural break classification method in ArcGIS 10.6. The Jenks Natural Breaks categorization (or optimization) system is a data categorization methodology that aims to maximize the organization of a given set of values into distinct and meaningful classes. A natural class refers to the class range considered the most ideal and is observed to occur “naturally” within a given dataset. A class interval consists of elements exhibiting comparable attributes, constituting an inherent grouping within a given dataset. The approach employed in this study is to minimize the variance within classes while simultaneously maximizing the variance across types (Jenks, 1967; Liu and Duan, 2018). Numerous studies have employed natural break (Jenks) and quantile approaches to classify fire risk maps (Gheshlaghi et al., 2020; Moayedi et al., 2020; Mohajane et al., 2021; Sivrikaya et al., 2022; Sivrikaya and Küçük, 2022; Tang et al., 2020; Tiwari et al., 2021). At last, the data from the four vegetation indices was used to draw fire risk maps. Fire risk class range values for vegetation indices are given in Table 3.

Table 2
Vegetation indices used for fire risk mapping in association with Landsat 8 OLI images.

Vegetation Index	Formula	Reference
NBR	(NIR-SWIR2)/(NIR + SWIR2)	García and Caselles, 1991
NBRT	(NIR-SWIR2*T)/(NIR + SWIR2*T)	Smith et al., 2007
NDVI	(NIR-Red)/(NIR + Red)	Tucker, 1979
NDWI	(NIR-SWIR1)/(NIR + SWIR1)	Gao, 1996

NIR, near-infrared; SWIR, shortwave-infrared.

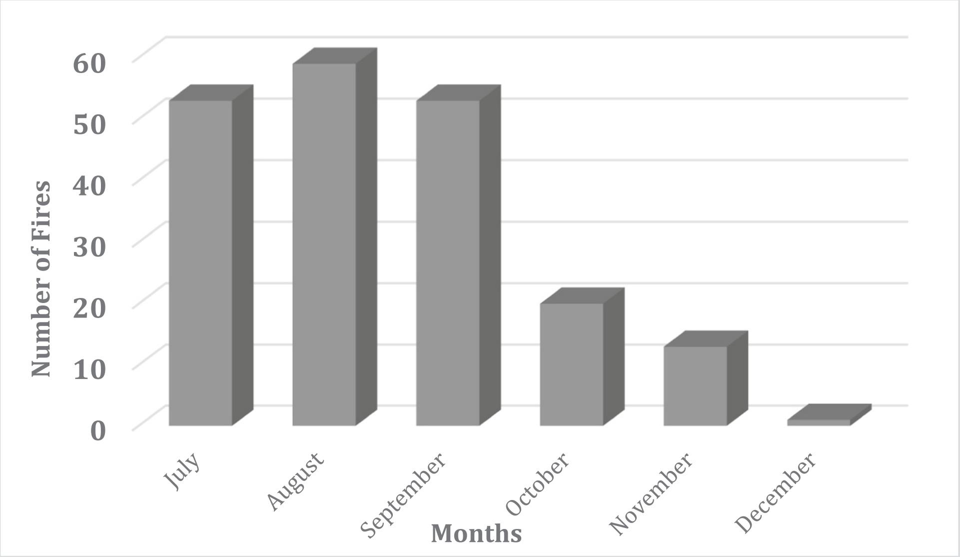

Fig. 2. Distribution of forest fire numbers in the study area by months in 2021

Table 3
Burnt areas in hectares and numbers of forest fires according to vegetation indices.

Vegetation Index	Fire Risk Class	Risk Class Range	Area (ha)	Percentage of Total Area (%)	Number of Fires	Percentage of Total Fires (%)
NBR	Low	< 0.07	335,997.5	16.4	4	2.1
	Medium	0.07–0.14	640,045.7	31.3	4	2.1
	High	0.14–0.22	741,251.9	36.3	71	36.3
	Extreme	> 0.22	326,054.9	16.0	116	59.5
NBRT	Low	< −0.56	669,447.5	32.8	4	2.1
	Medium	−0.56 to −0.50	743,095.3	36.4	38	19.5
	High	-0.50 – −0.43	522,245.1	25.6	111	56.9
	Extreme	> −0.43	108,562.2	5.3	42	21.5
NDWI	Low	< −0.01	413,416.5	20.2	2	1.0
	Medium	−0.01–0.05	700,797.9	34.3	13	6.7
	High	0.05–0.12	636,695.3	31.2	77	39.5
	Extreme	> 0.12	292,440.3	14.3	103	52.8
NDVI	Low	< 0.13	191,225.9	9.4	1	0.5
	Medium	0.13–0.21	738,956.9	36.2	11	5.6
	High	0.21–0.29	891,182.5	43.6	116	59.5
	Extreme	> 0.29	221,984.7	10.9	67	34.4

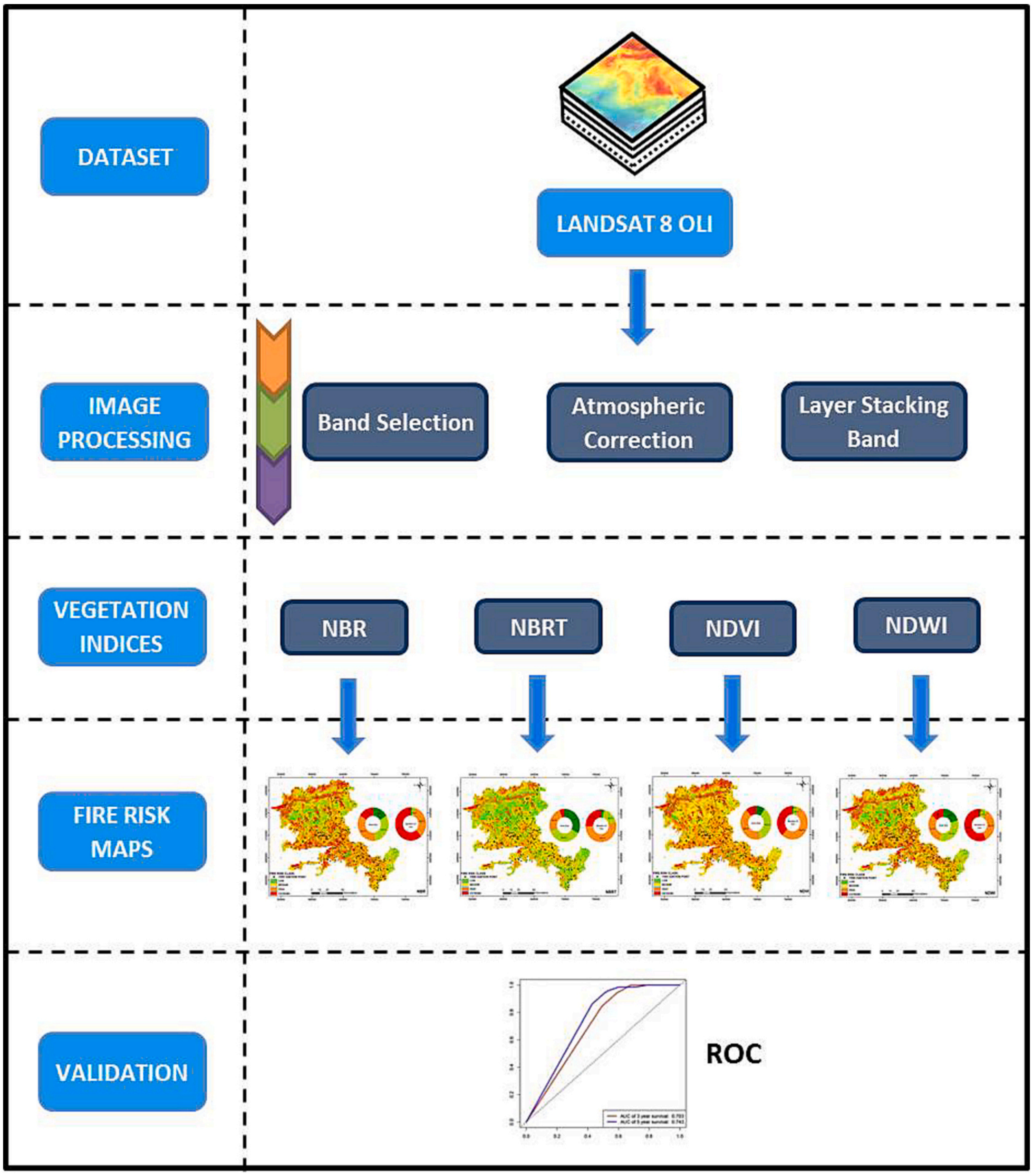

Fig. 3. Methodology of fire risk mapping using Landsat 8 imagery and the vegetation indices.

2.4. Validation of the accuracy of fire risk maps based on vegetation indices

Validating the accuracy of the forest fire risk maps developed using various vegetation indices was one of the most critical steps of this study. The receiver operating characteristic (ROC) is widely used in landslide, forest fire risk, and beetle infestation mapping (Hussain et al., 2022; Özcan et al., 2022; Salavati et al., 2022; Sevinç et al., 2020; Sivrikaya et al., 2022). ROC analysis uses a graph that plots the true positivity on the vertical axis and the false positivity on the horizontal axis. The area under the curve (AUC) value close to 1 indicates that the model's accuracy is high, and the number of 0.5 denotes that the model's accuracy is relatively low. The AUC score can be categorized between 0.5 and 1.0 as poor, moderate, good, very good, and excellent with 0.1 intervals (Gheshlaghi et al., 2020). The ROC analysis was used in this study to evaluate the accuracy of risk maps created according to different vegetation indices. Fig. 3 displays the study's flowchart.

3. Results and discussion

Four vegetation indices, NBR, NBRT, NDVI, and NDWI, were calculated from Landsat 8 images to determine the fire risk. Based on the vegetation indices, the fire risk was categorized into four categories: low, medium, high, and extremely high (cf. Figs. 4 and 5). The fire information on each fire risk category is shown in Table 3. Approximately 96% of the total forest fires (i.e., 187 of 195 forest fires) took place in areas categorized as having a high fire risk (i.e., the high and extremely high categories) on the fire risk map based on NBR. Approximately 52% of the study area (1,067,306.8 ha) was in high-risk and extremely high-risk areas. 335,997.5 ha was not at risk for forest fires, and only four occurred in this area. In the fire risk map based on NBRT, 2.1% of a total of 195 forest fires occurred in low-risk areas, 19.5% in medium-risk areas, 56.9% in high-risk areas, and 21.5% in extremely high-risk areas. However, 743,095.3 ha (or 36.4% of the total study area) were in medium-risk areas, and most fires (111 fires) were seen in high-risk areas. According to NDWI, 39.5% of a total of 195 forest fires occurred in high-risk areas and 52.8% in extremely high-risk areas. Approximately 46% of the study area and about 92% of the forest fires were in high-risk areas. Of 195 forest fires, 0.5% occurred in low-risk areas, 5.6% in medium-risk areas, 59.5% in high-risk areas, and 34.4% in extremely high-risk areas, according to NDVI. 891,182.5 ha (or 43.6% of the total area studied) was in high-risk areas, and the most significant number of fires (116) was seen in high-risk areas.

When the vegetation indices were compared regarding fire risk, the percentages of areas with a high fire risk were 30.9% in NBRT, 45.5% in the NDWI, 52.3% in NBR, and 54.5% in NDVI. >90% of the fires were in areas with a high or extremely high fire risk based on NBR, NDWI, and NDVI. This result reveals that the study area was sensitive to fire, and these three vegetation indices accurately predicted the fire risk. The study's findings confirmed the conclusions of several experts who claimed that burnt regions and fire ignition points were quite accurately predicted as being in high-risk areas on fire risk maps (Eskandari, 2017; Nasiri et al., 2022; Sivrikaya and Küçük, 2022). The results showed that the fire risk maps created utilizing NBR, NBRT, NDWI, and NDVI were accurate and consistent. Sivrikaya and Küçük (2022) tried to estimate the fire risk using the analytic hierarchy process. The researchers found that most fires (43.6%) occurred in extremely high-risk areas. Eskandari et al. (2013) stated that the greatest number of forest fires (51%) happened in extremely high-risk areas. Colak and Sunar (2020) conducted a risk assessment of forest fires using Landsat 8 imagery. They concluded that 22% of the burned areas were in the high-risk class and 78% in the medium-risk class.

One of the most critical steps of the study was to test the accuracy of fire risk maps based on vegetation indices to see which of the indices was most accurate. The accuracy of fire risk maps based on NBR, NBRT, NDWI, and NDVI was estimated using ROC analysis in this study (cf. Fig. 6). Historical fire ignition data were used to confirm the maps. The ROC analysis revealed that the AUC values ranged between 0.810 and 0.842. According to the ROC curve, the most accurate index was NBR, and the least accurate was NDVI. When the AUC values were evaluated, it was seen that NBR and NDWI were very accurate, and NBRT and NDVI were less accurate yet still helpful (see Fig. 6). It can be concluded that NBR and NDWI produced more reliable results than NDVI and NBRT for fire risk mapping. In other studies, the accuracy of the ROC curve for fire risk maps was 76.6% (Adab et al., 2013), 86.8% (Jaafari et al., 2017), 89.4% (Nguyen et al., 2018), 78% (Sivrikaya and Küçük, 2022), 82% (Gheshlaghi et al., 2020), 80% (Ghorbanzadeh et al., 2019), and 94% Kantarcioglu et al. (2023). Adab et al. (2013) carried out a study on fire risk mapping in Iran using GIS and RS and the Fire Risk Index (FRI), Structural Fire Index (SFI), and Hybrid Fire Index (HFI). The accuracy of the indices was evaluated through fire data obtained from MODIS imagery and ROC analysis. The ROC values were 0.76 for HFI, 0.68 for SFI, and 0.64 for FRI. Karimi et al. (2021) determined the fire risk using six vegetation indices: NDVI, moisture stress index (MSI), weighted difference vegetation index (WDVI), optimized soil adjusted vegetation index (OSAVI), global vegetation moisture index (GVMI) and NDWI, and images from Landsat 8. The data from the vegetation indices and the information on fire ignition data acquired from MODIS were used to assess the accuracy of the fire risk map. The overall classification success was 94.7%, and the kappa value was 0.9170, with NDWI being the most accurate.

In this study, it has been demonstrated that some vegetation indices based on images from the Landsat 8 can be used in fire risk mapping and that NBR, NBRT, NDWI, and NDVI vegetation indices successfully provided data for mapping. Many studies have shown that NBR performed very well in determining the fire risk and severity (Dos Santos et al., 2020; Key and Benson, 2006; Pádua et al., 2020; Veraverbeke et al., 2011). Vegetation exhibits a low absorption and high reflectance and transmittance of NIR wavelengths, whereas it has a low reflection and transmittance and a very high absorption of SWIR wavelengths. In areas affected by fires, recently burned zones have a high reflectivity of the SWIR band and a relatively low reflectance of the NIR band. (Pepe and Parente, 2018; Roy et al., 2016). With RS images such as Landsat 8, NBR has been successfully used to detect burned areas and fire risk categories (Vanderhoof et al., 2021). NBR is a convenient vegetation index for detecting forest fires and fire risk in the forest ecosystem (Keeley, 2009; Parker et al., 2015). Epting et al. (2005) stated that NBR was useful in determining the fire area and fire severity, especially in fires occurring in forest areas. In contrast, Roy et al. (2006) found that NBR was ineffective in determining fire areas and fire severity in a study conducted in Australia, South America, South Africa, and Russia. Previous studies have demonstrated that NBR's effectiveness differed between ecoregions and plant species (De Santis et al., 2010; Murphy et al., 2008). Therefore, there is a need to test NBR in different forest ecosystems (Kokaly et al., 2007; Veraverbeke and Hook, 2013).

NDVI is one of the most prevalent vegetation indices used to predict fire severity in both single-time images (post-fire) and two-time images (pre-fire and post-fire differences) (Escuin et al., 2008; Veraverbeke et al., 2011). Chung et al. (2019) identified fire-affected areas with NDVI and NBR through data obtained from Sentinel 2 images (for 2018 to 2019) to assess wildfire damage in coniferous forests in South Korea. They found that NDVI provided better results by calculating the kappa statistics. García-Llamas et al. (2019) made estimates using dNDVI (differenced NDVI) and dNBR (differenced NBR) indices and images obtained from the Sentinel 2 and Landsat 8 satellites to evaluate fire damage in Spain. It was confirmed that NBR is a more effective tool for assessing fire severity, and it was observed that when NBR utilized high-resolution Sentinel 2 images, the results were superior to those obtained from Landsat 8 images.

Nguyen et al. (2018) employed three distinct machine learning algorithms, namely Support Vector Machine, Multilayer Perceptron Neural Network, and Random Forests, to evaluate fire risk in tropical

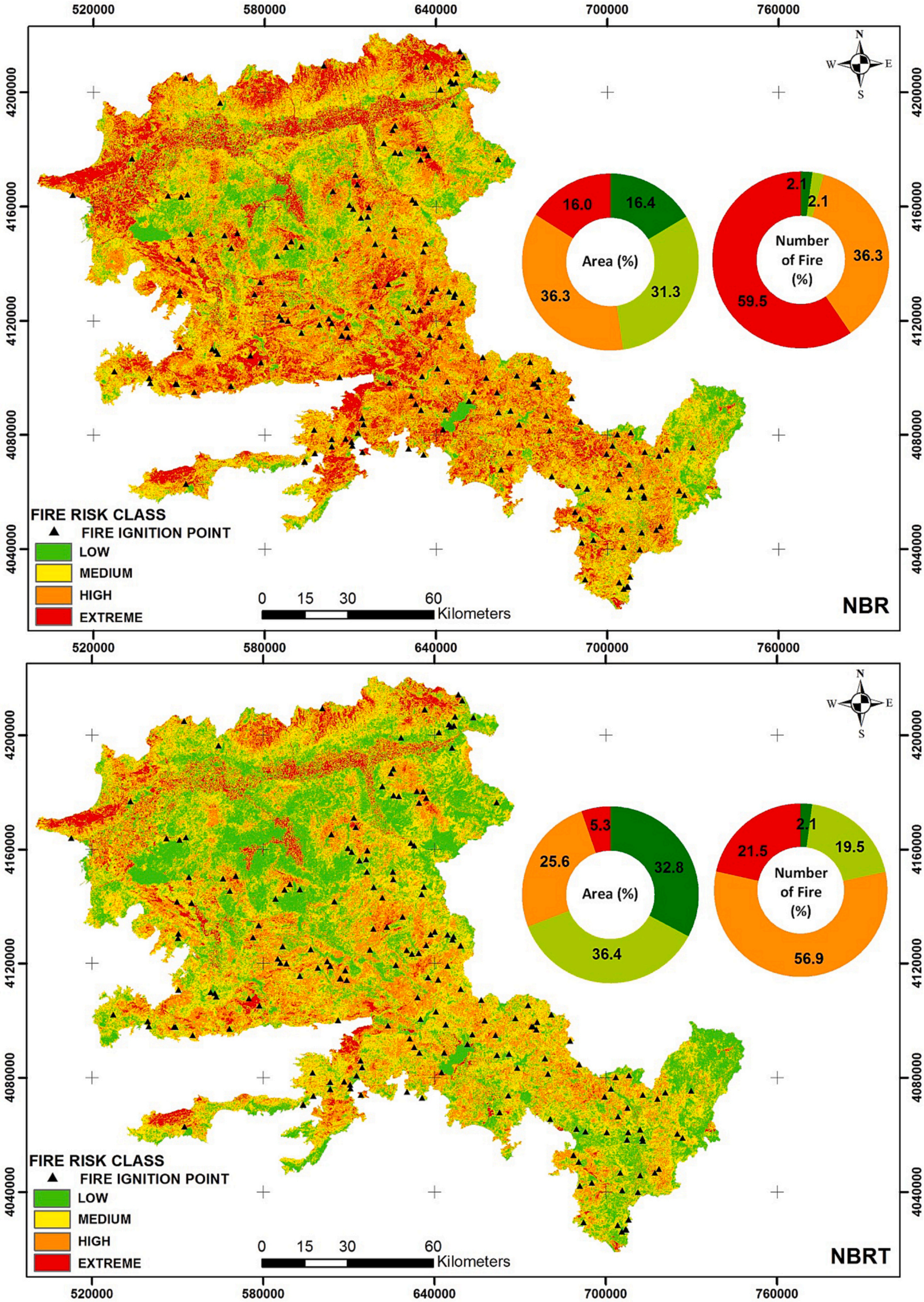

Fig. 4. Fire risk maps for NBR (top) and NBRT (bottom).

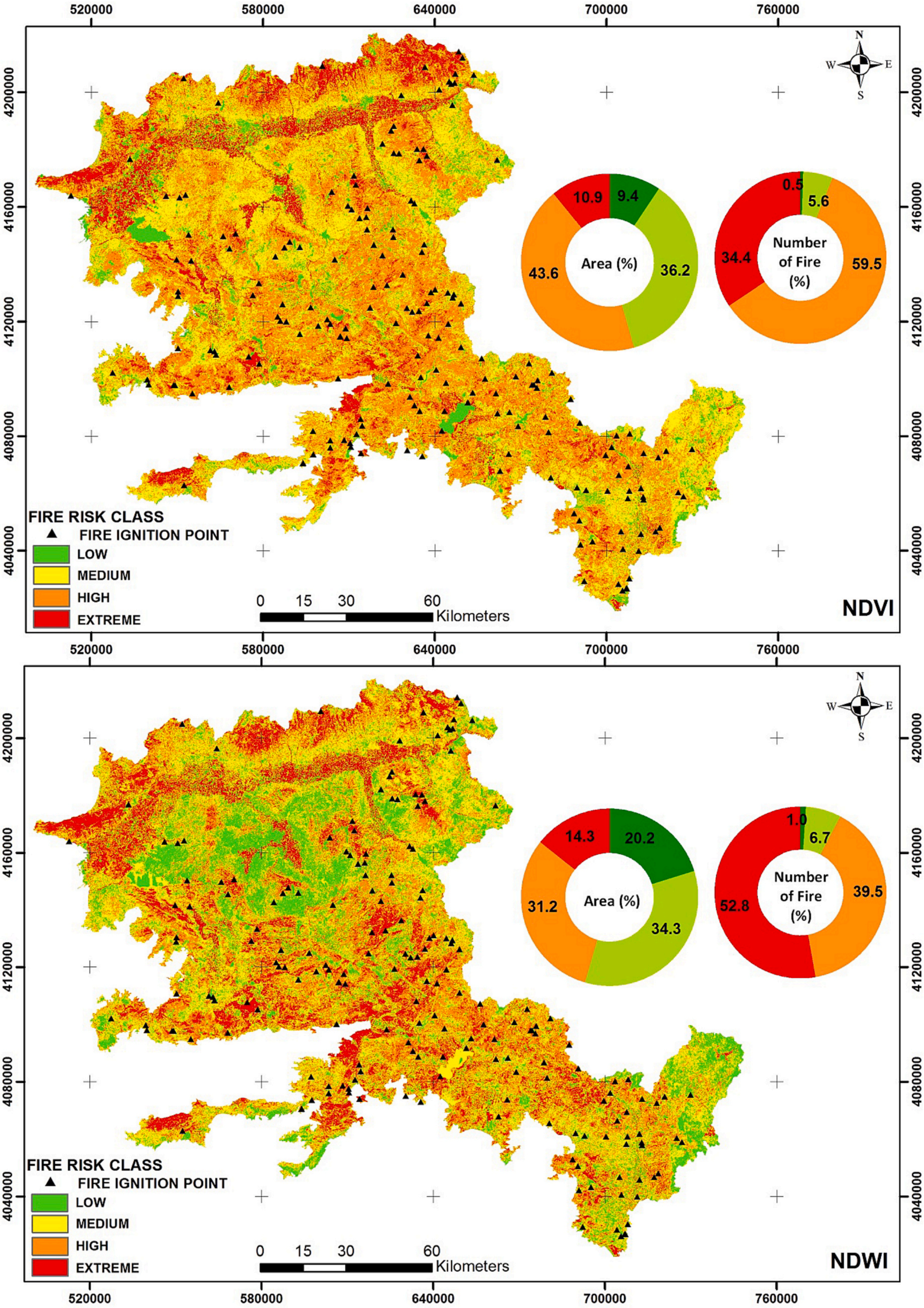

Fig. 5. Fire risk maps for NDVI (top) and NDWI (bottom).

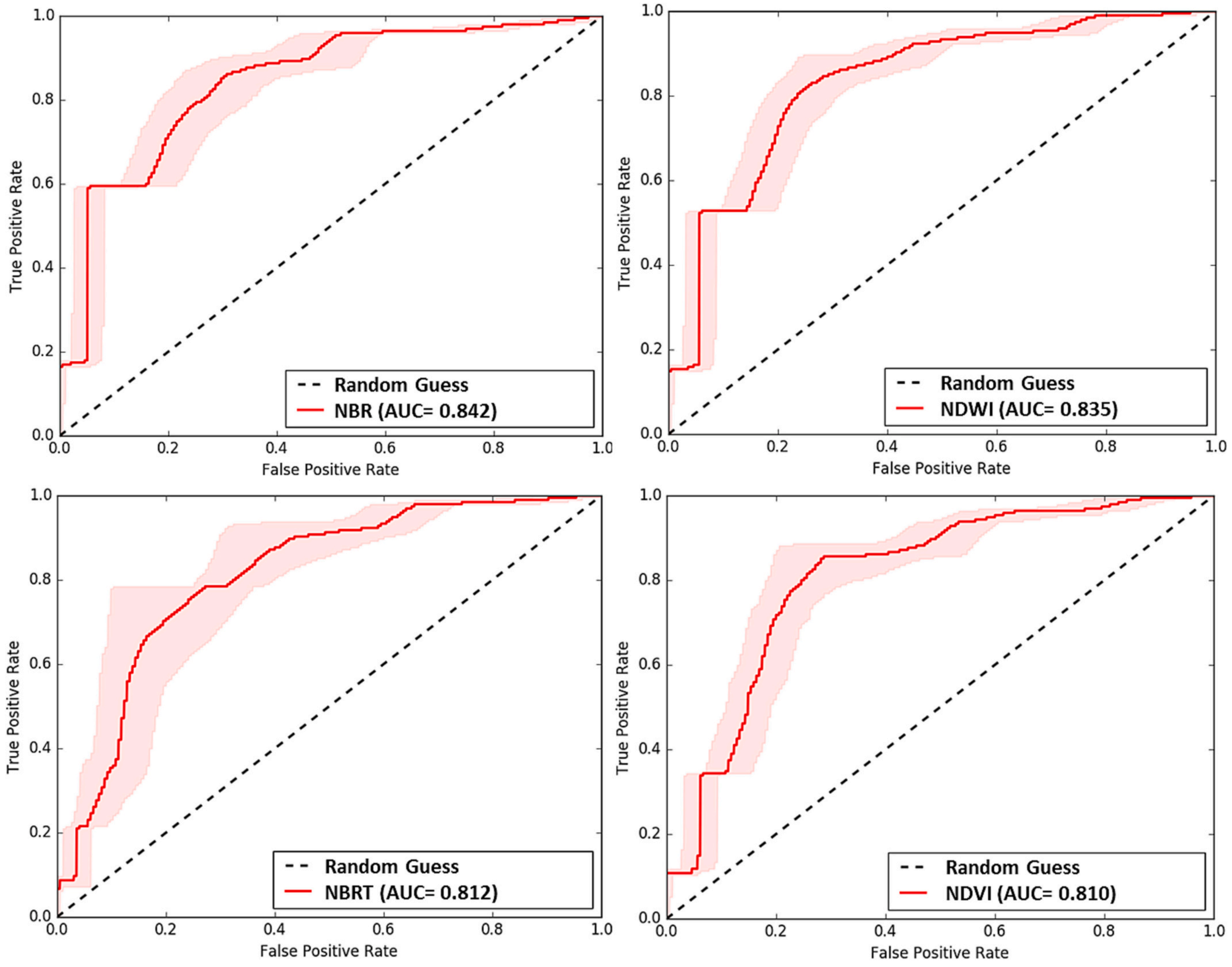

Fig. 6. ROC curves of fire risk maps according to NBR, NDWI, NBRT, and NDVI.

forests using 564 fire ignition points and ten different variables. The Multilayer Perceptron Neural Network (AUC = 0.894) demonstrated the best performance, and NDVI was among the variables analyzed. Correlation analysis of forest fire ignition points and variables showed that the NDVI ($r = 0.51$) index was the most reliable predictor of fire occurrence.

In contrast, Iban and Sekertekin (2022) developed a fire risk map using seven machine learning techniques, RS data, and GIS. Thirteen different variables affecting forest fire risk were employed in this study. The accuracy of the maps obtained using seven machine-learning techniques ranged from 0.817 to 0.879, as measured by AUC values. NDVI was among the variables used in this study. The correlation analysis showed that the elevation variable ($r = 0.626$) had the highest correlation with fire risk, while NDVI ($r = 0.256$) exhibited a low correlation. These results demonstrate that the variables affecting forest fires differ based on forest ecosystems and tree species, particularly regarding NDVI.

Afira and Wijayanto (2022) conducted a study to identify burned areas using pre- and post-fire Sentinel 2 satellite images and seven vegetation indices (dNDVI, dCSI, dBAIS2, dNBR, dNBR2, dSAVI, and dMIRBI) with two machine learning techniques (XGBoost and Random Forest). The XGBoost machine learning technique achieved the best performance with an AUC value of 0.97, and the dMIRBI, dNBR2, and dNBR indices were the most significant contributors to the model. The study also achieved satisfactory results in identifying fire areas using pre- and post-fire data. Similarly, our research used post-fire data and found that NBR and NDWI indices effectively identified fire areas.

Morante-Carballo et al. (2022) evaluated forest fires using Landsat 8 imagery and four vegetation indices (dNDVI, dNBR, NBR, and NDVI). The NDVI provided vegetation density and type information, while NBR was useful in calculating the burned area. The indices dNDVI and dNBR contributed to determining the degree of fire severity by comparing the situation before and after the fire. The study employed 31 fire data to determine the success levels of the indices, with a 99.1% success rate achieved in high and extreme fire severity classes using dNBR and dNDVI indices.

Van Le et al. (2021) conducted a study using Landsat 8 OLI satellite imagery to determine the risk of forest fires in the Tropical climate region. The study utilized 12 variables that affect fire and produced a highly accurate spatial prediction of forest fire risk (AUC = 0.894). Among the factors affecting forest fires, NDVI, NDWI, and NDMI indices were the most influential. These results are consistent with those found by Bui et al. (2017) in their investigation.

Tian et al. (2022) conducted a study on the spread of forest fires using variables affecting fire and NBR and dNBR indices. The combination of NBR and dNBR indices can precisely extract fire lines and detect fire conditions, a finding that is consistent with the results of Mazuelas Benito and Fernández Torralbo (2012) study. Additionally, Sobrino et al. (2019) analyzed the relationship between vegetation indices (NBR, NDVI, dNBR, and dNDVI) derived from Landsat 8 and Sentinel 2 images and fire ignition data through regression analysis. They found better correlations between the dNBR and dNDVI indices derived from Sentinel 2 images and fire ignition data compared to Landsat 8. In a study conducted by Liu et al. (2023), four different indices (NDVI, NBR, NDMI, and EVI) obtained from Landsat satellite images were used to identify burned areas. When the results were examined, it was observed that the NDVI indice better results compared to the other indices.

Upon comparing our study with previous research, it was observed that the success rates of the correlations between four distinct indices and field data of burn severity were lower. This may be because fire indices derived from satellite imagery, typically comprising two-time data (pre-fire and post-fire), better align with field data of burn severity. However, it is not always possible to attain satisfactory results using fire indices based on two-time data in these studies, as evidenced by certain studies wherein low correlations were found between fire data and fire indices.

For instance, Veraverbeke et al. (2011) found a success rate of $R^2 = 0.65$ between dNBR and burn severity field data. Our study found that NBR and NDMI indices yielded superior results for evaluating fire severity than NDVI. Moreover, a nonlinear relationship was observed between dNBR and dNDVI and field data of burn severity, while a linear relationship was observed between dNDVI. Notably, using the dNBR index, the best result for determining fire intensity was in olive groves ($R^2 = 0.95$), followed by coniferous forests ($R^2 = 0.72$), broadleaf forests ($R^2 = 0.66$), and the lowest result was observed in scrubland ($R^2 = 0.56$).

In a study by Escuin et al. (2008), the relationships among fire intensities were investigated using NDVI and NBR indices obtained from Landsat TM/ETM+. It was observed that NBR produced better results than NDVI, which is consistent with our results. Similar results were obtained in the study by Hoy et al. (2008), where the relationships between fire intensities were analyzed using difference indices, and it was concluded that dNBR was superior to dNDVI.

The results obtained in the studies to determine the fire severity using various indices vary according to the type of combustible material in the fire area (Veraverbeke et al., 2011). In the study conducted by Epting et al. (2005), high correlations were found between field data of burn severity and indices in forest areas, but the same relationships could not be found in scrubland. Another study by Allen and Sorbel (2008) found different relationships between field data of burn severity and dNBR in coniferous forests, broadleaf forests, and tundra areas. In the study by Zhu et al. (2006), on the other hand, achieved better results in forested areas than in less sparse areas.

The advantage of fire difference indices calculated using two-time satellite images (pre-fire and post-fire) over fire indices obtained using single-time satellite images is that they clearly separate unburned sparse vegetation areas and burnt areas in the indices obtained from two-time images. However, it is very difficult to determine this situation in single-time satellite images (Veraverbeke et al., 2011). At the same time, the success level of the relationships between the indices obtained using two-time satellite images and the field data of burn severity depends on the time of the post-fire image. Another study by Veraverbeke et al., 2010 aimed to determine the fire severity using dNBR. Two satellite images were used after the fire, and two dNBR indices were calculated. The relationships between field data of burn severity according to both calculated indices were investigated. The results concluded that the dNBR ($R^2 = 0.72$) index obtained from the image used early after the fire gave better results than the dNBR ($R^2 = 0.56$) index obtained from the image used late after the fire. Especially in the case of using two-time satellite images in such fire areas, it would be beneficial to use the earliest satellite imagery after the fire due to the rapid recovery of vegetation in the Mediterranean ecosystem. However, the primary drawback of post-fire indicators is their poor performance in differentiating burnt regions from bare soil and sparsely vegetated areas (Heredia et al., 2003).

4. Conclusion

Our study demonstrated that four vegetation indices, the NBR, NBRT, NDWI, and NDVI, generated from Landsat 8 OLI images could assess fire risks in forests. Of these four, the best result was obtained from the NBR. The results can be used to assist in planning in places vulnerable to wildfires, particularly in forest management strategies in the Mediterranean region. When the NBR, NBRT, NDWI, and NDVI indices obtained from Landsat 8 OLI satellite images were used, it was possible to assess the risk of forest fires in the case study area. Thus, the risk categories for future fires in this region could be estimated with this method.

The utilization of vegetation indices in this research has the potential to facilitate the evaluation of fire susceptibility in the designated region and similar forest ecosystems. Fire risk maps would enhance comprehension of the spatial distribution of fire risks in places prone to fire incidents. This will facilitate forest managers in optimizing resource allocation and implementing more effective and efficient forest fire management techniques. In addition, this research will provide valuable assistance to decision-makers in implementing proactive measures to mitigate the occurrence of forest fires within the designated study area, as well as in other comparable forest ecosystems. More studies are needed to test and validate fire risk maps based on remote sensing data in different forest ecosystems to better reveal the ecological effects of fire in fire-sensitive forest ecosystems. In future studies, the generation of fire risk maps that exhibit enhanced efficacy in fire-sensitive forest ecosystems can be achieved by utilizing diverse remote sensing data characterized by high spatial resolution, particularly Unmanned Aerial Vehicle (UAV) images incorporating multispectral bands. Additionally, employing various modeling techniques such as artificial neural networks, deep learning, and logistic regression can further contribute to refining these maps.

CRediT authorship contribution statement

Fatih Sivrikaya: Writing – review & editing, Writing – original draft, Software, Methodology, Conceptualization. **Alkan Günlü:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Ömer Küçük:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Okan Ürker:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization.

Declaration of competing interest

The authors state that they are aware of no personal or financial conflicts that would have seemed to have an effect on the research shown in this study.

Data availability

Data will be made available on request.

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