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Determination of Spatial Distribution of Damage Intensity of Tınazlı-Izmir Forest Fire Using Remote Sensing Indexing Techniques

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Abstract

Forest fires is one of the leading natural disasters that endangers the living creatures and the environment in forests. Every year, millions of forested areas burn out in the world and Turkey is one of the mostly affected countries in terms of forest fires. In this study, forest fire started near Karabaglar at 18th of August, 2019 was investigated w.r.t spatial distribution of forest fire damage intensity. Using Landsat 8 satellite images, spatial distribution and damage intensity of the fire in the area was detected by using five different remote sensing indexing methods (dNDVI, dNBR, dNBRT, dBAI, RBR) and the fire area was then mapped for this purpose. Thus, burn damage intensity distribution in terms of forest damage density in the region was estimated and the distribution of burn damage intensity was mapped w.r.t density of damaged trees in the forested area. In addition to this, performance analyses of these indexes are also given. As a result of the analysis, it is found that the most convenient results come from the RBR analyses with a 99% of consistency when they are compared with the data of burned trees along with spatial data obtained in the field by the General Directorate of Forestry. Since this study is focused the spatial extent and the damage caused by the fire in terms of tree intensity, fuel loss which requires tree types to be collected was not estimated. The remote sensing technique has also demonstrated its ability to distinguish fire damage intensity levels w.r.t tree density distribution, even including undamaged sections in an entire forest fire damage zone, in a way that cannot be completely done in a field work.

Keywords: Forest fire damage assessment, burn damage intensity analyze, NDVI, NBR

Introduction

Forest is natural resource at the top of the ecosystem formed by living and non-living environment on Earth. Forest is also an ecosystem where trees and plants, animals, organisms living in the soil and non-living environment interact with each other (Sabuncu and Ozener 2019). Forest fires are a major natural disaster that poses a threat to both living and non-living components of the environment, including the existence of forests and their ecosystems (Keeley 2009). Forest fire is also an important natural disturbance that has a great impact on the environment, people, weather and climate (Li et al. 2003). A fire in a forest emerges when the photosynthesis process occurs in the opposite direction than it is performed by the vegetation normally in the forest (Lentile et.al 2006). During a forest fire, the energy stored in the forest trees by photosynthesis is released by fire (Cansler and McKenzie 2012). Three elements are also needed for the fire to occur: oxygen, heat and fuel. The occurrence of forest fires depends on the availability of these three elements in the same environment at the same time in appropriate proportions. In the absence of any of these elements, a fire does not occur (Corumluoglu et al. 2015; Mashhadi and Alganci, 2021; Wu et al., 2022).

Since Mediterranean climate dominating the Mediterranean and Aegean coasts of Turkey causes long and dry summer days (Erlat et.al 2022, Topçu 2022). Number of forest fires is high in the Aegean, Mediterranean and Marmara regions in Turkey exposed to their regional climate (Yeşilköy and Şaylan 2022). Therefore, 41% of the forest fires in Turkey in the Aegean region, 24% in the Mediterranean region, 22% in the Marmara and the other 13% occur in the other regions (Doganay 2011). According to the statistics obtained from the General Directorate of Forestry for 2018, more than 90% of forest fires have been caused by human and less than 10% have been caused by natural causes in the country. The most important reason of human-caused forest fires is negligence. Millions of hectares of forest areas are disappearing every year in the country because of forest fires. Forest fires also cause the death of humans and animals and enormous amount of economic losses. Therefore, it is necessary to determine the extent of damage after forest fires, to evaluate the economic losses, to monitor the changes on the land, the total amount of all losses and to model the damage and then to model the atmospheric and climatic effects of the fire in the region (Potapov et al. 2008). For this reason, mapping forest fire damages is an important task to be done after any forest fire happens (Comert et al. 2017).

In recent years, the most contemporary technique used for such purposes is remote sensing. Thus, satellite images obtained by remote sensing technology are used to detect burned areas and assess the amount of damage after a forest fire happens (Zhang et.al 2011). Fire effected areas are determined by examining the images obtained by remote sensing even without going to the land. Thus, fire damage assessment with low cost is performed in the areas exposed to fire in a short time without being in the field by the support of remote sensing. Remote sensing is the best tool for mapping burned areas in large and inaccessible areas in the case of forest fires (Gale et al. 2020). Changes in the spectral characteristics of the land cover before and after the fire are predicted through analyzing data obtained by remote sensing. The data obtained by remote sensing are of high temporal resolution and provide the observation of large surfaces. For this reason, they are used as the most effective source of information on fire projects (Shimabukuro et al. 2020). Therefore, remote sensing is used in many areas such as fire detection, fire risk mapping in forest fires, burn damage intensity assessment, damage extension and damage intensity distribution. On the other hand, forest fire damage intensity analyses need fuel types of forest trees and therefore, a damage intensity map appears totally different than the damaged trees' intensity distribution map which analyses only tree intensity distribution without accounting the tree types. So that, such analyses provide a quick sight for the extension of the forest fire and as an estimation on how fire damage intensity distributes in terms of tree distribution density in the forest (Cansler and McKenzie 2012). Afterword, burn damage intensity analyses can be focused on by accounting the forest tree types distribution in the burned areas. Here in this research, the only forest fire damage intensity analyses were studied.

The use of multi-spectral analysis is very useful in determining burned forest areas in case of large wild fires. Landsat data are also the most suitable satellite data for these sorts of studies (Rozario et al. 2018). Burn damage map and spatial distribution map of wild fire effected areas are used to reduce the harmfully effected and damaged areas after the forest fires. In addition, the effects of forest fires on wildlife and plant communities can then be evaluated according to creating and analyzing burn damage intensity maps (Allen and Sorbel 2008). Many indices are used to obtain burn intensity maps. Even dough there is no certain evidence of which index performs the best (Filipponi 2018). NBR and dNBR are among the indexes preferred while producing burn intensity maps in this study. Burned areas are separated from unburned areas with these indices. In this way, it gives the opportunity to distinguish burned trees w.r.t density levels after a wild fire (Murphy 2008).

In this study, the forest fire area exposed to fire on the 18th of August, 2019 in Karabaglar and then expanded to Menderes and Seferihisar region was investigated. The burned areas caused by forest fire in the Menderes region were first detected as forest fire damage areas by using Landsat 8 satellite images. Maps showing the fire damage in different degrees were produced with remote sensing data obtained before and after the fire.

Materials and Dataset

Study Area

The forest fire which is subject to this study started at 12:42 in a region near Tinazli on 18th of August, 2019. Tinazli is in the territory of Karabaglar district of Izmir province, located on the Aegean Sea coast at Izmir Gulf. Later, it expanded to Menderes and Seferihisar districts. Forest fire; it was mostly effective in Menderes District, Catalca Village, Yeniköy District and Seferihisar District, Kuyucak, Eski Orhanlı, Yeni Orhanlı and Beyler neighborhoods (Fig.1). The fire lasted in 53 hours according to official records and it was taken under control at 17.42 on 20.08.2019 (TOD 2019).

In the initial stage of the fire, the climate conditions are in those; the temperature is 35 degrees Celsius, the relative humidity is 29%, and the wind speed is 60-80 km / h. The east by north wind dominated the region. However, the wind direction varied throughout the forest fire. According to the investigations made in the fire area, the fire first appeared in a high area and proceeded in the northwest direction (TOD 2019). The study area shown in the images below is obtained from satellite data as seen in Figure 1. Almost all of the burning area consists of rejuvenation areas. According to TOD data, an area of 6647 hectares has been affected in forest fire (TOD 2019).

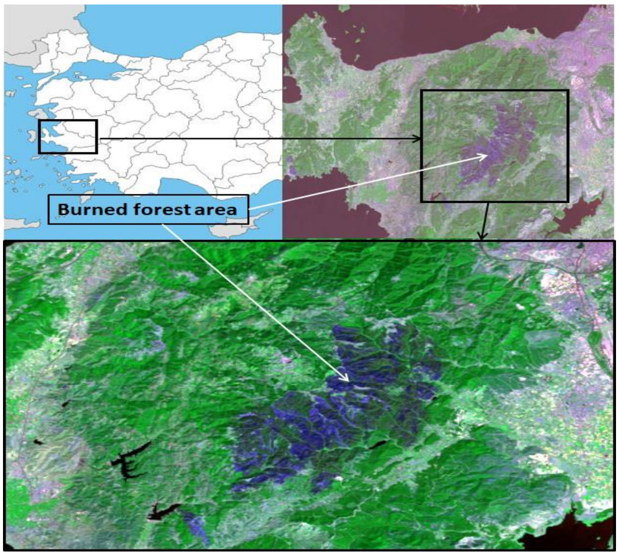

Fig. 1. Location of study area in Karabaglar, Seferihisar and Menderes district of Izmir.

Dataset

In this project, forest fire affecting the region in Menderes and Karabağlar districts, İzmir was examined using data obtained before and after the fire started on 18th of August, 2019 and controlled on 20th of August, 2019 after 53 hours. 6647 hectares burned as a result of the forest fire and hence satellite images were used to detect the area destroyed after this fire. Satellite images were taken from the United States Geological Survey (USGS) website (Earthexplorer 2020). At this stage, the images obtained from LANDSAT 8 satellite are preferred. LANDSAT 8 satellite was launched on 11th of February, 2013. the satellite carries two sensors on board: Operational Land Imager (OLI) and Thermal Infrared Sensors (TIRS). OLI sensors have nine spectral bands and TIRS sensors have two spectral bands. LANDSAT satellites have a resolution of 15-30 meters. This is sufficient for determining the area and analyzing the damage caused by fire (USGS 2020).

Table 1 Two Landsat 8 satellite images before and after the fire.

Number	Spacecraft	Data type	WRS number	Acquisition date	File date	Pre and Post Fire
1	lc08	l1tp_181033_20190807_20190820				Pre
2	lc08_l1tp_181033_20190908_20190917					Post

In this study, it is aimed to compute the total area damaged after the fire. To determine the total damaged area, pre and post fires data were analyzed to obtain specific indices' images, then the results from both indices were compared by using these pre and post-fire image indices. Thus, two satellite images before and after the fire were downloaded from the USGS website as seen Table 1 (Earthexplorer 2020). The downloaded raw satellite images were then pre-processed to correct the atmospheric, geometric, radiometric and spectral discrepancies by using the ERDAS IMAGINE and ArcMap software because of temporal analyses to be performed. In this study, 4-5-7 bands were used to detect the burning area and to determine the indices. The bands are stacked together by using the layer stack option in the software. The band order in the stack was chosen as 7-5-4 for RGB color combination and for the visual representation of the burned area before and after the fire. Thus, water areas are seen in dark, vegetation areas are seen green and burned areas are seen reddish colors in that stacked post fire color combination image (Fig.2).

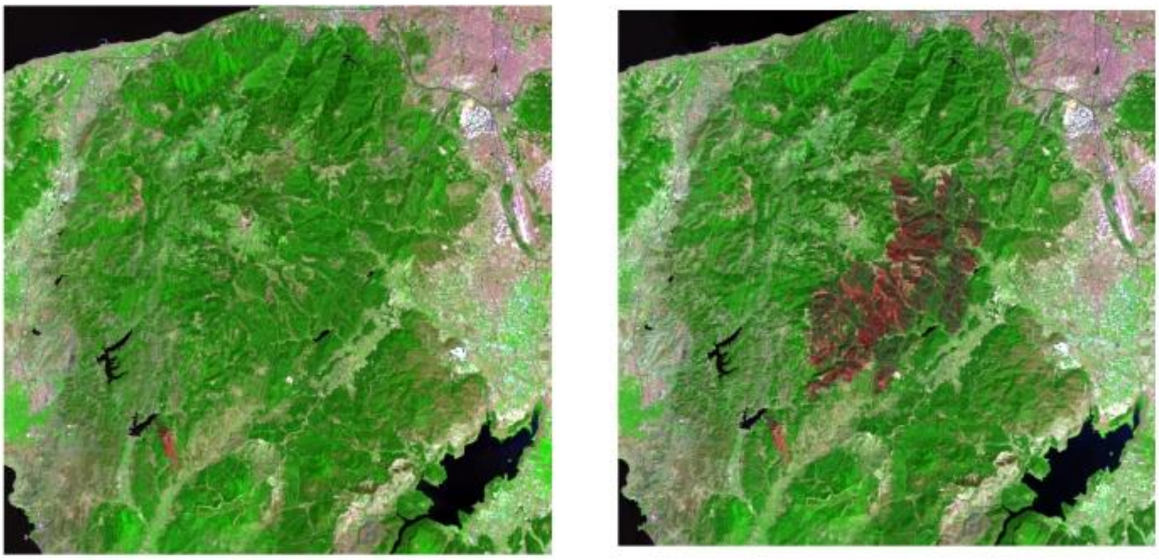

Fig.2. Pre and Post Fire RGB (4-5-7 bands) images

As mentioned earlier, a preprocessing step must be done to convert the digital numbers in the raw band images to reflectance values for each band to be used in the further processes. After pre-processing, the following indices were computed.

Methods

Normalized Difference Vegetation Index

NDVI recommended by Rousse is calculated by combining the near infrared and red bands (Eq. 1). NDVI is created by exposing the high reflectance capability of chlorophyll in vegetation (Viana-Soto et al. 2017). Green vegetation uses the wavelength range of 0.63 µm-0.69 µm of electromagnetic energy from the sun during photosynthesis. NDVI index is used very often to detect the change of chlorophyll content in green vegetation on the ground over time. NDVI index is expressed by Near Infrared (NIR) and the red bands' normalized difference ratio (Eq. 1). Results obtained as NDVI values give information about vegetation coverage on the ground part in interest. NDVI values are between -1 and +1. NDVI values approach to + 1 at the regions where green vegetation coverage is intense.

On lands where vegetation is sparse and bare lands occur, it moves away from +1 and approaches 0. NDVI value approaches to -1 in the areas of cloud, water, snow, river and lake. In short, if NDVI value is close to +1, it refers to the region where vegetation is plenty and healthy. Vegetation becomes rear and rearand then disappears as NDVI approaches to the value of 0. In areas with negative values, there is absolutely no vegetation (Sabuncu 2019; Lacoture 2020; Panchal et al., 2021).

$$NDVI = (NIR-Red)/(NIR+Red) \quad (Eq.1)$$

After taking the difference of NDVI values, unsupervised classification was applied to the byproduct image obtained. In the study using the techniques above, the fire area destroyed by the fire was found as 6614.19 hectares in total. According to the damage assessment studies carried out by the General Directorate of Forestry after the fire, a forest area of 6647 hectares was found as burned region. Thus, there was a omittable minor difference between data from General Directorate of Forestry and the determined forest fire region from NDVI process. In other words, NDVI values and data from General Directorate of Forestry are consistent with 99.5%.

Normalized Burn Ratio

Classification result of NDVI differences between pre and post fire was used to determine the total amount of vegetation change occurred in the region because of forest fire. It means different indices are used for the determination of burned area in the forest from the NDVI changes. The other one of these indices is the Normalized Burn Ratio (NBR) index. Changes between pre-fire and post-fire are determined with this index as well. This index provides information about the vigor and moisture of vegetation by combining near infrared and mid-infrared bands reflectance values (Veraverbeke et al. 2010). It is formed by expressing NBR using near infrared and mid-infrared bands as a mathematical normalized difference ratio (Eq. 2) (Sabuncu 2019).

$$NBR= (NIR-SWIR)/(NIR+SWIR) \qquad (Eq.2)$$

In the pre-fire images obtained for NBR index, the index values for the areas containing vegetation approach to + 1 and negative values are received for barren or wetlands. It was noticed that the NBR values after the fire were close to zero or they appear with low index values in the fire zones (Key and Benson). As seen in the Figure 3, when NBR images are examined for the before and the after fire, the distribution of damage intensity levels and related areas are even visually noticed. An area of 6594.39 hectare as total fire zone was determined as damaged area affected in different levels. When this total value is compared with the field value from the General Directorate of Forestry, it is found that the computed total fire zone from NBR analyses consists 99.2 % with the field data.

Normalized Burn Ratio – Thermal

A thermal band is used to develop an advanced NBR index such as the normalized burn ratio-thermal index (NBRT). Thus, it provides a better distinguishability for the differences between burned and unburned areas. NBRT uses near infrared, short-wave infrared and thermal bands as represented in the normalized difference mathematical ratio equation below with expressed SWIR band as thermal band (Eq. 3).

$$NBRT=(NIR-\mathit{Ther}/1000)/(NIR+\mathit{Ther}/1000) \qquad (Eq.3)$$

Unsupervised classification was performed after computing NBRT differences between before and after fire cases. Thus, the total fire area affected and destroyed was found as 6448.86 hectares. When the total fire damage zone covering an area of 6448.86 hectares from NBRT analyses is compared with the damaged area of 6647 hectare from the damage assessment studies carried out by the General Directorate of Forestry after the fire, it was determined that the area from NBRT analyses consists 97 % with the field data.

Burned Area Index

Burned area index was introduced by Martin (1998) (Martin et al. 2005). Highlighting the charcoal signal in post-fire images reveals the burned area in the red and near infrared spectrum. The index was calculated by using the spectral distances for each pixel appearing in recently burned area converge with respect to reference spectral values for both red and NIR bands. Brighter areas therefore indicate burned areas (Chuvieco et al. 2002). The BAI formula is shown by the mathematical ratio of the red and near infrared bands below (Eq. 4).

$$BAI=1/((0.1-Red)^2+(0.06-NIR)^2) \qquad (Eq.4)$$

Post-fire burn area index image was extracted from the pre-fire burn area index image. Then unsupervised classification was applied. Total burned region was found as 6518.61 hectares. Consistency of that value is 98 % with the obtained area from field work.

Relativized Burn Ratio

The differences between the normalized burn ratio images for pre and post fire are divided by the values obtained after adding 1.001 to the values of normalized burn ratio image before the fire and the relativized burn ratio image values are then obtained (Eq. 5). By adding the value of 1.001 to the denominator, the denominator can never result zero. Thus, the equation does not yield failed results (Parks et al. 2014).

$$RBR= dNBR/(NBR(pre\text{-}fire)+1.001) \qquad (Eq.5)$$

Unsupervised classification was applied to the relativized burn ratio image. The image was divided into five classes and examined. As a result of the classification, the fire area was determined in several damage levels w.r.t the given values in Table 2. As the result of the process explained here, the total area of burn and damage zone was determined as 6620.40 hectares. According to the area of 6647 hectares as total forest fire damage zone from the damage assessment studies carried out by the General Directorate of Forestry after the fire, the total burned area determined as 6620.40 hectares from RBR analyses is consistent 99.6 % with this field data. Here in this research, RBR which is the product of NBR therefore gives the most consistent result w.r.t the total damage area calculated from the fieldwork.

Discussion and Results

Burn Damage Damage intensity

We can locationally define the burn damage intensity levels w.r.t green vegetation losses as degrees which represent the areas under different damage intensity caused by the fire. Burn damage intensity reveals the changes because of exposure to fire and in soil with living and non-living biomass (Eidenshink et al. 2007). In other words, burn damage intensity represents the physical change in vegetation cover of a land part and that occurs as a result of a fire in the area. Burn damage intensity at a specific area appears because of intensity of vegetation cover along with fire strength mostly dominated by atmospheric conditions like temperature, humidity, wind direction and strength. The sudden effects of the fire on the soil cause the destruction or partial destruction of the plant (Diaz Delgado et al. 2003).

To obtain burn damage intensity distribution in the study area, NBR index values before and after the fire are used. Difference between NBR values before and after the fire gives the difference index as dNBR. Thus, we can distinguish the damage intensity of burning for the post-fire case (Cocke et al. 2005). Burned areas are indicated by dark pixels (L3harrisgeospatial 2020). In this way, high dNBR value shows seriously damaged forest areas. Areas with negative dNBR values show post-fire regrowth. dNBR is calculated by the formula given below (Eq. 6).

$$\Delta NBR = NBR(\text{pre-fire}) - NBR(\text{post-fire}) \qquad (\text{Eq.}6)$$

United States Geological Survey (USGS) has proposed the following classification table to interpret the burn damage intensity levels of a forest fire w.r.t dNBR (Table 2). NBR index values are between -1 to +1, while dNBR values are between -2 to +2. To describe the burn damage intensity, values for burnt areas are arranged between 0.10 to 1.30 (Sabuncu and Ozener 2019).

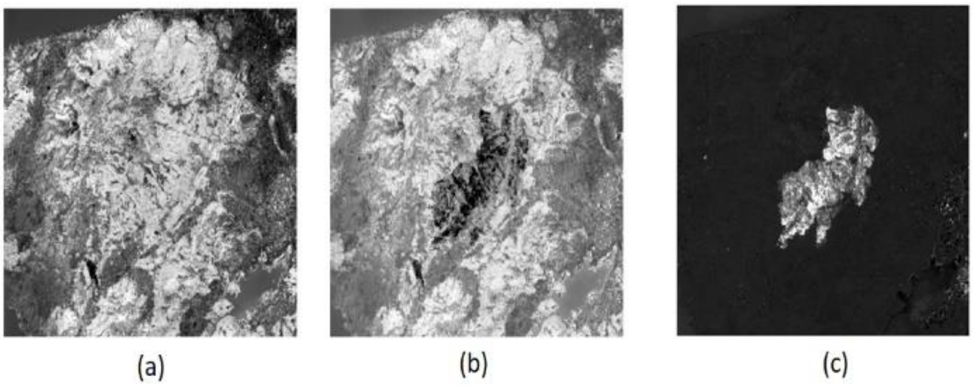

Fig. 3. (a) NBR Pre Fire (b)NBR Post Fire and (c) dNBR Images

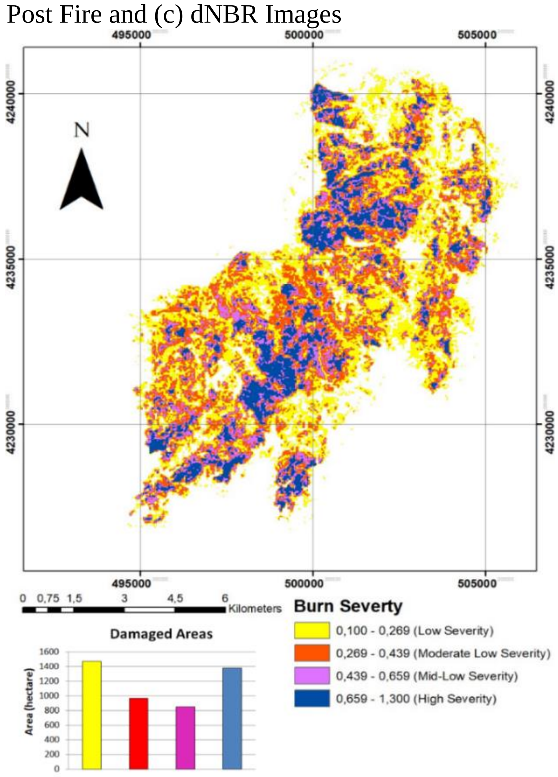

Fig. 4. Burn damage intensity map.

NBR and dNBR are widely used indices to map burned areas. NBR and RBR as the product of NBR reveal significantly fire-related changes by comparing pre-fire and post-fire images. NBR index algorithm was therefore run for the forest fire area in interest in this project for analyzing pre and post fire cases. So that, as a next step, the pre fire NBR image was subtracted from the post fire NBR image. Thus, dNBR image of the region was produced. August pre-fire, September post-fire and dNBR difference images are seen in the Figure 3.

Burn damage intensity map was then produced from the dNBR image. Thus, the effects of the fire are examined. The damage intensity of the fire is evaluated according to the damage intensity values in Table 2 obtained from USGS (Un-spider 2020). Total damaged fire area affected in different damage intensity levels is determined as 6594.39 hectares as a result of the NBR index that it is 99.2 % compatible with the damage area (6647 hectares) obtained in the field after the fire by a surveyor team working for the General Directorate of Forestry.

Table 2. Burn damage intensity levels (Un-spider 2020), burned areas in different damage intensity levels and total fire damage.

Damage intensity Levels	dNBR Range	Area (hectare)	Percentage	Damaged/ Undamaged
Unburned	-0.100 to +0.099	1930,12	29	Undamaged
Low Damage intensity	+0.100 to +0.269	1468,29	22	Total 4664,47 hectares % 71 damaged in different intensity levels
Moderate-Low Damage intensity	+0.270 to +0.439	965,64	15	
Mid-Low Damage intensity	+0.440 to +0.659	849,6	13	
High Damage intensity	+0.660 to +1.300	1380,94	21	

To assess the damages in the forest fire area in different intensity levels, fire damage intensity distribution in the region was divided into five levels following to the classes suggested by USGS (Un-spider 2020) as given in Table 2 and w.r.t the burn damage intensity values as used in Figure 4. Therefore, five classes were created during the classification process of dNBR image. After producing the burn damage intensity map as seen in Figure 4, some comments can now be made about the fire damage intensity distribution. The first damage intensity class represents the low burn damage intensity distribution in the forest fire area within yellow color in the Figure 4 where it covers 1468,29 hectares and 22 % of the fire area, the second class is for the moderate-low burn damage intensity distribution in the fire area given with the red color in the same image where it covers 965,64 hectares and 15 % of the fire area, the third class includes the mid-low damage intensity distribution in the fire areas shown in magenta color in the same image where it covers 849,6 hectares and 13 % of the fire area, fourth damage intensity class highlights the most severely damaged forest areas in dark blue color in the same image which it covers 1380,94 hectares and 21 % of the fire area. On the other hand, some areas in the forest fire zone were found as unburned regions. So, these areas are represented with white color in Figure 4 and they cover 1930,12 hectares and 29 % of the total fire field. Shortly, 29 % of the fire area (1930,12 hectares) left as unburned sections in the total forest fire damage zone, contrary to that a total area of 71 % was left as damaged forest sections (4664,47 hectares) in different damage intensity levels in the entire forest fire damage zone after the fire.

Conclusion

Forests have an important place in the ecosystem. Living and non-living environments live together in harmony. The presence of forests that are sources of oxygen are endangered by fire. Forest fires cause many living creatures to die and economic losses. One of the most countries affected form forest fires is Turkey. Especially in the Mediterranean, Aegean and Marmara Regions where the Mediterranean climate is effective, the number of forest fires is quite high and over the country average. Remote sensing plays an important role in determining forest fires essentially in damage assessment after the fires even if there would be no field data available and in a quite short time never been before. Thus, damage assessment is made in a short period of time and thus, with an economically most cost-effective way.

In this study, the forest fire area where the fires started in the Karabaglar district in Izmir on 18th of August, 2019 and then expand to the Menderes and Seferihisar districts was investigated. LANDSAT satellite images were used as remote sensing data source for analyzing the before and after fire cases. 5 different remote sensing forest fire burn damage intensity determination and analyze methods using satellite images were examined in the study. Thus, the fire area and damage intensity levels of the damage were determined and a forest fire area map with damage intensity levels was produced. As a result of the analysis, the total forest fire area was calculated and compared with the total fire area data obtained in the field by the General Directorate of Forestry. According to the data from the General Directorate of Forestry, a total forest zone of 6647 hectares was found to be damaged due to the fire. On the other hand, as a result of one of the remote sensing techniques applied here and so, from the change analyze of NDVI images for pre and post fire cases, the total fire damage zone was determined as 6614.19 hectares. As a result of the difference NBR image change analysis, the total fire damage area was found as 6594.39 hectares. The area of the forest effected by the fire was also found to be 6448.86 hectares from the difference image through NBRT image change analysis. Additionally, the total fire damage area was determined as 6518.61 hectares with the difference image from BAI image change analysis. And even from RBR image change analysis, the total forest fire damage area was calculated as 6620.40 hectares. As a result of all those analyses, it is concluded that the data obtained from the General Directorate of Forestry from the field work is consistent with the results of remote sensing analysis. All remote sensing results from different forest fire damage area determinations depending on different remote sensing image indexing techniques provide significantly accurate results for the assessment of total area and intensity distribution of forest fire damage in the fire region as they can be followed from the consistency rates computed for RBR as 99.6 %, for BAI as 98 %, for NBRT as 97 %, for NBR as 99.2 % and for NDVI as 99.5 % however the most satisfied result comes from the RBR analyze when they were compared with the field data from the General Directorate of Forestry of Turkiye.

RBR index which gives the most consistent result is actually a product of NBR index. The least convenient forest fire area was obtained from the difference image of NBRT index images for pre and post fire. Thus, the accuracy of RBR change analysis was observed as the highest. Thus, the image of the fire area was obtained as subset area in the most appropriate way.

dNBR image was used to reveal and to map fire related changes according to pre and post fire cases in the forest fire region. For this reason, dNBR difference image was obtained from the images before and after the fire. Burn damage intensity map was then created with dNBR different image. According to the damage classes given in table 2 and suggested by USGS, the damage intensity of the fire was evaluated based on these classes and then the burn damage intensity map was produced. When the burn damage intensity map is examined, it is seen that the most intensely effected areas of the fire region is 21% and mid-low intensely effected areas is 13%. So that, totally more than one third of the entire region is affected severely from the Karabağ forest fire. As a result, remote sensing is an important tool for analyzing forest fires and determining the total damage and even damage intensity levels caused by the fire at the different locations in the forest fire zone in a shortest time it has never been before and without being necessarily in the field. In this way, remote sensing benefits appear as time, labor and cost saving technique. The fact that the results obtained by remote sensing analysis methods are consistent with the results of the General Directorate of Forestry also shows the success of remote sensing in post-fire evaluations. The remote sensing technique has also demonstrated its ability to distinguish damage intensity levels, even including undamaged sections in an entire forest fire damage zone, in a way that cannot be completely done in a field work.

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