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Detection of Burnt Areas by Remote Sensing Techniques: Antalya Manavgat Forest Fire[#]

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ABSTRACT

In this study, the forest fire that occurred in Manavgat district of Antalya on 28 July 2021 and lasted for 15 days was analysed by remote sensing techniques using Landsat 8 satellite images. Satellite images of the study area dated July 2021 before the forest fire and August 2021 after the forest fire were obtained. Burnt areas were identified using data's such as Normalized Burned Ratio (NBR) and Normalized Vegetation Index (NDVI) indices and Difference Normalized Burned Ratio (DNBR) and Difference Normalized Vegetation Index obtained by using the differences of these indices. The maximum similarity algorithm of pixel-based controlled classification was also applied to the data set. The area destroyed by burning after the forest fire was tried to be calculated with these two indexes. It was investigated whether the results of three different methods were compatible and consistent with the results of the General Directorate of Forestry. Although there are differences between the results, it was determined that the selected method and the materials used were suitable for such studies.

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Introduction

Forests are one of the most important ecosystems in the world and are natural resources that play an important role in maintaining the ecological balance. The productivity of the forests is the most obvious indicator of the ecological conditions in its region. In its most general and comprehensive definition, forest is an ecosystem in which trees, plant and animal communities interact. In this ecosystem, there is a mutual balance between invisible organisms in the soil and the inanimate environment. As a result of unconscious use, fires, etc. in the world, forest areas are being destroyed and are decreasing in the areas. According to the latest statistical data, annual deforestation has reached 13 million hectares (ha) in the world (Sabuncu and Özener, 2019). In Turkey, the total of forest and forest areas is 27 million ha and only 1.6% of this is under the protection. In addition, Turkey is among the richest countries in the world in terms of different plant species. It is estimated that more than 10,000 vascular plants live in Turkey and about 34% of them are classified as endemic species (Özhatay and Kültür 2006; Özhatay et al. 2009; Özhatay et al. 2011). One of the main reasons for the deterioration of the ecological balance and the destruction of forests is the forest fires (Ager et al., 2011; Atmaca et al., 2022). After forest fires, data collection from the fields is generally not possible because it is difficult or impossible to reach the burnt areas and the cost of field studies is high. Due to these restrictions, remote sensing technologies have been used for post-forest fire studies in recent years. Versatile data collection and synoptic imaging is possible with remote sensing satellites (Alganci et al. 2010). Remote sensing technologies are also used for risk estimation, detection and assessment at different stages of fire management (Sabuncu and Özener, 2019). With Geographical Information Systems (GIS), operations such as the detection and modelling of fire hazard areas, the creation of fire risk maps, the prediction of fires, the planning of fire extinguishing works, the detection of damage after a fire can be done systematically (Cleve et al., 2008).

In the literature, it has been seen that there is no consensus on the inputs in the analyses used in the creation of fire risk maps. For example, Massada et al. (2009) examined flammable material and topography inputs, weather data and human activities data as inputs to analyze fire risk. Kavlak et al. (2021), on the other hand, used topographic features, stand features and human-induced factors to create the forest fire risk map in GIS. When the studies in the literature are evaluated, it is seen that many different criteria are widely used in the estimation of forest fire risk, including vegetation (amount of combustible material), topographic characteristics (altitude, aspect and slope), climatic characteristics and human factor (Novo, 2020; Parajuli, 2020; Gheshlaghi, 2020).

The methods used to reveal and map the fire probabilities of large-scale areas and regions using these criteria are diverse. Kernel density analysis (Koutsias et al., 2004), multi-criteria evaluation analysis (Sarı 2021), use of artificial intelligence (Zhang et al., 2019), frequency ratio (Gai et al., 2011) and logistic regression (Deng et al., 2013) are some of them.

However, logistic regression is the most widely used among these methods due to its flexible nature (Goldarag et al., 2016; Pan et al., 2016; Milanovic et al., 2020). Thanks to the rapid developments in remote sensing technologies, the diversification of satellite data and the detection of areas destroyed by fire after forest fire are more effective and faster. Many studies on detecting burnt areas with different classification techniques (pixel or object-based) applied to satellite data are available in the literature today (Koutsias and Karteris, 2000; Rogan and Franklin, 2001; Li et al., 2003; Dragozi et al., 2014; Chen et al., 2016; Kavzoglu et al., 2016). In Turkey, on the other hand, started to work on forest fires only after the 1990s (Türkeş and Altan, 2014; Göktepe and Avcı, 2015; Küçükosmanoğlu et al., 2015; Atmış and Günşen, 2016; Avcı and Boz, 2017; Sabuncu and Özener, 2019).

In this study, the forest fire that occurred in Manavgat district of Antalya on 28 July 2021 and lasted for 15 days was analysed by remote sensing techniques using Landsat 8 satellite images. Satellite images of the study area dated July 2021 before the forest fire and August 2021 after the forest fire were obtained. Burnt areas were identified using data's such as Normalized Burned Ratio (NBR) and Normalized Vegetation Index (NDVI) indices and Diffference Normalized Burned Ratio (DNBR) and Difference Normalized Vegetation Index obtained by using the differences of these indices. The study has some limitations. The resolution of Landsat imagery used in the study is 30 m. x 30 m. This shows that each pixel is equal to 900 m² within the scope of the study. Therefore, the amount of burnt areas obtained as a result of the study may differ from the results obtained using lower resolution satellite images. For example, SPOT-6 or SPOT-7 satellite images have a resolution of 1.5 meters. Therefore, one pixel corresponds to 2.25 m². Naturally, the data provided by the area of 900 m² and 2.25 m² will not give the same results. It is not known from which satellite images the General Directorate of Forestry obtained the burnt area determination.

This point should not be forgotten when comparing the value differences obtained as a result of the study. Landsat images have been used in many studies because they are easy to obtain. Also, Considering that 30 meters resolution is suitable for large study areas, Landsat satellite images were used for this study.

Materials and Method

In this study, the forest fire that started on July 28, 2021 in the Manavgat district of Antalya province was handled, and satellite images were used to determine the burnt areas after the fire. According to the results of the damage estimation studies carried out by the General Directorate of Forestry after the fire, 60,000 ha of forest area was burnt. Medium resolution satellite images were used to detect the area destroyed after the fire in the region. Satellite images were obtained free of charge from the United States Geological Survey (https://earthexplorer.usgs.gov/) website. Landsat satellite data is one of the most important data sets to evaluate the effects of forest fire. The 30 m resolution of the Landsat 8 satellite, which has 11 spectral bands, is considered a sufficient resolution to detect forest fires. In addition, the 16-day temporal resolution just before and immediately after the fire provides a good opportunity to detect burnt areas without greening. Because the start date of the forest fire is 28 July 2021, there are satellite images of 12 July 2021 before the fire and 28 August 2021 after the fire. Antalya is surrounded by the Mediterranean in the south, Muğla in the west, Burdur and Isparta in the north, Konya in the northeast, Karaman and Mersin in the east. Manavgat is located between 31°26'28.6152'' east longitude and 36°47'12.7284' north latitude. Manavgat is the 4th largest district of Antalya and has a great tourism potential (Figure 1).

Figure 1. Location of the study area

Antalya region is located in the Mediterranean climate zone. The summers are hot, dry and humid, and the winters are generally rainy. In summer, the temperature can be measured as 28 to 40 degrees. In the winter months, the average temperature was measured as 10 to 20 degrees. Very rarely, frost events and snowfalls, which are seen to drop to minus degrees, can be seen at high altitudes. Antalya, which is located in the Mediterranean climate, is also called the warm sea climate. The vegetation of Antalya is Maquis. 60% of the region is covered with Pinus brutia forests. It has a green appearance due to the high humidity and rainy winter months. The annual average amount of precipitation is 950 mm/m^2. Due to these rich forest areas, many forest fires occur in the Antalya region.

In this study, which aims to determine the damage of the forest fire that occurred on July 28, 2021 and lasted for about 15 days in the Manavgat District of Antalya, calculations were made using various indices on the satellite images obtained. NDVI used in the determination of green areas, NBR used in the determination of burnt areas, dNDR determined by the differences of these two indices are the main indexes used within the scope of the study.

In addition to these indices, the pixel-based controlled classification technique was applied to the satellite data on the study area. The study consists of a total of five main parts: supplying the data to be used within the scope of the study, making it suitable for the analysis obtained, namely pre-processing, applying the determined indexes to the obtained satellite images, pixel-based controlled classification and accuracy analysis. All operations on satellite images were performed using ENVI 8.4 software. After classification, all obtained results were compared with the damage estimation results from Forest General Directorate.

Normalized Difference Vegetation Index (NDVI)

The most commonly used vegetation index in practice is the Normalized difference vegetation index (NDVI). The algorithm of the Normalized Difference Vegetation Index is the ratio of the difference between the Near Infrared Band (NIR) and the red band to the sum of the difference (Formula 1). Classified result image data were created from the generated plant index image data. The results vary between -1 and +1 values depending on the condition of the area where the vegetation is located. Likewise, it was observed that the NDVI values of the forest areas destroyed by burning in the images after the fire approached -1. Therefore, while the NDVI threshold value was taken as positive values for the images before the fire, the NDVI threshold value of the same region was taken as negative values after the fire and filtering was performed. Since Landsat 8 satellite images were used in the study, the bands of those images were written in the formula.

$$NDVI = \frac{NIR\ (Band\ 5) - Red\ (Band\ 4)}{NIR\ (Band\ 5) + Red\ (Band\ 4)} \quad (1)$$

In this study, regions with high green vegetation (mean NDVI more than 0.5), low green vegetation (mean NDVI value between 0.4-0.0) and no vegetation (mean NDVI value less than 0.0) were considered. These distinctions were determined as control areas and controlled classification was made.

After the forest fire that occurred in the region, pre-fire and post-fire NDVI values were calculated and a change detection analysis was performed for the change in these values.

Normalized Burn Intensity (NBR) vs. Difference Normalized Burn Intensity (dNBR)

After forest fires, chemical changes occur in the vegetation apart from physical properties. Significant changes in spectral reflections are observed as a result of decreased transpiration in vegetation, covering of the surface with ash, and a sudden increase in surface temperature (Lanorte, 2013). Apart from NDVI for the sudden vegetation change in the region after forest fires, spectral indices created with satellite images are actively used in the detection of burnt areas. It is seen that the Normalized Burning Severity Index (NBR) is frequently used in the literature for the detection of forest fires. This index is the expression of the 7th band and the 5th band with a mathematical ratio in order to detect the change between the images before and after the fire, especially in forest areas. Band 5 covers infrared wavelengths 0.76–0.90 μm, which are sensitive to the chlorophyll content of living vegetation, while band 7 covers water content in both soil and vegetation, the content of non-photosynthetic vegetation, and aqueous minerals such as clay, mica, and some oxides and sulphates. It is sensitive to and removes these substances. Also, the wavelengths of the 7th band were found to be sensitive in the separation of non-wood (dead) wood from soil, ash, and charred wood in a post-fire environment. NBR is particularly sensitive to changes in living vegetation, moisture content, and some soil conditions that may occur after a fire as a result of using these two bands (Formula 2). For this reason, the Normalized Burning Intensity (NBR) index is used to determine the burnt green areas. The normalized combustion intensity index (NBR) is expressed by mathematical formulas obtained using near infrared (NIR) and short wave infrared (SWIR) bands (Roy et al., 2006; Veraverbeke et al., 2010; Sabuncu and Özener, 2019).

$$NBR = \frac{NIR\ (Band\ 5) - SWIR\ (Band\ 7)}{NIR\ (Band\ 5) + SWIR\ (Band\ 8)} \quad (2)$$

Today, to determine the most widely used forest burnt severity map, Miller et al., (2007) developed the Differenced Normalized Burn Ratio (dNBR) method with their study and classified the extent of damage to vegetation. The Difference Normalized Burn Ratio-dNBR (Differenced Normalized Burn Ratio-dNBR) is obtained by subtracting the normalized burning intensity indices before and after the forest fire (Formula 3). In addition, the intensity of combustion is determined by calculating the changes in carbon emission, aerosol production and biomass parameters with the dNBR index (Miller and Thode, 2007; Sabuncu and Özener, 2019).

$$\Delta NBR = NBR_{Before\ Fire} - NBR_{After\ Fire} \quad (3)$$

Theoretically, when the Difference Normalized Burning Intensity index was examined, it was observed that the values it received were between -2.00 and +2.00. Of these values, values for burnt areas range from 0.10 to

1.35, while unburnt areas range from -0.10 to +0.10. In addition, it was observed that values between -0.50 and -0.10 were observed for vegetation that showed advanced re-growth after the fire (Key and Benson, 2006; Sabuncu and Özener, 2019) (Table 1).

Table 1. Burn severity categories

dNBR	Burning Intensity
< - 0.25	High Post-Fire Greenery
-0,25/ -0.1	Low Post-Fire Greenery
-0.1/0.1	Unburnt
0.1/0.27	Low Burning Intensity
0.27/0.44	Medium/Low Burning Intensity
0.44/0.66	Medium/High Burning Intensity
>0.66	High Burning Intensity

Source: (Sabuncu and Özener, 2019)

Pixel Based Controlled Classification

Pixel Based classification methods use pixel values in an image to assign each image pixel to a class. Each pixel is assigned a class based on its spectral characteristic; this process is known as Spectral Pattern Recognition. The purpose of pixel-based classification is to assign all pixels in the image to specific classes or themes (eg water, coniferous forest, deciduous forest, agriculture, etc.). The number and type of classes are decided by the analyst. Pixel-based classification is examined under 2 groups as Uncontrolled (Unsupervised) and Controlled (Supervised) classification. In controlled classification, each pixel in the image is assigned to the most similar class by using training samples (training data) representing different classes, while in uncontrolled classification, pixels with similar spectral values are grouped and these spectral groups are compared with local data to define which cover class they belong to.

While classifying within the scope of the study, past studies (Sabuncu and Özener, 2019) on the subject were used. In addition to the NDVI and NBR indices, the pixel-based controlled classification method, which is a method frequently used in scientific studies on medium spatial resolution satellite data, was used to classify satellite images. In the images before and after the forest fire, 432 (RGB) Landsat bands were used to obtain the wrong colour combination, and in the vegetation classification, the band order was chosen that shows healthy vegetation and strongly reflects infrared light. In the next stage, the control regions belonging to the classes were selected homogeneously to produce 6 control regions (sea/lake, green area, burnt area, city, agricultural area, bare soil). Using the Maximum Similarity Algorithm based on the probability that each pixel belongs to a class, 6 classes were generated (Sabuncu and Özener, 2019).

Results and Discussion

First of all, NDVI analysis was done for the study area. Two different maps were produced for pre-fire and post-fire, and then the burnt areas were determined using NDVI analysis (Figure 2).

NBR analysis was done for the study area. Two different maps were produced for pre-fire and pro-fire, and then the burnt areas were determined usimg NBR analysis (Figure 3).

Using the Maximum Similarity Algorithm based on the probability of each pixel belonging to a class, 6 classes were generated (Figure 4).

Conclusion

Forest fires are an inevitable phenomenon in Turkey, as in all Mediterranean countries. Although thousands of hectares of forest areas are destroyed every year, it causes irreparable ecological losses and causes great economic damage. Although forest fires cannot be prevented today, risk analyzes and identifying areas with high fire potential provide great convenience for managers and practitioners.

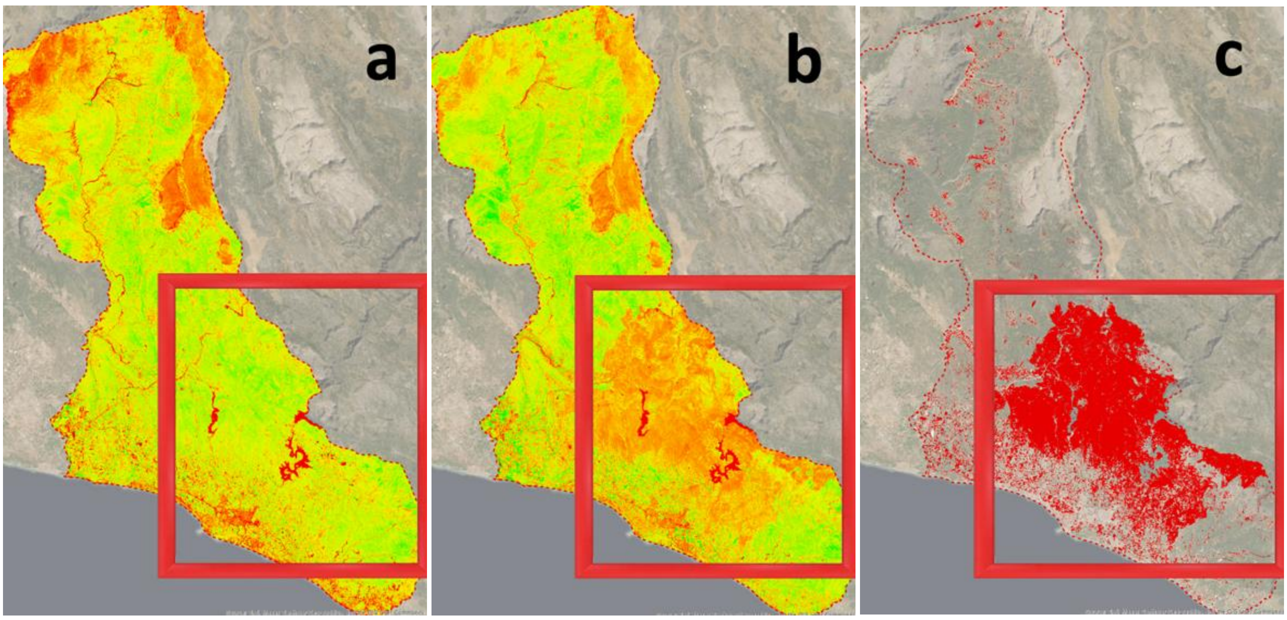

Figure 2. NDVI conversion a) Pre-fire b) Post-fire c) Pre-fire and post-fire change detection analysis result

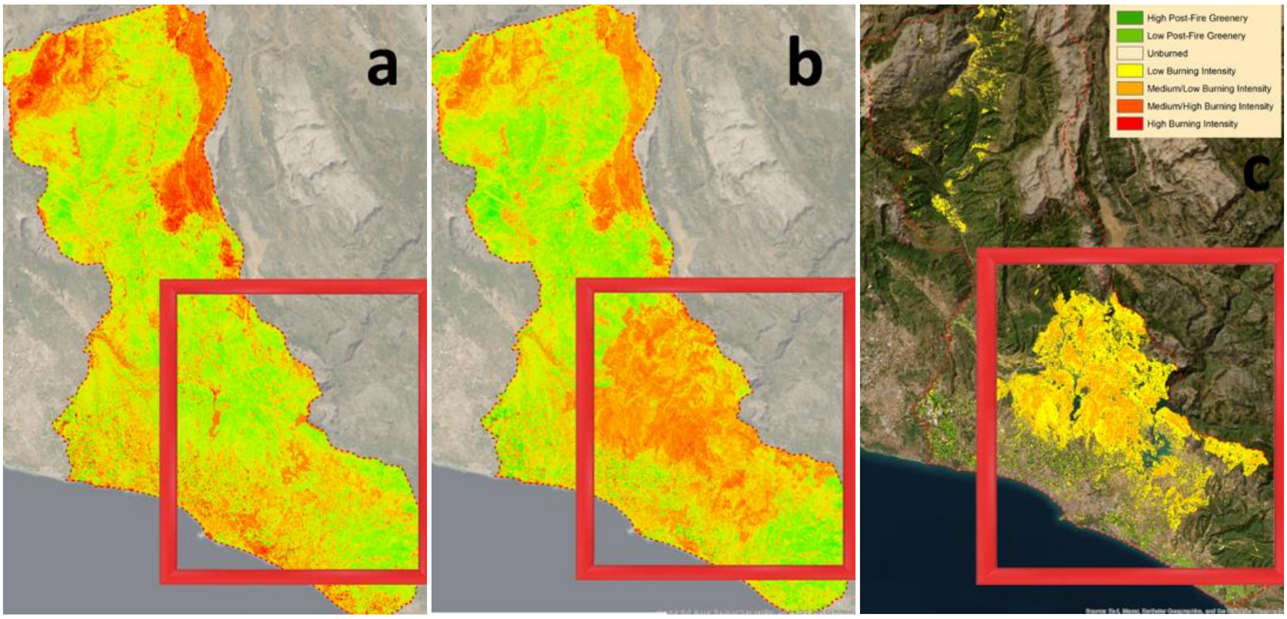

Figure 3. NBR conversion a) Pre-fire b) Post-fire c) Pre-fire and post-fire change detection analysis result

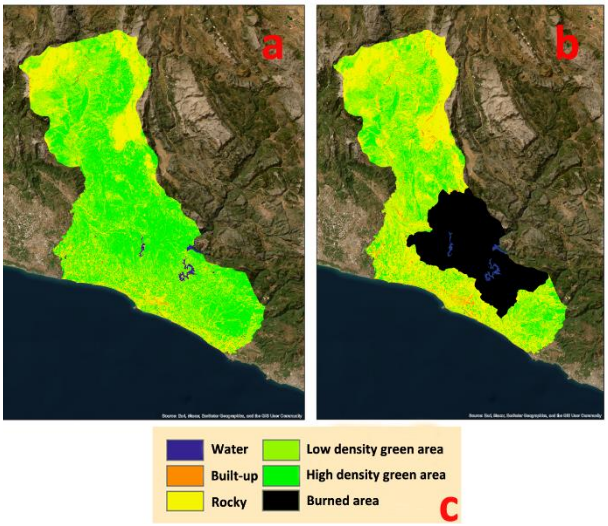

Figure 4. Controlled classification a) Pire-fire b) Post-fire c) Classes

The development of forest fires under the control of many geographical factors necessitates the evaluation of dense data sets together. Since GIS has the ability to evaluate dense datasets at the same scale, it can be used as a very effective tool in forest fire risk analysis. On the other hand, the development of data standards in firefighting studies is of great importance in ensuring local, national and international coordination. In order to make the right decisions, more than one analysis should be made and necessary precautions and interventions should be made.

In this study, 3 different remote sensing analysis methods were used to detect and map the area burnt as a result of the forest fire in Muratpaşa district of Antalya on July 28, 2021, via Landsat 8 satellite images. These methods are NBR- dNBR, NDVI-NDVI, change detection analysis, pixel-based controlled classification, respectively. The forest areas destroyed by burning were found to be 44,371 ha using NBR-dNBR, 56,865 ha using NDVI-NDVI change detection analysis, and 58,365 ha using pixel-based controlled classification method.

As a result of the damage assessment studies carried out by the General Directorate of Forestry in the region after the fire, it was determined that approximately 60,000 ha of forest area was burnt and therefore it was concluded that it was consistent with the remote sensing analysis results. The accuracy of this method is also supported by other studies. Sabuncu and Özener (2019), in their study, analysed the forest fire that occurred in Seferihisar district of İzmir province on August 9, 2009 and lasted for 4 days, using Landsat 5 satellite images with remote sensing techniques. They used NDVI, NBR and dNBR indices in their studies to determine the burnt areas. The area destroyed by burning after the forest fire was calculated as 711 ha with dNDVI, 695 ha with dNBR, and 665 ha with the maximum similarity algorithm of the pixel-based controlled classification method. It was concluded that the results of the three different methods were compatible and consistent with the results of the General Directorate of Forestry.

Aksoy and Çabuk (2018), within the scope of their work, worked with Landsat 8 satellite images of the 200 hectares damaged area in the fire on 1 July 2017 in the Menderes district of İzmir. As a result of the study, it is aimed to reveal the regeneration ability and the severity of the burn with the NBR calculation. Finally, they determined that the method used was appropriate.

Liu et al., (2021), their study compares eleven spectral indices for burnt area detection in the savanna area of southern Burkina Faso using Landsat data ranging from October 2000 to April 2016. The same reference data are adopted to assess the performance of different spectral indices. The results indicate that Burnt Area Index (BAI) is the most accurate index in burnt area detection using our method based on harmonic model fitting and breakpoint identification.

With satellite data, the developments before, during and after the fire can be monitored easily, with high sensitivity and economically. By combining heat bands, satellite images and ground information (meteorology, topography…) with the help of a GIS to be developed, strategies and response programs can be developed in the light of fire development and response models. In addition, it is possible to follow up and early detection of non-forest uses with afforestation activities after the fire. At this point, remote sensing techniques are one of the most important tools in terms of both pre-fire and post-fire intervention.

As a result, Remote Sensing and Geographic Information Systems techniques, which are widely and effectively used by many countries before, after and briefly at every stage of forest fires, cannot be sufficiently utilized in our country. The use of Remote Sensing and Geographic Information Systems techniques will provide significant contributions to the planners by providing efficiency in the fire management plans of our country. It is important to establish and monitor fire safety zones as soon as possible, especially in settlements with high fire risk, located in and adjacent to the forest, in terms of preventing possible loss of life and property. This study revealed the benefits of remote sensing techniques in terms of post-fire monitoring studies.

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