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Determining The Forest Fire Risk with Sentinel 2 Images

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ABSTRACT

Forest fires are one of the most important disasters since past. The necessary preventions should be taken promptly to prevent these disasters. Remote sensing, which is a very effective and practical tool, is one of these tools that provide a timely receipt of measures with the development of technology. In this study, a forest fire that started at 07.23.2018 in Athens, in Greece and continued until July 26 was discussed. Mati region where the most loss of life was examined as the study area. Sentinel 2 images were used in order to detect forest fire risk class. Normalized Burn Ratio (NBR), Differenced Normalized Burn Ratio (dNBR), Relativized Burn Ratio (RBR) spectral indices and Normalized Difference Vegetation İndex (NDVI) were used in order to determine the forest area damaged by fire and to establish fire risk classes. According to the results of the study, the size of the vegetation area that was destroyed due to fire determined, and the probability of forest fire exposure of these areas established.

1. INTRODUCTION

Forest fires are one of the most important disasters of our time. An increasing trend in forest fires has been observed all over the world from past to present. There are 2 main factors that cause forest fires: Nature and human. Unplanned urbanization, sabotage, carelessness, recklessness, and global warming are among the few factors that cause forest fires. In recent years, many big forest fires have occurred in the world. 271,350 ha in Greece in 2007, 450,000 ha in 2009 in Australia, 500,000 ha in Russia in 2010, and 25,000 ha in Bolivia in 2010 were destroyed due to fires. A total of 1,200,000 ha of land was destroyed by the forest fire in Canada in 1825, and this was recorded as the largest known forest fire in history. (Özkazanç and Ertuğrul, 2011; Francos et al., 2016). These fires, which cause damage to large natural areas, lead to disruption of the natural ecosystem, cause human and living creature deaths.

While preventing forest fires requires a very important environmental management, identifying forest fire risk areas is another pillar of environmental management. With the identification of risk areas, necessary precautions will be taken on time, the number of forest fires will be reduced or minimized. Remote sensing could be used to identify areas damaged by forest fires, and besides, these areas could be classified according to forest fire possibility. Remote sensing also provides speed, practicality, and efficiency in detecting and monitoring forest fire risk areas. Nowadays, with the development of technology, the use of remote sensing in the detection of forest fires, damage detection studies and the detection of risky areas has increased gradually and there are many studies on this subject (Kerr and Ostrovsky, 2003; Boer et al., 2008; Delgado et al., 2010; Matin et al., 2017; Navarro et al., 2017; Yuan et al., 2017).

Different methods can be applied in these studies related to a forest fire in remote sensing. Fire-damaged areas could be identified by classifying optical satellite images such as Landsat or MODIS. Object-based classification and spectral classification are some of these methods. In addition, calculating land surface temperature with thermal bands of optical images is used to determine fire areas. Besides, topographic parameters such as elevation, slope, and aspect could be produced from

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the Shuttle Radar Topographic Mission (SRTM) in order to determine fire risk severity. Topographic factors can be integrated into a geographic information system and these areas can be determined by giving certain weights to them. Also, spectral fire indices are used to identify forest fire zones and risk areas (Delgado et al., 2010; Comert et al., 2017; Matin et al., 2017; Navarro et al., 2017; Comert et al., 2019).

In this study, a forest fire that started on July 23 and continued until July 26 in Athens, Greece, was discussed. The fire occurred in 2018 and caused many damages. The fire started simultaneously at many different points. That's why the cause of the fire was considered arson. A total of 79 people were killed and more than 100 people were injured due to the fire. Most of the people who died were reported to be from the Mati region in the northeast. This study aims to detect the area destroyed by fire with remote sensing and also to evaluate the fire risk of other areas. In this context, Sentinel 2 satellite images and Normalized Burn Ratio (NBR), Differential Normalized Burn Ratio (dNBR), Relativized Burn Ratio (RBR) spectral fire indices were used to create fire risk classes. In addition, Normalized Difference Vegetation Index (NDVI) was utilized to identify the forest area damaged by fire.

2. MATERIALS AND METHODS

2.1. Study Area and Materials

The study area is the Mati region, one of the areas where fires occur simultaneously, in the north-east of Athens, Greece. The texture of the region consists of a mixture of forest and urban - wooded areas including summer houses and hotels (figure 1). The Mediterranean climate is dominant in the region and scrub-type pine forests are common.

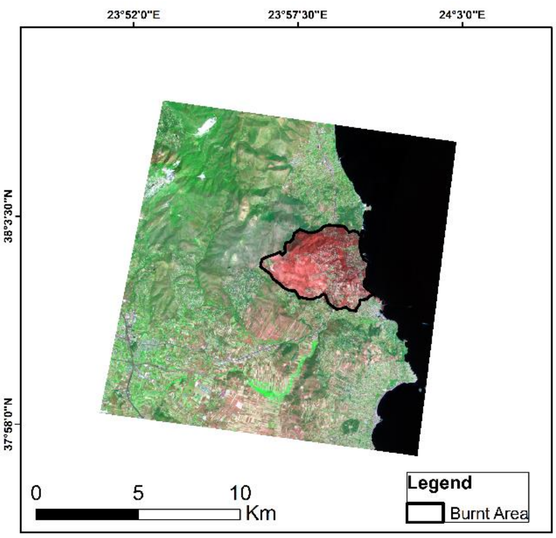

Figure 1. Study area (Red areas indicate the burnt area)

Sentinel 2 images were used as satellite images within the scope of the study. Sentinel 2 was placed in orbit by the ESA (European Space Agency) in 2015. It has also 13 bands that could obtain multispectral images (Clevers et al., 2017; (table 1)).

Table 1. The satellite images used in the study

Satellite Image	Date
S2B_MSIL1C_20180705T091019	05.07.2018
L1C_T35SKC_A007655_20180824T091603	24.08.2018
S2B_MSIL1C_20181222T091359	22.12.2018

2.2. Method

The satellite images used within the scope of the study were obtained free of charge from the United States Geological Survey (USGS) site in the UTM projection system as defined in the 34th region. In order to eliminate or minimize topographic factors, atmospheric effects, shadow effects, and sensor-induced errors on satellite images, atmospheric correction is required (Canbaz et al., 2018; Kalkan and Maktav, 2018). The atmospheric correction of the images was performed first, for this reason.

NBR, dNBR and RBR were performed as spectral indices of forest fire. The indices utilized were derived from the near-infrared and short wave infrared regions of the electromagnetic spectrum (Table 2).

Table 2. The forest fire indices used in the study

Spectral Indices	Formula Description
NBR	NBR= (NIR – SWIR) / (NIR + SWIR)
dNBR	dNBR = [NBRpre-fire – NBRpost-fire]
RBR	RBR = dNBR/(NBRpre-fire + 1.001)

The indices were created through images taken immediately after the fire (pre) and a few months later (post). Among the indices used in the study, the pixels in the RBR take values between -2 and +2, while in the NBR and dNBR take values between -1 and +1. In the assessment of fire risk, pixels with an index value greater than 0.55 are high; 0.25 to 0.54 moderate and 0.1 to 0.24 were categorized as low fire severity (Key and Benson, 2006). Besides, the NDVI was used to detect vegetation status and destruction before and after the fire. NDVI is also an index sensitive to the red and near-infrared regions of the electromagnetic spectrum. While the values representing vegetation cover between 0 and 1 in the index, it means that the density of the plants increases when the pixel values approach 1 (Tucker, 1979). The Indices were created using images just before the forest fire occurred and just after the fire occurred. The following pixel ranges are used to classify the pixels in the indices (Holben, 1986; (Table 3)).

Table 3. NDVI classification pixel range

Pixel Range	Class
<0	water
0.03 – 0	bare soil
0.03 – 0.3	sparse vegetation
0.3 – 0.5	moderate vegetation
0.5>	dense vegetation

3. RESULTS

Using fire indices and NDVI, areas that pose a fire risk and vegetation cover destroyed by fire have been identified. First of all, dNBR and RBR were applied to images, respectively. Then, the indices' results are classified according to pixel values and the regions that pose fire risk has been determined (figure 2).

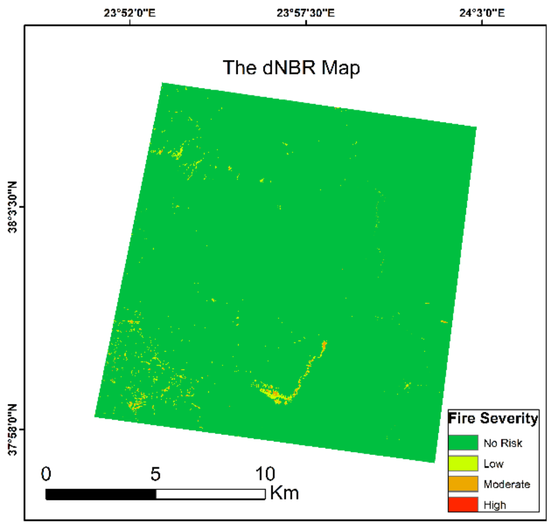

Figure 2. The dNBR map

According to the risk severity map made according to the dNBR index, it is understood that almost all of the study area does not pose a risk of a forest fire. Also, the sizes of these classes were calculated (Table 4).

Table 4. Distribution of calculated areas after applying dNBR

Fire Severity	Area (km^2)
No Risk	232.281
Low	1.9912
Moderate	0.4308
High	0.0016

After the RBR was calculated, the classification was made and the areas with risk of fire were identified (Figure 3). According to the results obtained, a large part of the field of study was in the low-risk category.

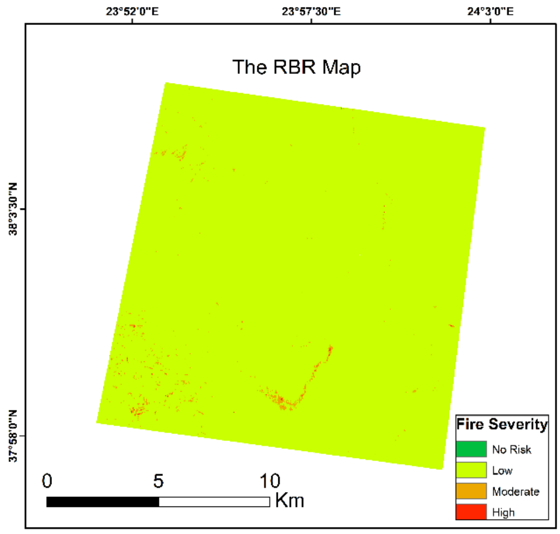

Figure 3. The RBR map

Afterward, the sizes of these areas were calculated (Table 5).

Table 5. Distribution of calculated areas after applying RBR

Fire Severity	Area (km^2)
No Risk	0.0016
Low	233.1837
Moderate	1.4421
High	0.0768

In addition, the NDVI was calculated using images taken just before and after the fire in order to determine the vegetation status before and after the fire (Figure 4-5).

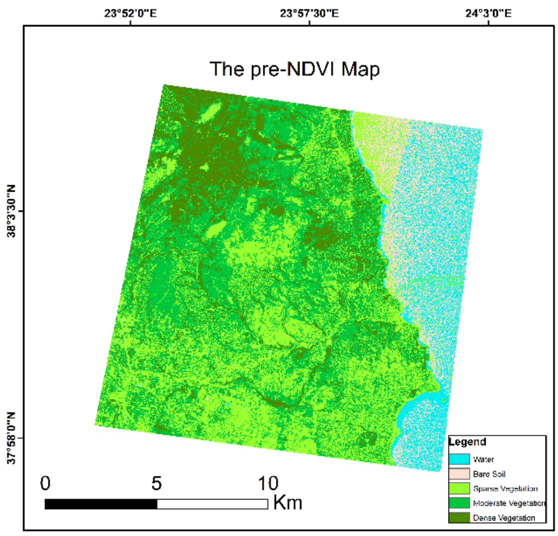

Figure 4. The pre-NDVI map (Indicates the vegetation condition before the fire)

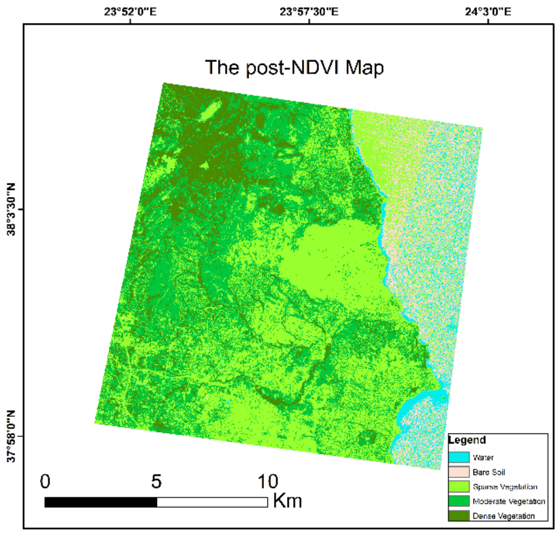

Figure 5. The post-NDVI map (Indicates the vegetation condition after the fire)

It was seen that some pixels in the water class in the NDVI map were assigned to the bare earth class. This is thought to be due to the fact that the fine fog and cloud layer above the water affects the classification accuracy. This was caused by the fact that the pixels in the bare soil were classified by taking the values between 0 and 0.03 and the cloud getting 0.02 in NDVI. To analyze the vegetation change after the fire, the NDVI status in the burnt area illustrated in the study area was also examined. It is understood that the number of dense vegetation and moderate vegetation classes decreased, while the pixels in the sparse vegetation class increased, according to NDVI (Table 6).

Table 6. Vegetation density before and after the fire

Vegetation Density	Pre Fire (m^2)	Post Fire (m^2)
Sparse Vegetation	34121	139101
Moderate Vegetation	79198	6334
Dense Vegetation	32728	413

Besides, in the NDVI map, the pixel values of the area destroyed by fire ranged between 0.1 and 0.3. Therefore, in the NDVI maps obtained after the fire, these regions are assigned as sparse vegetation and moderate vegetation as a result of classification (Figure 6).

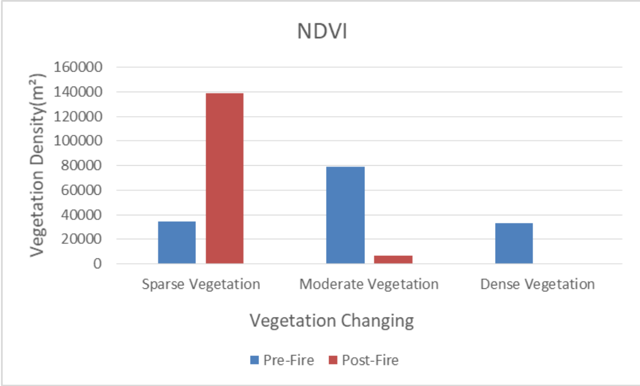

Figure 6. Vegetation distribution before and after the fire

4. DISCUSSION AND CONCLUSION

According to index results, it was understood that the RBR generates more sensitive results in determining the forest fire risk classes according to the dNBR. Also, it has been understood that the classified pixels in RBR pose more risk in terms of a forest fire risk than the same classified pixels in dNBR. dNBR is a powerful tool to detect burned area but also it is sensitive to water and thus sometimes, pixels that are classified as high severity maybe water (Bolton et al., 2015). However, since there is no water body in the study area, a water mask was not performed. According to the fire risk maps, it is seen that the areas with high forest fire risk in the study area are quite low. This is due to the fact that the study area consists of a mixture of urban texture together with the sparse forest cover. In addition, the fact that both forest and urban texture within one pixel in some pixels have affected the results by causing mixed pixel problems. On NDVI maps, these regions are classified as moderate vegetation and sparse vegetation. As supported by the results obtained from the fire index maps, it was concluded that a forest fire that may occur in this region is quite difficult to come out for natural reasons. This led to the thought that the incident in Mati in 2018 was due to arson. In addition, the fact that the fire started simultaneously at different points strengthens this argument.

In this study, by evaluating the forest fire that occurred in Athens Mati on 23.07.2018, risk classes for future fires in this region were estimated. Besides, the detection of vegetation that was destroyed by fire was also carried out. It is thought that using a higher resolution satellite image or an image obtained with a multispectral camera mounted on UAV will increase the accuracy of the study. In addition, categorizing the trees in the vegetation texture according to their types will increase the accuracy of the study. This methodology was not followed in this study since the restricted spatial resolution of the satellite images used in the study did not allow the classification of tree species in the forest texture and the data of the stand map of the region were not available.

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