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Determination of burned areas using Sentinel-2A imagery and machine learning classification algorithms

Ceydanur Arıkan*[1], İlay Nur Tümer[1], Samet Aksoy [1], Elif Sertel [1]

[1]Istanbul Technical University, Faculty of Civil Engineering, Department of Geomatics Engineering, Istanbul, Türkiye

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Abstract

We aimed to determine the spatial extent of burned areas using remote sensing (RS) data and machine learning methods. It is often difficult, time-consuming and costly to collect in-situ data after fires; therefore, RS is used in determining burnt regions. We selected the Manavgat district of Antalya province as the study area due to the major forest fires occurred in 2021. We used pre-post Sentinel 2A images due to the ability of Sentinel in burned area mapping, fire density and damage determination, and being openly available. Then we implemented indices to determine the changes caused by fires. The indices are Normalized Burned Ratio (NBR), Normalized Vegetation Index (NDVI), Relative differenced Normalized Burn Ratio (RdNBR), Relativized Burn Ratio (RBR), Burned Area Index (BAI), and Modified Soil Adjusted Vegetation Index (MSAVI), Soil Adjusted Vegetation Index (SAVI). Afterwards, we utilized Random Forest (RF) Algorithm, Support Vector Machine (SVM), and Classification Regression Tree (CART) for the Machine Learning (ML) classification. We used the Google Earth Engine (GEE) platform to obtain satellite images and apply indices and ML based classification. Results illustrated that, RF was the most accurate algorithm with 98.57% overall accuracy and SVM has the lowest overall accuracy with 86.19% for the region.

1. Introduction

Forests are essential for natural balance in terms of the sustainability of ecosystem services, and human survival. However, wildfires, occurring as the result of accidents, intentional, or global warming, has been threatening forest areas and nearby regions. Wildfire frequencies have been increasing in recent years throughout the world, and aside from that Turkey faced a critical year in 2021. Because "major fires," which are exceptionally fast-moving, high-intensity, and catastrophic, occurred between the end of July to mid-August both in Turkey and nearby countries such as Greece, when meteorological conditions were beyond the normal (Bilgili et al., 2021). According to information from the European Forest Fire Information System, 227 forest fire incidents occurred in Turkey in 2021, affecting a total area of 192 hectares, with the fires that began on July 28 in the Manavgat district of Antalya and continued in the Mediterranean, Aegean, Marmara, and the Black Sea regions during August, causing loss of life and property in large areas (Kavzaoğlu et al., 2021). Accurate, fast and timely detection of fire damages in is a challenging task. Satellite images have a vital role to provide support during the fire and to understand its effects immediately after the fire event (Sertel & Algancı, 2016).

Since the land surface changes after a fire, many indices could use to determine these changes and estimate the extent of the burnt regions. Even though there are various methods to detect damaged areas, the most widely used and functional approaches are based on the spectral differences of burnt forest areas after and before fires (Algancı et al., 2010). The Differenced Normalized Burn Ratio (dNBR) measures a decrease in the near infrared (NIR) region and an increase in the shortwave infrared (SWIR), which are the most widely utilized bands (Masshadi & Alganci, 2021). Furthermore, for the Normalized Difference Vegetation Index (NDVI), the difference between NIR and red spectral bands is used to estimate different vegetation conditions and then it can be used to detect vegetation loss. To sum up, indices integrate different spectral bands to deduce

* **Corresponding Author**

*(arikan17@itu.edu.tr) ORCID ID 0000-0002-5174-9471
(tumer17@itu.edu.tr) ORCID ID 0000-0002-1102-4505
(aksoysa@itu.edu.tr) ORCID ID 0000-0001-6420-7316
(sertele@itu.edu.tr) ORCID ID 0000-0003-4854-494X

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information about different features and surface characteristics.

Sentinel-2 satellites provide various spectral bands, spatial and temporal resolution capabilities and Sentinel-2 images have been used to monitor natural resources and burned scar mapping (Bar et al., 2020).

Machine Learning (ML) classification methods such as Random Forest (RF) and Support Vector Machines (SVM) have been used by different researchers to determine the extent of forest fires and identify the burned areas (Masshadi & Alganci, 2021). The Classification Regression Tree (CART) is an alternative machine learning algorithm for predictive mapping (Bar et al., 2020).

Google Earth Engine (GEE) is a cloud-based service that may instantly connect for encoding large geospatial data without dealing with the computer processing challenges (Aksoy et al., 2022). It includes extensive geospatial data and various functions that can be used collaboratively.

We investigated the Antalya Forest fires for this research using Sentinel-2 images and GEE platform. Firstly, we applied the indices RBR, RdNBR and differences in the pre-and post-fire indexes MSAVI, SAVI, NBR, NDVI, BAI, and SWIR (Short Wave Infrared) The second phase of the project involves the creation of classification images using several ML approaches such as RF, SVM, and CART. Lastly, we compared different methods to propose the most appropriate one for our selected case study.

2. Method

2.1. Study area

We focused on the research area which is the Mediterranean region and time intervals selected according to forest fires that occurred due to high temperatures in the summer of 2021 in Turkey. So, forest fires occurred in many of the provinces on this coast, and one of them is the province of Antalya.

2.2. Data

Sentinel-2 satellite images for the post- and pre-fire dates were chosen in GEE based on cloud cover rate. We tried to find clear images which are closely collected before and after the fire to accurately deal with the changes caused only by the result of the fires but no other conditions. As a result, Sentinel-2 satellite image obtained on 20 July 2021 just before the fire and another image obtained on 14 August 2021 just after the fire were used in this study. It is also important to consider whether the fire was entirely extinguished or not to find out the exact distribution of burned areas.

2.3. Burn Severity Indices and Mapping

RS platforms are providing spectral information of burned objects which can be easily to related spatial burn severity field measurements. In addition to spectral information, RS indices can also be applied to improve this relationship. Therefore, RS indices combined with the field measurements are the foundation for producing burn severity maps (Zheng et al., 2016). In this research, we applied 8 different indices to determine the burned areas and classify the severity. These indexes are dNDVI, dNBR, RdNBR, RBR, dSAVI, dMSAVI, dSWIR, and dBAI. Over time, NDVI potential uses and data sources have changed significantly. From the 1990s to the 2010s, forest estimation is done in at least one third of the total number of publications. The ultimate goal of NDVI implementation is to improve the evaluation of RS data for vegetation information (Huang et al., 2021). Variations in vegetation, humidity levels, and specific ground conditions in the NIR and SWIR bands which might happen after the fire are acutely susceptible to the NBR (Nasery & Kalkan, 2020). By dividing dNBR by the pre-fire NBR value, RdNBR was a form of the dNBR that took into account the approximate amount of before and after fire variations (Miller et al., 2009). Fire-affected regions can be especially targeted by BAI. The reverse spectral range to an intersection, specified by the lowest reflection of burnt vegetation in the NIR and the highest in the red band is used to create BAI (Chuvieco et al., 2008).

2.4. Burned Area Detection and Classification

We carried on the ML classification by using the Red, Green, and Blue (RGB) bands of the Sentinel 2A post-fire image and a composite image that consists of the indices that were created before. Then we added the indices to the Sentinel post-fire image as a band to create the composite image. Using SVM, RF, and CART algorithms pixel-based classification is applied to images. The SVM classifier which is an effective analytical algorithm provides defining the hyperplane which helps to separate the different groups (Masshadi & Algancı, 2021). In order to get the accurate result, gamma and cost parameters are significant in the SVM algorithm. For this reason, while the RGB image is classified, the gamma value is taken as 1e-2 and the cost value as 1e7, while the gamma value for the composite image is taken as 1e-6 and the cost value as 1e14. The CART classifier relies on Decision Tree approaches, which are widely used in Land use/land cover classification (Bar et al., 2020). Through a robust accumulated sample of the training set, the RF classifier builds associated classification and regression trees (Masshadi & Algancı, 2021). For each algorithm, we used the same training samples for comparability. While the number of training polygons is 28, the number of validating polygons is 12 according to the %70 and %30 ratio of training and testing respectively. By using the GEE, we obtained three classified images from composite of indices and RGB bands and three classified images from only RGB bands.

3. Results

We investigated the performance of ML derived burnt areas severity maps. The first algorithm was the SVM algorithm, and it has the lowest overall accuracy for our study area, providing 86.19% overall accuracy. On the other hand, the CART algorithm is providing 86.64% overall accuracy and the RF algorithm with the highest overall accuracy is 87.54%. Instead, when the burned area indices and post-fire image's RGB bands become a composite image and are used to classify burning areas severity, the SVM algorithm provides 95.3% overall accuracy, and it has the lowest overall accuracy for this study. The CART algorithm is 97.9%, and the RF algorithm has the highest overall accuracy which is 98.57%. The results are shown in Figure 2. When we compare burned areas statistics across ML algorithms in the burn severity classification maps which are made with the composite image, the total burned area in the CART algorithm produced maps is 450 km^2, while the unburned area is 1156 km^2.

Table 2. Burnt severity indices classification intervals

INDEX	Regrowth after fire	Unburned	Low Severity	Moderate Severity	High Severity
dNBR	<-0.1	-0.1<x<0.1	0.1<x<0.27	0.27<x<0.66	0.66<
dNDVI	<-0.23	-0.23<x<0.1	0.1<x<0.35	0.35<x<0.50	0.50<
RdNBR	<-9	-9<x<0.30	0.30<x<1.0	1.0<x<1.6	1.6<
RBR	<-0.15	-0.15<x<0.10	0.10<x<0.30	0.30<x<0.50	0.50<
dSAVI	<-0.1	-0.1<x<0.1	0.1<x<0.23	0.23<x<0.32	0.32<
dMSAVI	<-0.1	-0.1<x<0.1	0.1<x<0.22	0.22<x<0.32	0.32<
dBAI	25<	-20<x<25	-150<x<-20	-340<x<-150	<-340
dSWIR	0.1<	-0.01<x<0.1	-0.13<x<-0.01	-0.13<x<-0.06	<-0.13

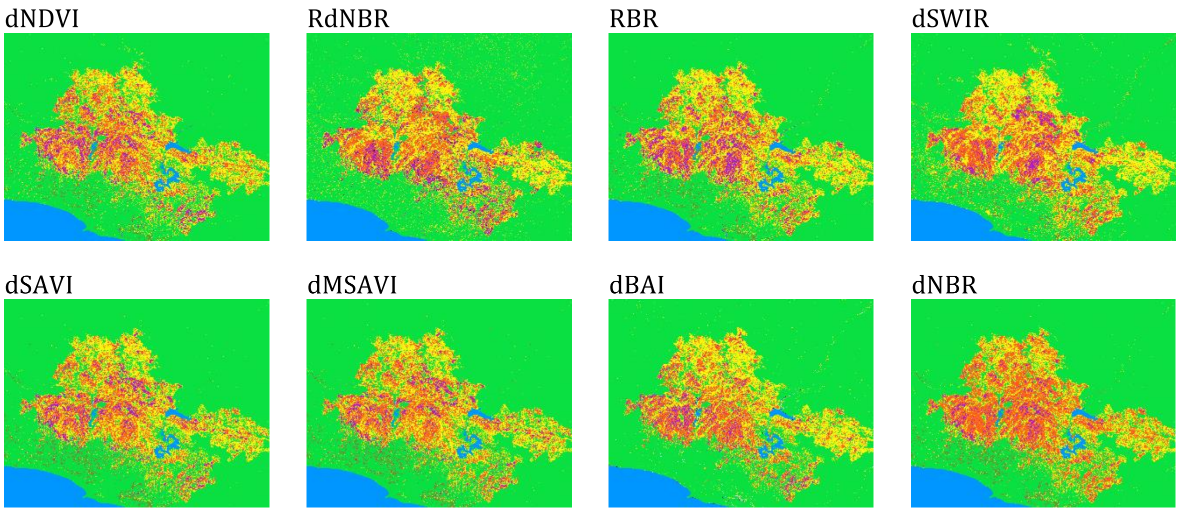

Figure 1. Burn severity indices classified images

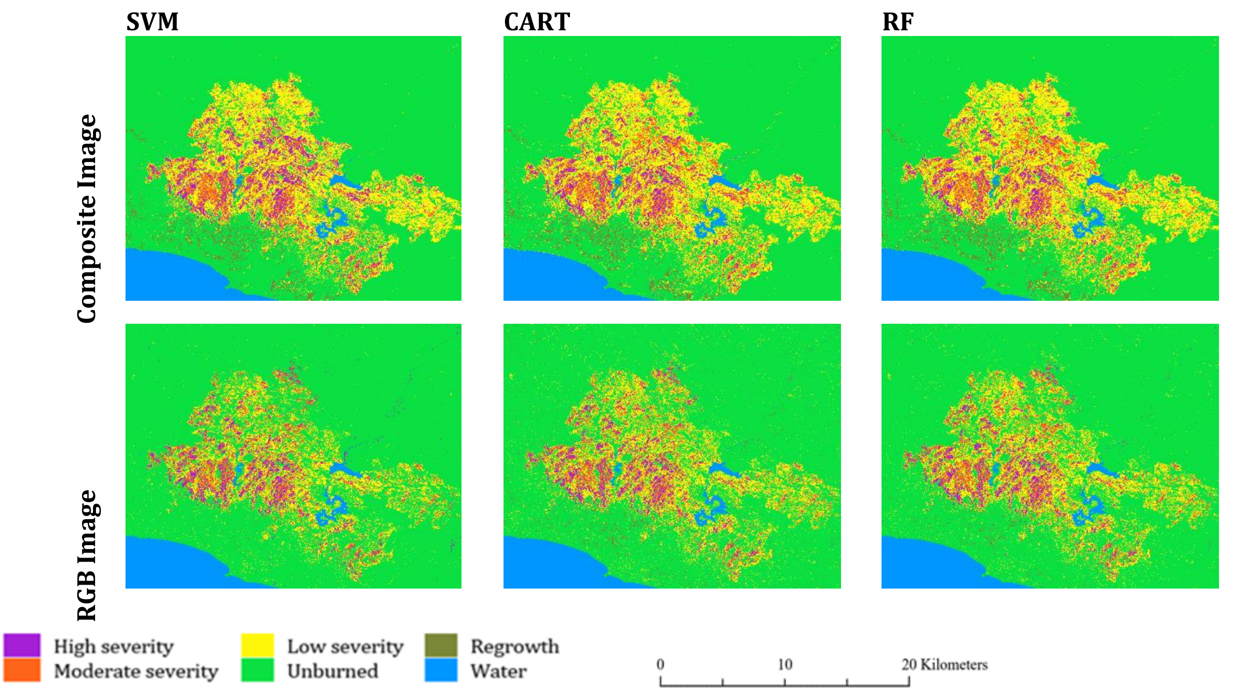

Figure 2. Machine Learning burn severity classifications

Whereas the total burned area in the SVM algorithm produced maps is 439 km^2, the unburned area was 1167 km^2. Furthermore, in the burn severity classification maps which are made with RGB images, the CART algorithm has a total burned area of 341 km^2, and the unburned area is 1265 km^2. For the RF algorithm, the total burned area is 329 km^2, and the unburned area is 1277 km^2.

SVM algorithm found the total burned area is 300 km^2, and the unburned area is 1306 km^2. In the calculation of the burned area, we considered high severity, moderate severity, and low severity regions, and for the unburned areas, the sum of the areas of the unburned and regrowth classes.

4. Discussion

In this research, we intended to evaluate and compare the results from images obtained from the medium-resolution Sentinel-2A satellite in the Antalya Province, in terms of fire severity, by using various ML methods. Firstly, it is clear that CART and RF are slightly better than the SVM algorithm in terms of overall accuracy. Bar et al. (2020) mentioned in their article, that they applied ML algorithms to identify forest fires using Sentinel-2 images, and CART and RF algorithms outperformed the SVM algorithms in terms of kappa values. As seen in Figure 2, there is no significant difference between fire severity classes in classification using composite images. When burn severity maps which are produced using RGB and composite images are compared, the amount of burned and unaffected areas have similar bias. For both of them, CART estimated the highest amount of burned area, and SVM estimated the lowest amount of burned area. As a result of the classification of CART, RF and SVM algorithms using RGB bands, less burning and regrowth area was obtained compared to the composite image.

5. Conclusion

In the scope of the project there are six classified images which are composite and RGB. While for the composite and RGB image the SVM algorithm has the lowest overall accuracy, RF has the highest overall accuracy. Although there are no significant differences between algorithms, there is a difference approximately 120 km^2 between the burned and unburned area amounts for the RGB and composite classified images. In conclusion, this study shows that by using different types of indices and ML algorithms the burnt areas and their severities can be determined effectively using Sentinel 2A imagery in the Google Earth Engine platform. Determining the burnt forest fire areas is important for understanding its impact on the environmental life cycle.

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