International Journal of Environment and Geoinformatics 11(4):070-077 (2024)
DOI: 10.26650/ijegeo.1508429

Research Article

Determining the Regeneration Dynamics of Burned Forest Areas Using Satellite Images and Climate Parameters

Dilek Küçük Matcı*[1], Uğur Avdan[1], Murat Kuruca[1], Deniz Hakan Durmuş[2], Sümeyye Aktaş[3]

[1]Eskişehir Technical University, Institute of Earth and Space Sciences, Türkiye
[2]Eskişehir Regional Directorate of Forestry, Eskişehir, Türkiye
[3]Eskişehir Technical University, Institute of Earth and Space Sciences, Türkiye

Corresponding author: D. Küçük Matçı
E-mail: dkmatci@eskisehir.edu.tr

Received 01.07.2024
Accepted 18.12.2024

Abstract

Forest fires significantly impact ecosystems by reducing biological diversity and sustainability. Observing the regeneration process of burned areas and identifying factors influencing this process, monitoring the regeneration status, determining the spread of invasive species, and understanding the impact on wildlife and its evolution contribute to assessing the consequences of this disaster. However, on-site monitoring of burned areas is a time-consuming and challenging process. Therefore, in this study, the regeneration processes of burned forest areas and the factors influencing these processes were investigated using data from remote sensing systems. In this context, the regeneration processes of areas affected by the forest fire in Antalya Kumluca and Adrasan in 2016 were examined. Landsat-8 satellite images of the study areas were obtained with the assistance of Google Earth Engine (GEE). NBR (Normalized Burn Ratio) showing the severity of the burn and NDVI (Normalized Difference Vegetation Index) indicating the vitality status of the forest were calculated using these images. In addition, parameters such as wind speed, soil moisture, precipitation amount, Land Surface Temperature (LST), and air temperature were obtained from data provided by remote sensing systems through GEE. Multiple regression analysis was conducted to identify the parameters affecting the regeneration process.

Keywords: Forest Fires, NDVI, NBR, Regeneration Process

Introduction

Forest fires are a natural and significant part of many ecosystems; they play an important role in clearing dead vegetation, promoting new growth, and maintaining overall biological diversity (Keeley and Pausas, 2022). However, in recent years, it has been observed that fire regimes are changing due to various factors such as land use changes, global climate change, or forest management policies. Due to increasing droughts, fires are becoming more severe and their frequencies are also increasing (Chu et al., 2016; Kuplich, 2006). Despite the destructive nature of fires, forests exhibit remarkable resilience, and regeneration can occur naturally. However, especially in areas severely affected by fire, human intervention may be necessary to facilitate and expedite the process. Regeneration strategies typically involve a combination of ecological restoration techniques aimed at restoring forest structure, biological diversity, and ecosystem function. Monitoring the regeneration processes of post-fire vegetation, analyzing ecosystem resilience, determining environmental dynamics, and providing valuable information for forest management objectives are therefore crucial (Aguilar, 2005).

Remote sensing technologies have been providing data on the Earth dynamics since the 1970s. Data obtained through remote sensing techniques are safely used in many fields of research due to their free availability and regular, frequent updates. These data are used in various studies such as climate change analysis, identification of natural disaster risks, damage assessments, or agricultural research (Akosman and Makineci; 2023; Aliyazıcıoğlu et al., 2023; Avdan, 2021; Çömert et al., 2017; Ocer et al., 2020; Şimşek; Yiğit and Uysal, 2020) . Remote sensing systems captures high-resolution images and data from satellites, unmanned aerial vehicles, and other platforms, allowing researchers, land managers, and policymakers to track changes in vegetation, soil, and landscape characteristics over time (Akça, 2023; Basara et al., 2022; Başaran et al., 2022; Gilbert and Shi, 2023, 2024; Kucuk Matci, 2022; Shafiq and Mahmood, 2022). Remote sensing provides a cost-effective and efficient tool that can be used for monitoring the success of regeneration efforts in burned forest areas. By comparing pre- and post-restoration images, researchers can assess changes in vegetation structure, species diversity, and ecosystem function, enabling adaptive management decisions. Accessing and processing field data after forest fires is costly and time-consuming, making it challenging for researchers. Remote sensing methodologies and satellite datasets provide powerful functionality for assessing the damage caused by forest fires (Çömert et al., 2019; Matcı and Avdan, 2020; Polat et al., 2022).

Google Earth Engine (GEE) is a platform developed for acquiring and analyzing remote sensing data. Providing free data, wide spatial coverage and the ability to perform operations in a short time make it easy to work with remotely sensed data (Kazemi Garajeh et al., 2024; Mutanga and Kumar, 2019). GEE also offers a wide range of data catalogs, including climate data such as Terra Climate and satellite images such as Landsat and MODIS, which can be used in a wide variety of studies. These data can be analyzed with Java script codes. Many studies such as land use change, burnt area determination, drought analysis, air quality determination and flood determination were carried out using the GEE (Capolupo et al., 2020; Güngör et al., 2022; Makineci and Arıkan, 2024; Matarira et al., 2022; Rasul et al., 2021).

Several studies in the literature have elucidated the regeneration processes of burned forest areas through field research (Cai et al., 2013; Johnstone et al., 2011). Observing post-fire forest regeneration using satellite imagery is an increasingly popular method (Lemesios and Petropoulos, 2024; Lopes et al., 2024; Stankova and Avetisyan, 2024). In one of these studies, the regeneration process in the area affected by the 2009 fire in Attica, Greece was monitored. When the results of the study using Landsat images were examined, it was determined that there was a recovery in the vegetation cover two years after the forest fire (Lemesios and Petropoulos, 2024). Another study aimed to develop an algorithm for monitoring burned forest areas. When the results were monitored in this study, it was observed that the accuracy rates varied between 48.4% and 73.9% (Stankova and Avetisyan, 2024).In this study, the use of data obtained through remote sensing methods and climatic parameters to examine the regeneration processes of Kumluca and Adrasan forests affected by wildfires constitutes the original contribution of this research. In this direction, Landsat 8 images, wind speed, LST and mean temperature data, soil moisture, precipitation were obtained. Regression analysis was carried out to determine the factors affecting the regeneration process.

Study Area and Materials

The study areas selected to monitor the regeneration process of burned areas is depicted in Figure 1. Within the scope of the study, areas affected by the July 2016 wildfire in Kumluca district, in Antalya, were investigated. Kumluca district is located on the Teke Peninsula in the western part of the Antalya Gulf, within the Western Mediterranean region. It is situated between Antalya Gulf and Fethiye Gulf and is approximately 90 km away from Antalya (KumlucaBelediyesi, 2019).

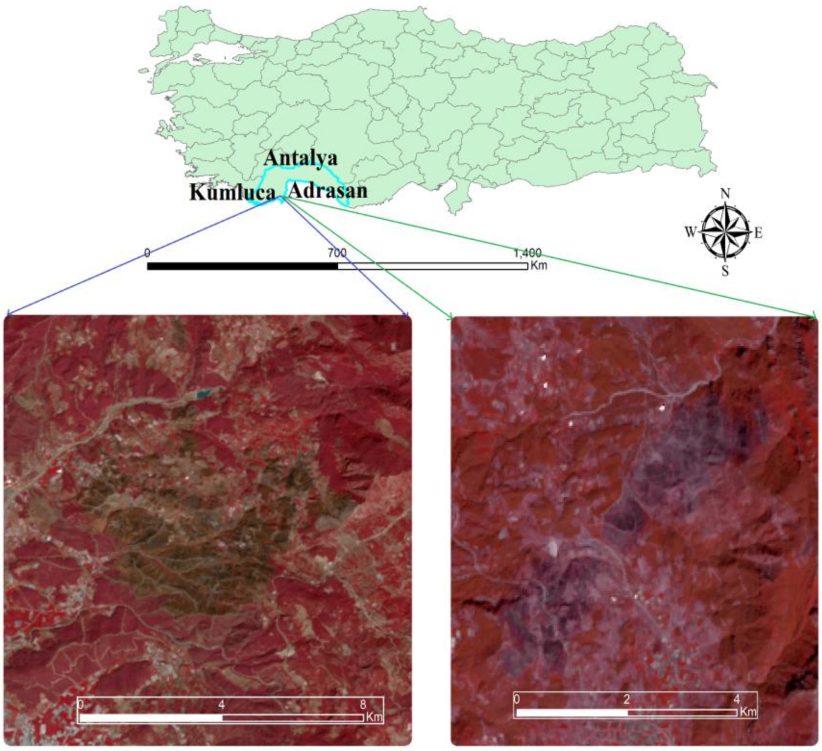

Fig. 1. Study Areas.

The total area of the district is 1253 km². Kumluca is bordered by the Mediterranean Sea to the south, Korkuteli district to the north, Kemer district to the east, Finike district to the west, and Elmalı district to the northwest. The vegetation of the region mainly consists of Turkish pine and maquis, although much of the forested area has been destroyed for agricultural purposes, particularly greenhouse farming (KumlucaBelediyesi, 2019; Yalçın and Boz, 2007). The second study area is Adrasan, a historical center in Antalya. Adrasan is 95 km from Antalya, 55 km from Kemer, 24 km from Çıralı and 8 km from Olympos. According to official records, the fire broke out on June 26, 2016 (OGM, 2017).

In this study, wind speed and soil moisture data were obtained from TerraClimate, precipitation data from Climate Hazards Group InfraRed Precipitation with Station (CHIRPS), and LST (Land Surface Temperature) and mean temperature data from ERA5-Land sources. TerraClimate is a dataset of monthly climate and climatic water balance for global terrestrial surfaces. Additionally, TerraClimate produces monthly surface water balance datasets using a water balance model that incorporates reference evapotranspiration, precipitation, temperature, and interpolated plant extractable soil water capacity (Abatzoglou et al., 2018). The precipitation data used in the study were obtained from station observations of CHIRPS. CHIRPS was created in collaboration with the United States Geological Survey (USGS) and the World Resources Observation and Science Center (EROS) to provide up-to-date datasets for trend analysis and drought monitoring (Funk et al., 2015). ERA5-Land, from which LST and mean temperature data were obtained, is a reanalysis dataset providing a consistent view of the evolution of land variables over several decades at an enhanced resolution compared to ERA5. ERA5-Land has been produced by replaying the land component of the ECMWF ERA5 climate reanalysis, combining model data with observations from across the world into a globally complete and consistent dataset using the laws of physics (Muñoz Sabater, 2019).

The burned areas in the study area and the calculated NBR (Normalized Burn Ratio) and NDVI (Normalized Difference Vegetation Index) indices for these areas were determined using Landsat 8 imagery. The band specifications of Landsat 8 are provided in Table 1. Bands 4, 5, and 7 were used in the study. NDVI (Normalized Difference Vegetation Index) indicating plant health and density, and NBR (Normalized Burn Ratio) indicating burn severity were calculated using these bands.

Table 1. Landsat 8 Band Specifications (USGS, 2015)

Bands	Wavelenght (micrometer)	Resolution (meter)
Coastal aerosol	0.43-0.45	30
Blue	0.45-0.51	30
Green	0.53-0.59	30
Red	0.64-0.67	30
NIR	0.85-0.88	30
SWIR 1	1.57-1.65	30
SWIR 2	2.11-2.29	30
Panchromatic	0.5-0.68	15
Cirrus	1.36-1.38	30
TIRS 1	10.60-11.19	100
TIRS 2	11.5-12.51	100

Method

The method applied to monitor the regeneration process of burned areas in the study is provided in Figure 2. The applied method can be generally summarized as image pre-processing, extraction of plant conditions and burning severity from satellite images and Regression analysis.

Accordingly, in the first step, the satellite images were selected to cover the study area. Subsequently, they were filtered temporally and spatially. Then, wind speed and soil moisture data of the study area were obtained from TerraClimate, precipitation data from CHIRPS and LST, and average temperature data from the Era 5 data catalog using GEE.

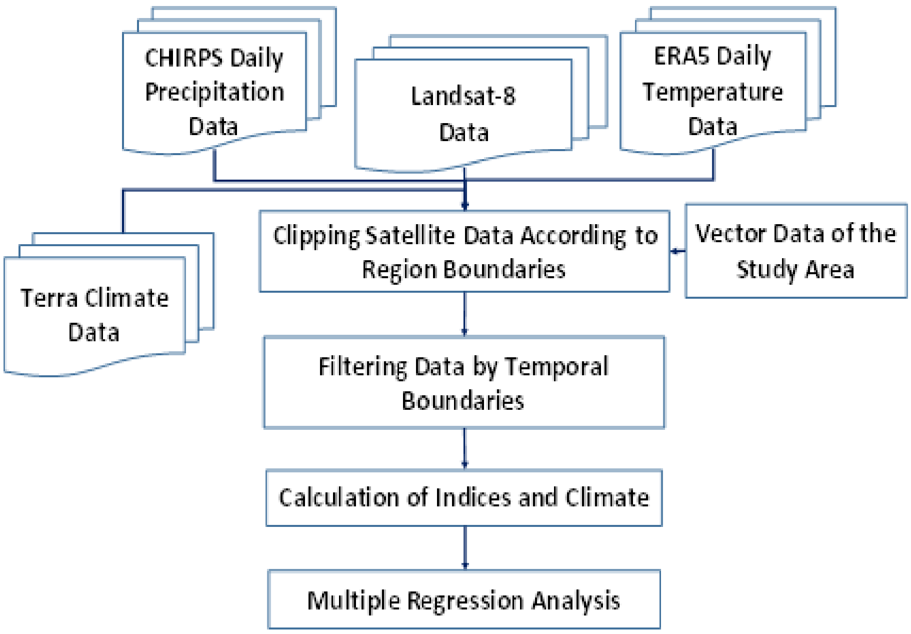

Fig. 2. Flowchart of the study.

In the continuation of the study, burned areas were identified using Landsat 8 imagery for the study area. The NDVI and NBR indices for this area were calculated using Landsat 8 data. NDVI is a measurement used to determine the density and health of vegetation. This index is calculated using the equation given in Formula 1, using reflectance data obtained from satellite or aerial imagery. NDVI is an important tool in many fields such as agriculture, environment, climate science, and disaster management, and it has a wide range of applications when used in conjunction with remote sensing technologies (Tucker, 1978).

NDVI=(Band 5-Band 4)/(Band 5+Band 4) (Eq.1)

NBR (Normalized Burn Ratio), is a measurement used to assess and monitor the effects of fires. NBR aids in the identification of burned areas resulting from fires and the detection of changes occurring in the post-fire area (Roy et al., 2006).

NBR=(Band 5-Band 7)/(Band 5+Band 7) (Eq.2)

At the end of the study, multiple regression analysis was conducted to examine the relationship between NDVI values, which indicate the regeneration extent of burned vegetation, NBR values representing burn severity, and climate data. Multiple regression analysis involves creating an equation that explains the relationship between one dependent variable and one or more independent variables. This equation quantitatively measures the impact of independent variables on the dependent variable (Aalen, 1989).

Results

The vegetation status during the regeneration process of burned areas was examined based on NDVI values. Maps depicting NDVI values are provided in Figure 3. To analyze the regeneration process, the NDVI value for the year 2015 was considered as representing the normal condition of the region. It is seen that most of the healthy vegetation in the region was affected by the fire that occurred in 2016. It can be seen from the NDVI maps given in Figure 3 that the renewal has occurred over the years, starting from the north.

When evaluating NDVI maps in Figure 3, high values indicate healthy vegetation, values close to 0 indicate unhealthy vegetation, and values less than 0 indicate areas without vegetation. In this regard, upon visual inspection of the obtained maps, it is evident that the region was affected by fire in the year 2016 before the fire. Subsequently, the NBR index was calculated and mapped to determine the severity of the burn. The resulting map is provided in Figure 5.

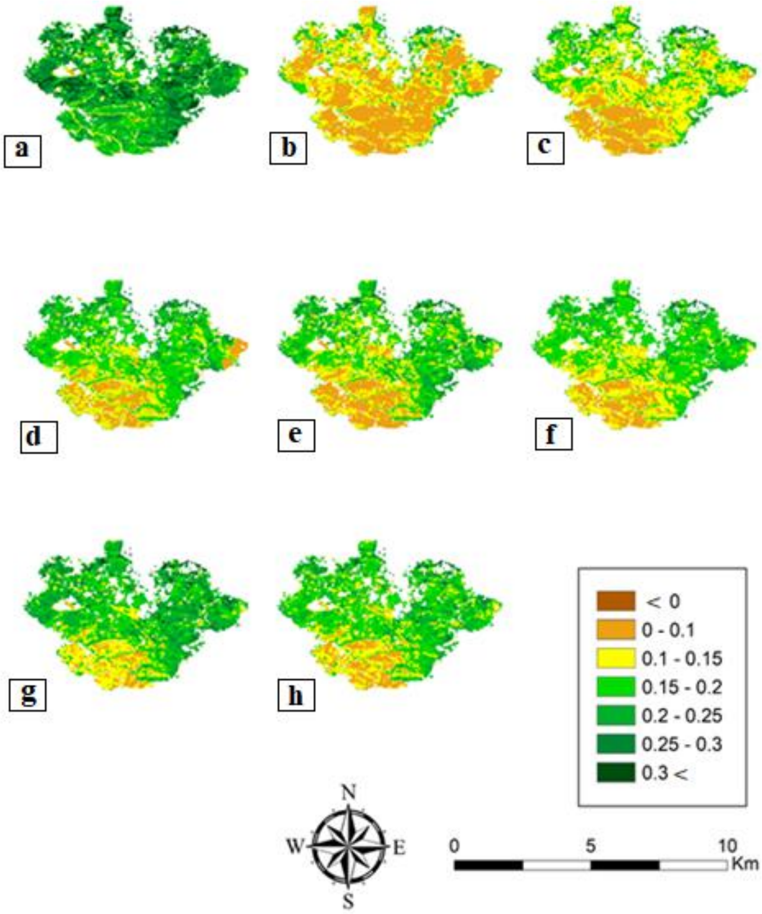

Fig. 3. Changes in NDVI values over the years in Kumluca a)2015 b)2016 c)2017 d)2018 e)2019 f)2020 g)2021 and h)2022

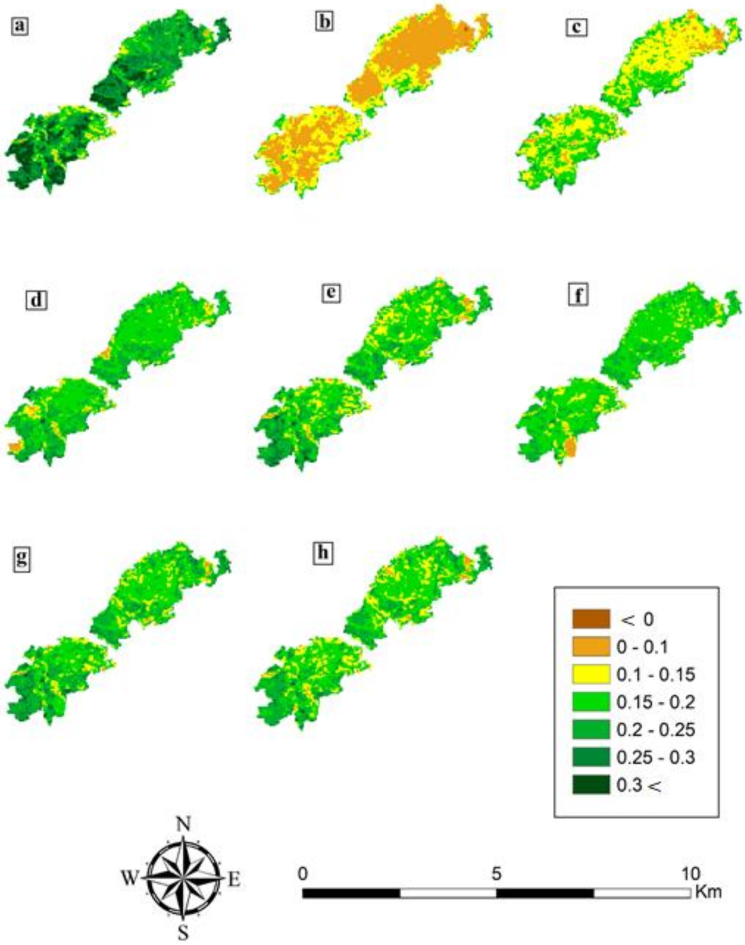

Fig. 4. Changes in NDVI values over the years in Adrasan a) 2015 b) 2016 c) 2017 d) 2018 e) 2019 f) 2020 g) 2021 and h) 2022

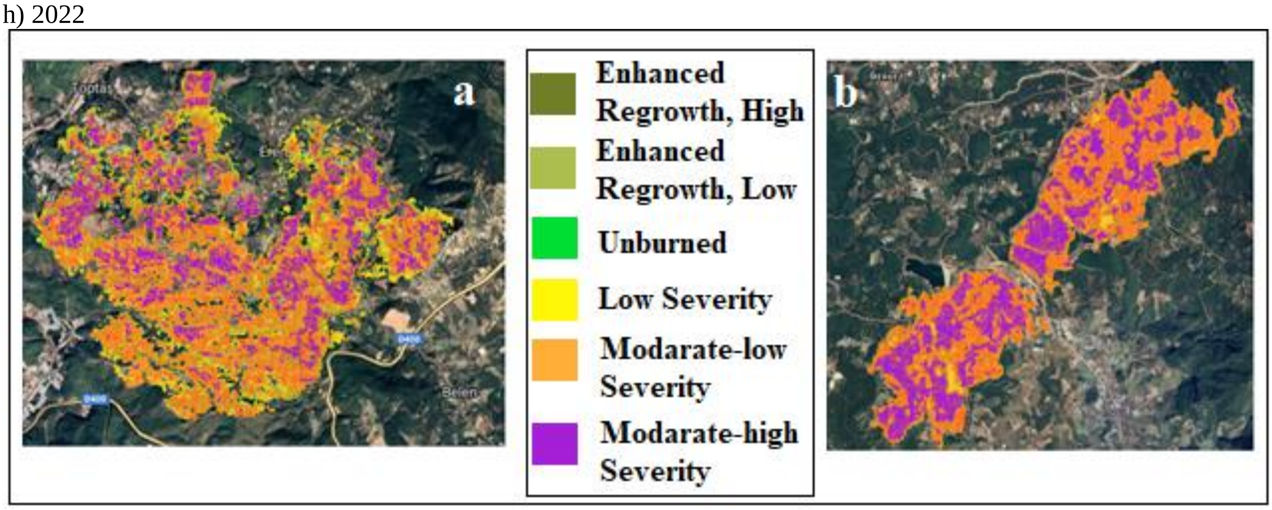

Figure 5. Detection of burn severity with NBR index (2016) a) Kumluca b) Adrasan

Table 2. Parameter values for the study area

Study Area	Date	NDVI	NBR	Wind Speed (m/s)	Soil Moisture (mm)	Precipitation (mm/d)	LST (C˚)	Air Temperature (C˚)
Kumluca	1-Sep-15	0.214	-0.205	2.5625	52.5042	1.386	20.173	19.37
	1-Sep-16	0.181	-0.156	2.4148	84.5804	2.035	19.229	18.318
	1-Sep-17	0.205	-0.188	2.45026	80.2956	1.859	20.448	19.394
	1-Sep-18	0.202	-0.191	2.46462	95.821	3.002	19.756	18.737
	1-Sep-19	0.212	-0.201	2.46093	93.5927	2.089	20.099	19.186
	1-Sep-20	0.22	-0.214	2.52979	85.5154	1.724	20.79	19.853

	1-Sep-21	0.225	-0.21	2.62011	92.8568	2.428	19.499	18.548
	1-Sep-22	0.207	-0.195	2.29779	29.6907	3.12	16.305	15.966
Adrasan	1-Sep-15	0.201	-0.158	2.60485	67.5157	1.533	20.638	19.363
	1-Sep-16	0.142	-0.072	2.45131	94.0744	1.739	19.778	18.349
	1-Sep-17	0.194	-0.144	2.44761	88.8377	2.016	20.935	19.419
	1-Sep-18	0.202	-0.171	2.50117	100.2344	2.889	20.284	18.766
	1-Sep-19	0.221	-0.186	2.4877	97.9064	2.236	20.542	19.118
	1-Sep-20	0.235	-0.204	2.57125	89.5059	1.84	21.179	19.71
	1-Sep-21	0.215	-0.178	2.70587	97.089	2.331	19.938	18.445
	1-Sep-22	0.2	-0.153	3.01683	26.454	0.159	28.423	25.513

Table 3. Multiple Regression Results

Study Area	Model	R^2	p
Kumluca	Ŷ = 0.234- 0.909*NBR -0.01* Precipitation + 0.045*LST - 0.057*Mean Temp	0.99	0.000179
Adrasan	Ŷ = 0.093- 0.69*NBR	0.99	1.175E-06

To create the map given in Figure 5, the threshold values mentioned by Mallinis et al. (2018), which they indicated to provide the most accurate result in determining the severity of burning in the area, were used (Mallinis et al., 2018). Accordingly, when classified, it was calculated that 28.85% of the area burned at high severity, 48.71% at moderate-high severity, and 15.23% at moderate-low severity.

After obtaining NDVI and NBR values, calculations for climatic parameter values were conducted. These data, including the period prior to the fire year 2016, are provided in Table 2. The data in the table represent annual average values.
Upon examining the obtained data, it is observed that the annual average NDVI value showed a significant decrease in the year 2016, which corresponds to the fire year. Although this value increased over the years, the increase slowed down in 2018 and subsequent years due to smaller-scale fires occurring in the Kumluca region.

After all the data were calculated, a regression analysis was conducted to determine the impact of burn severity and other parameters on the regeneration process. The results of the regression analysis conducted are presented in Table 3. As seen in Table 3, the obtained R2 value for the created model is 0.99, and the significance value is calculated as 0.000179.

Discussion

Monitoring the regeneration process of burned forest areas is a critical step for ecosystem recovery after a fire. In this study, various factors influencing the regeneration process were examined using data obtained through remote sensing methods.
Multiple regression analysis was employed in the study to determine the effects of parameters. The results of the regression analysis indicate that the parameters examined in the dynamics of burned area regeneration, namely burn severity, precipitation levels, land surface temperature, and average air temperature, are influential for Kumluca area and burn severity for Adrasan area.
These findings are consistent with the literature. For instance, a study on regeneration processes, examining burn severity and regeneration, noted a negative correlation between burn severity and regeneration (Díaz-Delgado et al., 2003). Another parameter found to affect regeneration processes in the study is precipitation levels. Similarly, positive effects of precipitation levels on regeneration processes can be observed in the literature (Petrie et al., 2016).
Previous studies have shown that land surface temperature and air temperature can influence regeneration processes at certain periods (Petrie et al., 2016). The results of the regression analysis conducted in this study confirm similar outcomes. Factors such as temperature and land surface temperature are among those affecting plant health and regeneration (Digavinti and Manikiam, 2021).
GEE provides a powerful tool for monitoring the dynamics of burned forests by facilitating easy access to extensive spatial satellite imagery, enabling large-scale analyses, time series monitoring, automated image processing, and integration of various datasets. For example, in a study by Delgado et al., eight images were examined to monitor forest regeneration processes whereas, this study was able to analyze nearly 70 images (Díaz-Delgado et al., 2003). Additionally, obtaining data such as precipitation, land surface temperature, soil moisture, and air temperature through ground measurements requires a lengthy and laborious process. In contrast, GEE allows for the rapid acquisition of such information in a short period.

Conclusion

The regeneration process of burned forest areas is a complex and dynamic phenomenon influenced by numerous factors. Ongoing monitoring and research efforts are crucial to advance the understanding of regeneration dynamics and to inform evidence-based management practices in landscapes under the threat of fire. Utilizing information obtained from remote sensing technologies can effectively facilitate ecosystem restoration by examining the regeneration processes. Accordingly, in this study, remote sensing data were used to investigate the regeneration processes of burned forest areas and the parameters influencing this process. Parameters such as fire intensity, precipitation, temperature, and soil moisture were calculated using Google Earth Engine (GEE). The results of the multiple regression analysis conducted with the obtained values revealed that fire intensity, precipitation amounts, surface temperature, and average air temperature were effective parameters in the regeneration process.

References

Aalen, O. O. (1989). A linear regression model for the analysis of life times. *Statistics in medicine*, *8*(8), 907-925.

Abatzoglou, J. T., Dobrowski, S. Z., Parks, S. A., Hegewisch, K. C. (2018). TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. *Scientific data*, *5*(1), 1-12.

Aguilar, A. (2005). Remote sensing of forest regeneration in highland tropical forests. *GIScience & remote sensing*, *42*(1), 66-79.

Akça, Ş. (2023). Hava Lidar Verisi Üzerinde K-Ortalamalar ve Bulanık C-Ortalama ile Bina Çıkarımı. *Türkiye Lidar Dergisi*, *5*(2), 45-51.

Akosman, E. N., Makineci, H. B. Sentinel-2A Verileriyle Trabzon İli 2019-2020 Yılları Arasında Ortaya Çıkan Sınıflandırma Farklarının Çeşitli Algoritmalarla Değerlendirilmesi. *Türkiye Uzaktan Algılama Dergisi*, *5*(2), 78-88.

Aliyazıcıoğlu, Ş., Öztürk, K. F., Günen, M. A. (2023). Analysis of Gümüşhane-Trabzon highway slope static and dynamic behavior using point cloud data. *Advanced Lidar*, *3*(2), 70-75.

Avdan, U., Kucuk Matci, D., Kaplan, G., Yigit Avdan, Z., Erdem, F., Demirtas, I. Mızık, E.T. . (2021). Evaluating the Atmospheric Correction Impact on Landsat 8 and Sentinel-2 Data for Soil Salinity Determination. *Geodetski list*, *75*(3), 255-240.

Basara, A. C., Tabar, M. E., Gulsun, S., Sisman, Y. (2022). Monitoring urban sprawl in Atakum district using CORINE data. *Advanced Geomatics*, *2*(2), 49-56.

Başaran, N., MATCI, D. K., Avdan, U. (2022). Using multiple linear regression to analyze changes in forest area: the case study of Akdeniz Region. *International Journal of Engineering and Geosciences*, *7*(3), 247-263.

Cai, W., Yang, J., Liu, Z., Hu, Y., Weisberg, P. J. (2013). Post-fire tree recruitment of a boreal larch forest in Northeast China. *Forest Ecology and Management*, *307*, 20-29.

Capolupo, A., Monterisi, C., Tarantino, E. (2020). Landsat Images Classification Algorithm (LICA) to automatically extract land cover information in Google Earth Engine environment. *Remote Sensing*, *12*(7), 1201.

Chu, T., Guo, X., Takeda, K. (2016). Remote sensing approach to detect post-fire vegetation regrowth in Siberian boreal larch forest. *Ecological Indicators*, *62*, 32-46.

Çömert, R., Matcı, D. K., Emir, H., Avdan, U. (2017). Nesne Tabanlı Sınıflandırma ile Yanmış Orman Alanlarının Tespiti. *Afyon Kocatepe Üniversitesi Fen Ve Mühendislik Bilimleri Dergisi*, *17*(4), 27-34.

Çömert, R., Matci Küçük, D., Avdan, U. (2019). Object Based Burned Area Mapping With Random Forest Algorithm. *International Journal of Engineering and Geosciences*, *4*(2), 78-87.

Díaz-Delgado, R., Lloret, F., Pons, X. (2003). Influence of fire severity on plant regeneration by means of remote sensing imagery. *International Journal of Remote Sensing*, *24*(8), 1751-1763.

Digavinti, J., Manikiam, B. (2021). Satellite monitoring of forest fire impact and regeneration using NDVI and LST. *Journal of Applied Remote Sensing*, *15*(4), 042412-042412.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., . . . Hoell, A. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific data*, *2*(1), 1-21.

Gilbert, K. M., Shi, Y. (2023). Land use/land cover change detection and prediction for sustainable urban land management in Kigali City, Rwanda. *Advanced Land Management*, *3*(2), 62-75.

Gilbert, K. M., Shi, Y. (2024). Using GlobeLand30 data and cellular automata modeling to predict urban expansion and sprawl in Kigali City. *Advanced Remote Sensing*, *4*(1), 46-57.

Güngör, R., Yilmaz, O. S., Sanli, F. B., Ates, A. M. (2022). Investigation of spatial change in Lake Surface with Google Earth Engine: Example of Marmara Lake. *Advanced Remote Sensing*, *2*(1), 8-15.

Johnstone, J. F., Rupp, T. S., Olson, M., Verbyla, D. (2011). Modeling impacts of fire severity on successional trajectories and future fire behavior in Alaskan boreal forests. *Landscape Ecology*, *26*, 487-500.

Kazemi Garajeh, M., Haji, F., Tohidfar, M., Sadeqi, A., Ahmadi, R., Kariminejad, N. (2024). Spatiotemporal monitoring of climate change impacts on water resources using an integrated approach of remote sensing and Google Earth Engine. *Scientific reports*, *14*(1), 5469.

Keeley, J. E., Pausas, J. G. (2022). Evolutionary ecology of fire. *Annual Review of Ecology, Evolution, and Systematics*, *53*, 203-225.

Kucuk Matci, D. (2022). Monitoring and estimating spatial-temporary land use changes of the Aegean region with remotely sensed data. *Environmental Science and Pollution Research*, 1-10.

KumlucaBelediyesi. (2019). *COĞRAFYA*.

Kuplich, T. M. (2006). Classifying regenerating forest stages in Amazonia using remotely sensed images and a neural network. *Forest Ecology and Management*, *234*(1-3), 1-9.

Lemesios, I., Petropoulos, G. P. (2024). Vegetation regeneration dynamics of a natural mediterranean ecosystem following a wildfire exploiting the

LANDSAT archive, google earth engine and geospatial analysis techniques. *Remote Sensing Applications: Society and Environment*, *34*, 101153.

Lopes, L. F., Dias, F. S., Fernandes, P. M., Acácio, V. (2024). A remote sensing assessment of oak forest recovery after postfire restoration. *European Journal of Forest Research*, *143*(3), 1001-1014.

Makineci, H. B., Arıkan, D. (2024). Seyfe lake seasonal drought analysis for the winter and summer periods between 2017 and 2022. *Remote Sensing Applications: Society and Environment*, *34*, 101172.

Mallinis, G., Mitsopoulos, I., Chrysafi, I. (2018). Evaluating and comparing Sentinel 2A and Landsat-8 Operational Land Imager (OLI) spectral indices for estimating fire severity in a Mediterranean pine ecosystem of Greece. *GIScience & remote sensing*, *55*(1), 1-18.

Matarira, D., Mutanga, O., Naidu, M. (2022). Google Earth Engine for Informal Settlement Mapping: A Random Forest Classification Using Spectral and Textural Information. *Remote Sensing*, *14*(20), 5130.

Matcı, D. K., Avdan, U. (2020). Comparative analysis of unsupervised classification methods for mapping burned forest areas. *Arabian Journal of Geosciences*, *13*(15), 1-13.

Muñoz Sabater, J. (2019). ERA5-Land monthly averaged data from 1981 to present, Copernicus Climate Change Service (C3S) Climate Data Store (CDS)[data set]. In.

Mutanga, O., Kumar, L. (2019). Google earth engine applications. In: Multidisciplinary Digital Publishing Institute.

Ocer, N. E., Kaplan, G., Erdem, F., Kucuk Matci, D., Avdan, U. (2020). Tree extraction from multi-scale UAV images using Mask R-CNN with FPN. *Remote Sensing Letters*, *11*(9), 847-856.

OGM. (2017). Orman İstatistikleri. In: Yayın.

Petrie, M., Wildeman, A., Bradford, J. B., Hubbard, R., Lauenroth, W. (2016). A review of precipitation and temperature control on seedling emergence and establishment for ponderosa and lodgepole pine forest regeneration. *Forest Ecology and Management*, *361*, 328-338.

Polat, N., Memduhoğlu, A., Akça, Ş. (2022). Determining the change in burnt forest areas with UAV: The example of Osmanbey campus. *Advanced UAV*, *2*(1), 11-16.

Rasul, A. O., Hameed, H. M., Ibrahim, G. R. F. (2021). Dramatically increase of built-up area in Iraq during the last four decades. *Advanced Remote Sensing*, *1*(1), 1-9.

Roy, D. P., Boschetti, L., Trigg, S. N. (2006). Remote sensing of fire severity: assessing the performance of the normalized burn ratio. *IEEE Geoscience and Remote Sensing Letters*, *3*(1), 112-116.

Shafiq, M., Mahmood, S. (2022). Spatial assessment of forest cover change in Azad Kashmir, Pakistan. *Advanced GIS*, *2*(2), 62-69.

Şimşek, F. F. (2024). Optik ve radar görüntüleri ile aşırı gradyan artırma algoritması kullanılarak tarımsal ürün desen tespiti. *Geomatik*, *9*(1), 54-68.

Stankova, N., Avetisyan, D. (2024). Postfire Forest Regrowth Algorithm Using Tasseled-Cap-Retrieved Indices. *Remote Sensing*, *16*(3), 597.

Tucker, C. J. (1978). Red and photographic infrared linear combinations for monitoring vegetation.

USGS. (2015). *Landsat 8 band designations*.

Yalçın, M., Boz, İ. (2007). Kumluca İlçesinde Seralarda Üreticilerin Kullandiklari Bilgi Kaynaklari. *Bahçe*, *36*(1), 1-10.

Yiğit, A. Y., Uysal, M. (2020). Automatic road detection from orthophoto images. *Mersin Photogrammetry Journal*, *2*(1), 10-17.