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# Determining the change in burnt forest areas with UAV: The example of Osmanbey campus

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**Abstract**

Satellite data provides information about the fire and makes a significant contribution to damage assessment and improvement studies. Especially with multi-band satellite systems, it is possible to precisely identify and quickly map the fire damaged areas. However, satellite systems may be insufficient in terms of both temporal and spatial resolution. In addition, it is not always applicable in terms of cost according to the area of the working area. Unmanned Aerial Vehicles (UAVs), which have become widespread in many disciplines in recent years and in which imaging systems are integrated, provide new opportunities in this regard. UAVs are relatively more economical, user-friendly and provide high spatial resolution, providing convenience and speed in examining land changes in a short time. It is possible to make different analyzes according to the features of the integrated imaging system. In this study, Triangular Greenness Index (TGI) was produced by using a UAV system with a digital camera with visible bands. The study area is the forested area damaged in the fire that occurred in 2020 on the Osmanbey campus of Harran University. The data used for the study were obtained from two UAV flights one week after the fire and two years later. Both flight altitudes were 120m. While the rate of green space in the study area was 0.3% after the 2020 fire, it was observed that this rate increased to 0.54% in 2022. Thus, the areas that were not damaged immediately after the fire and the areas that grew green after two years were determined. expressions should not be included in essence.

## 1. Introduction

Forests are indispensable ecosystems for humans and all other species. These ecosystems, which have been formed as a result of many years, have suffered heavy losses in recent years due to climate change and human effects [1]. Forest fires are among the natural disasters where this effect is felt the most. In recent years, forest fires have occurred in much larger areas with the effect of global warming and last much longer than in the past. In this context, information is needed at every stage from the planning to management of forests as well as to understand and follow the causes of forest fires, which cause great ecological and economic damage [2-3]. This information is basically obtained by satellite and aerial photographs from past to present. Aerial photographs, which are used more frequently with the advantage of higher resolution, are used in forestry: producing forest maps, taking inventory, tracking wildlife and forest fires [4].

UAV has been frequently used in engineering projects since last decade. Pond volume determination [5], landslide site [6-8], rockfall site [9], cultural heritage modelling [10-16] and soil erosion [17] are the most used ones.

The field of forestry, which obtains its basic information needs from aerial photographs, has also kept up with the developing technology and has started to use Unmanned Aerial Vehicles (UAV) to obtain these aerial photographs. UAVs are frequently used in forestry activities due to their advantages such as more compact, high resolution image acquisition and low cost compared to satellite and aircraft systems. High-resolution image data obtained from the UAV is converted into useful information necessary for the forestry field by using various image processing techniques [18]. Image processing techniques are frequently used for the detection of forest fires, as well as the examination of medical images, object recognition, detection of plant diseases [19]. In addition, UAVs can also be used for the purposes of detecting forest fire areas, examining the situation, and monitoring reforestation. It is important to obtain observations and data by UAV in these areas, as reclaiming the burned forest areas as forest is a long process that needs to be followed. In particular, the difference between the photographs obtained by the UAV flights made at certain time intervals can be revealed by using image processing techniques. In this way, it can be ensured that forest areas are healed quickly by monitoring the forest development in the burned areas and by intervening when necessary. In addition, these images are evidence and provide a basis for early detection and intervention of illegal human activities that attempt to build in burnt forest areas. In this context, the use of UAVs for forestry activities is a milestone in terms of providing fast and low-cost useful information.

Various vegetation indices related to plant cover and chlorophy ll content. In literature, vegetation indices are used precision agriculture [20-21], drought [22-24], plant yield [25-26], detection of irrigation inhomogeneities [27], evaluating of post fire vegetation recovery [28], vegetation [29] and forest [30] monitoring, assessment of forest fire damage [31].

Healthy plants show more reflection in the near infrared (NIR) and green wavelengths than in other wavelengths. Red and blue wavelengths are absorbed. At this point, various indices have been developed to detect healthy vegetation on satellite images. The indexes developed depending on the visible region (Vis), Vis+NIR and Red-NIR bands reflection range are given in Table 1.

**Table 1.** Reflection range indexes

| Region | Indexes | Equation | Reference |
|---|---|---|---|
| Visible (Vis) | Triangular Greenness Index | $TGI = -0.5[(\rho_r - \rho_b)(\lambda_r - \lambda_g) - (\rho_r - \rho_g)(\lambda_r - \rho\lambda_b)]$ | [32] |
| Visible | Green Leaf Index | $GLI = (2\lambda_g - \lambda_r - \lambda_b)/(2\lambda_g - \lambda_r - \lambda_b)$ | [33] |
| Visible | Visible atmospherically resistant index | $VARI = (\lambda_g - \lambda_r)/(\lambda_g - \lambda_r - \lambda_b)$ | [34] |
| NIR- RED | Ratio vegetation index (also called simple ratio) | $RVI = \lambda_n/\lambda_r$ | [35-36] |
| NIR- RED | Normalized difference vegetation index | $NDVI = (\lambda_n - \lambda_r)/(\lambda_n + \lambda_r)$ | [37-38] |
| NIR- RED | Soil adjusted vegetation index | $SAVI = (1 + 0.5)(\lambda_n - \lambda_r)/(\lambda_n + \lambda_r + 0.5)$ | [39] |
| Vis-NIR | Enhanced vegetation index | $EVI = 2.5(\lambda_n - \lambda_r)/(\lambda_n + 6.\lambda_r - 7.5\lambda_b + 1)$ | [40] |
| Vis-NIR | Triangular vegetation index | TVI = $0.5[120(\lambda_n - \lambda_g) - 200(\lambda_r - \lambda_g)]$ | [41] |
| Vis-NIR | Chlorophyll vegetation index | $CVI = \lambda_n.\lambda_r/\lambda_g{}^2$ | [42] |
| Notations: | $\rho_{r,b}$ : represent the center of wavelenghts<br>$\lambda_{b,g,r,n}$: Blue,Green, Red, NIR reflections | | |

Satellite data provides information about the fire and makes a significant contribution to damage assessment and improvement studies. Especially with multi-band satellite systems, it is possible to precisely identify and quickly map the fire damaged areas. However, satellite systems may be insufficient in terms of both temporal and spatial resolution. In addition, it is not always applicable in terms of cost according to the area of the working area. Unmanned Aerial Vehicles (UAVs), which have become widespread in many disciplines in recent years and in which imaging systems are integrated, provide new opportunities in this regard. UAVs are relatively more economical, user-friendly and provide high spatial resolution, providing convenience and speed in examining land changes in a short time. It is possible to make different analyzes according to the features of the integrated imaging system. In this study, Triangular Greenness Index (TGI) was produced by using a UAV system with a digital camera with visible bands.

## 2. Method

### 2.1. Study Area

In this study, the change in the forestation area of Harran University Osmanbey campus, which was damaged in the fire that occurred in 2020, was examined (Figure 1).

This region is an important area for Şanlıurfa. Because Harran University Osmanbey campus forestation area is the second largest area in the center of Şanlıurfa. Turkey's forest assets are 32% on average according to the surface area of the provinces, and Şanlıurfa forest assets are around 1% as the ratio of the city's surface area together with Ağrı and Iğdır.

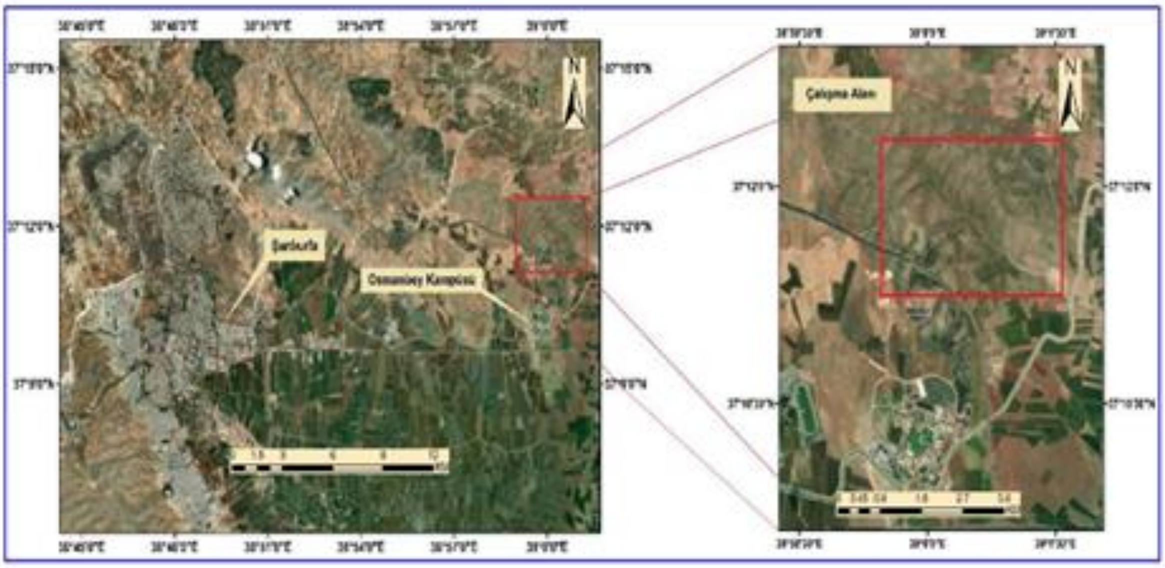

**Figure 1.** Study area: Harran University Osmanbey campus

### 2.2. Triangular Greenness Index

TGI (Triangular Greenness Index) was established in 2013 by Hunt et al. suggested by using visible (RGB) bands. This formula is designed to be sensitive to chlorophyll content (green color). It is a fast and advantageous method for situations where there is no infrared band. It is recommended as a low-cost method of monitoring plants, especially with digital cameras mounted on low-flying aerial platforms. It is reported to give very similar results with NDVI in green plant detection. Equation 1 is used in the analysis.

$$TGI = (GREEN - 0.39 * RED - 0.61 * BLUE) \quad (1)$$

## 3. Results

The study was carried out with UAV flights at two different times. The first flight took place in July 2020, one week after the fire. The second flight was carried out in March 2022. Both flights took place at an altitude of 120m. transverse and longitudinal overlaps are 70%. DJI Mavic 2 pro was used for the flight. The DJI Mavic 2 Pro was launched in late 2018 and was the first consumer drone to feature a one-inch sensor and adjustable aperture. The camera fitted to the Mavic Pro 2 is a Hasselblad L1D-20c, providing a full-frame equivalent focal length of 28mm with ISO 100-12,800 available for stills and ISO 100-6400 available for video.

RGB photos from both flights were processed in Pix4D software. As a result, the orthophoto of the region is obtained. TGI images were obtained using both orthophotos RGB bands. The resulting TGI images are given in Figure 2.

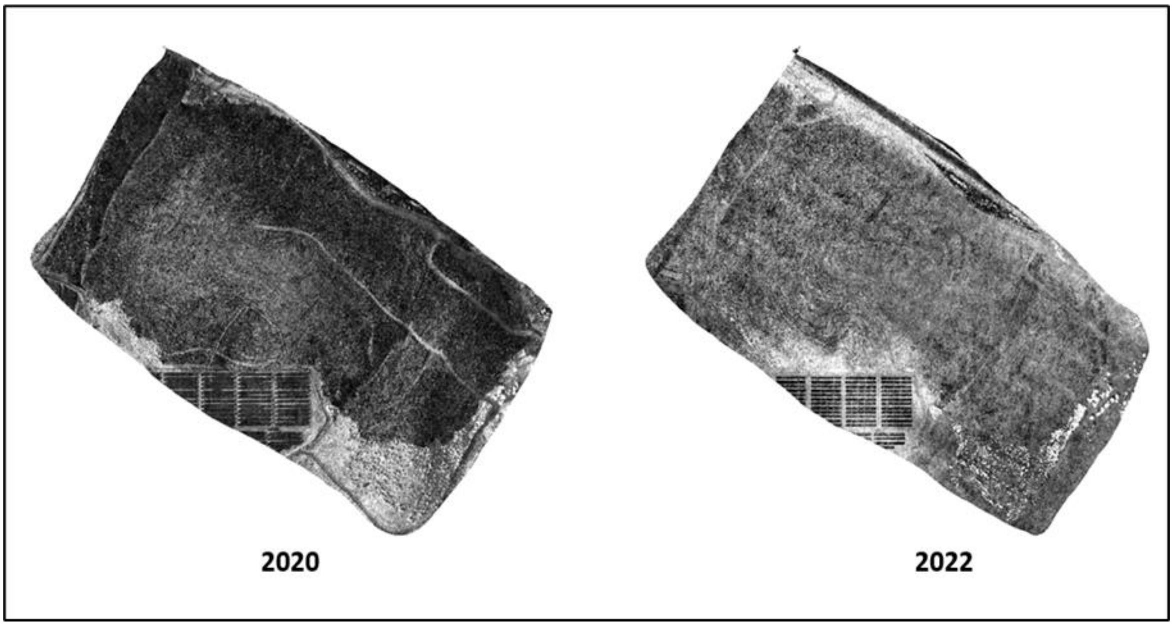


**Figure 2.** TGI images of Harran University Osmanbey campus for 2020 July and 2022 March

## 4. Discussion

When the TGI images obtained are examined, some changes can be noticed. The study area is the forested area damaged in the fire that occurred in 2020 on the Osmanbey campus of Harran University. The data used for the study were obtained from two UAV flights one week after the fire and two years later. Both flight altitudes were 120m. While the rate of green space in the study area was 0.3% after the 2020 fire, it was observed that this rate increased to 0.54% in 2022. Thus, the areas that were not damaged immediately after the fire and the areas that grew green after two years were determined. expressions should not be included in essence. When the areas with circle, triangle and square signs are examined, it is clearly seen that there are growths in some of the newly greening trees in some regions (Figure 3).

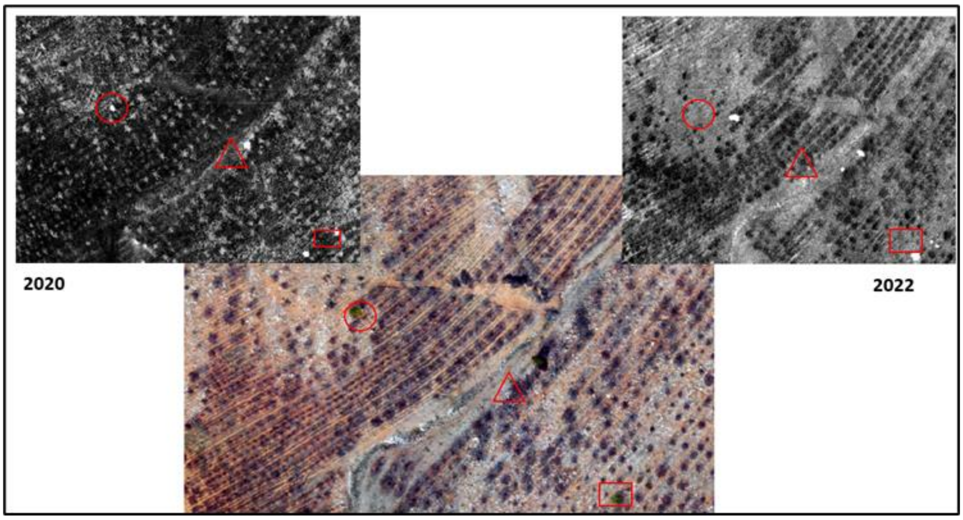


**Figure 3.** Growths and newly greening trees in the region

## 5. Conclusion

It is a fast and advantageous method for situations where TGI Infrared band is not available. It is recommended as a low-cost method for monitoring plants, especially with low-flying aerial platforms. Although it is mentioned that it gives similar results with NDVI in green plant detection, there are warnings that it also detects green objects. While the rate of green space in the study area was 0.3% after the 2020 fire, it was observed that this rate increased to 0.54% in 2022. Thus, the areas that were not damaged immediately after the fire and the areas that grew green after two years were determined.

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**Author contributions:**

**Nizar Polat:** Conceptualization, Methodology, Software **Abdulkadir Memduhoğlu:** Data curation, Writing-Original draft preparation, Software, Validation. **Şeyma Akça:** Visualization, Investigation, Writing-Reviewing and Editing.

**Conflicts of interest**

The authors declare no conflicts of interest.

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