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Triangular Greenness Index Analysis for Monitoring Fungal Disease in Pine Trees: A UAV-based Approach

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Research Article

Abstract − The Triangular Greenness Index (TGI) is a vegetation index derived from high-resolution aerial images acquired using unmanned aerial vehicles (UAVs). It serves as a valuable tool for quantifying vegetation health and dynamics in the visible spectrum. The TGI combines key components, including red reflectance and green reflectance, extracted from UAV-based imagery. The red component represents chlorophyll absorption and photosynthetic activity, while the green component reflects vegetation density and canopy structure. By integrating these components, the TGI offers a comprehensive measure of photosynthetically active vegetation, utilizing UAVs as a data collection platform. This study highlight the importance of the TGI derived from UAV-based imagery in monitoring vegetation changes, assessing ecosystem responses, and tracking variations in land cover and biodiversity. Furthermore, the application of TGI analysis using UAV-based aerial imagery shows promise in accurately identifying and monitoring vegetation affected by fungal diseases. This integrated approach enables the detection of diseased trees based on distinct changes in greenness observed in their foliage. Because fungal diseases dry the plant and cause the green areas to disappear. The integration of UAV technology enhances the accuracy and efficiency of TGI calculation, contributing to effective management and conservation strategies in the context of fungal disease detection in vegetation. In this study, TGI was produced using UAV-based orthophoto and healthy and sick trees were determined. According to the accuracy analysis, producer accuracy for detecting green plants was 99.7% and user accuracy was 98.5%. Fungal disease could be detected with 98.5% producer accuracy and 96.5% user accuracy. The overall accuracy of the study was calculated as 98.6%.

Keywords − *UAV Photogrammetry, visible region vegetation index, Triangular Greenery Index (TGI), fungal disease, pine tree*

Çam Ağaçlarında Mantar Hastalığının İzlenmesi için Üçgen Yeşillik İndeksi Analizi: İHA Tabanlı Bir Yaklaşım

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Araştırma Makalesi

Öz − Üçgen Yeşillik İndeksi (TGI), insansız hava araçları (İHA) kullanılarak elde edilen yüksek çözünürlüklü hava görüntülerinden türetilen bir bitki örtüsü indeksidir. Görünür spektrumda bitki örtüsünün sağlığını ve dinamiklerini ölçmek için değerli bir araç olarak hizmet eder. TGI, İHA tabanlı görüntülerden elde edilen kırmızı yansıma ve yeşil yansıma dahil olmak üzere temel bileşenleri birleştirir. Kırmızı bileşen klorofil emilimini ve fotosentetik aktiviteyi temsil ederken, yeşil bileşen bitki örtüsü yoğunluğunu ve kanopi yapısını yansıtır. Bu bileşenleri entegre eden TGI, İHA'ları bir veri toplama platformu olarak kullanarak fotosentetik olarak aktif bitki örtüsünün kapsamlı bir ölçümünü sunmaktadır. Bu çalışma, İHA tabanlı görüntülerden elde edilen TGI'nın bitki örtüsü değişikliklerinin izlenmesinde, ekosistem tepkilerinin değerlendirilmesinde ve arazi örtüsü ve biyoçeşitlilikteki değişimlerin izlenmesindeki önemini vurgulamaktadır. Ayrıca, İHA tabanlı hava görüntüleri kullanılarak TGI analizinin uygulanması, mantar hastalıklarından etkilenen bitki örtüsünün doğru bir şekilde tanımlanması ve izlenmesinde umut vaat etmektedir. Bu entegre yaklaşım, yapraklarında gözlemlenen yeşillikteki belirgin değişikliklere dayanarak hastalıklı ağaçların tespit edilmesini sağlar. Çünkü mantar hastalıkları bitkiyi kurutur ve yeşil alanların yok olmasına neden olur. İHA teknolojisinin entegrasyonu, TGI hesaplamasının doğruluğunu ve verimliliğini artırarak bitki örtüsündeki mantar hastalıklarının tespiti bağlamında etkili yönetim ve koruma stratejilerine katkıda bulunur. Bu çalışmada, İHA tabanlı ortofoto kullanılarak TGI üretilmiş ve sağlıklı ve hasta ağaçlar belirlenmiştir. Doğruluk analizine göre, yeşil bitkileri tespit etmek için üretici doğruluğu %99,7 ve kullanıcı doğruluğu %98,5'tir. Mantar hastalığı %98,5 üretici doğruluğu ve %96,5 kullanıcı doğruluğu ile tespit edilebilmiştir. Çalışmanın genel doğruluğu %98,6 olarak hesaplanmıştır.

Anahtar Kelimeler − *İHA fotogrametrisi, görünür bölge bitki örtüsü indeksi, Üçgen Yeşillik İndeksi (TGI), mantar hastalığı, çam ağacı*

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1. Introduction

Environmental monitoring is a crucial element in comprehending and effectively managing Earth's resources and ecosystems (Roy et al., 2022). It encompasses the systematic and efficient observation and evaluation of changes in land use, land cover, and natural processes over time. Remote sensing, a pivotal technique in Earth observation, plays a vital role in this endeavor by acquiring information about the Earth's surface and atmosphere without direct physical contact (Sohl and Sleeter, 2012; Chowhan and Chakraborty, 2022). It involves the utilization of sensors mounted on satellites, aircraft, or unmanned aerial vehicles (UAVs) to collect data by measuring the interaction between electromagnetic radiation and the Earth's features. Through remote sensing, environmental scientists and researchers can effectively monitor various phenomena such as deforestation, urbanization, soil erosion, and the impacts of climate change (Aksoy and Kaptan, 2020; Durkaya et al., 2020; Blaga et al., 2023). The utilization of remote sensing data provides valuable information for the development of effective environmental policies, resource management strategies, and conservation efforts.

Vegetation analysis (Demir and Başayiğit, 2021) is an integral aspect of environmental monitoring and management as it serves as a fundamental indicator of ecosystem health and dynamics. Assessing the health and dynamics of vegetation is crucial for understanding ecological processes, monitoring ecosystem responses to environmental stressors, and identifying changes in land cover and biodiversity. Greenness indices, including the Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974; Tucker, 1979), Enhanced Vegetation Index (EVI) (Huete et al., 2002), and Triangular Greenness Index (TGI) (Hunt et al., 2011)., are essential tools for quantifying vegetation health and dynamics. These indices exploit the differential reflectance properties of vegetation in the red and near-infrared (NIR) regions of the electromagnetic spectrum. Healthy and vigorously growing vegetation typically exhibits high reflectance in the NIR region due to strong chlorophyll absorption in the red region, resulting in higher greenness index values. The utilization of greenness indices, derived from remote sensing data, seamlessly integrates with the previous discussion on vegetation analysis.

In recent decades, unmanned aerial vehicles (UAVs) have gained significant popularity in various engineering projects. These projects include tasks such as determining pond volume (Kaya et al., 2019), assessing landslide sites (Kusak et al., 2021), analyzing rockfall sites (Yakar et al., 2022), creating cultural heritage models (Yilmaz et al., 2012; Yakar and Doğan, 2018), and evaluating soil erosion (d'Oleire-Oltmanns et al., 2012). These applications have emerged as the most utilized applications of UAV technology in engineering projects. It has now revolutionized detailed and up-to-date monitoring by providing a flexible, cost-effective platform for data collection in environmental studies.

UAVs have diverse applications across various fields, including water resource management (Kaya et al., 2023), product observation, equipment and building inspection, mapping, yield monitoring, soil erosion assessment, water stress analysis, disease (Bhupathi and Sevugan, 2021) and pest detection, as well as weed control (Türkseven et al., 2016; Özgüven, 2018; Şin and Kadıoğlu, 2019; Demir and Başayiğit, 2020). To combat these weeds, different types of cameras with specific features are utilized (Bannari et al., 1995; Brovkina et al., 2018). By collecting data from cameras mounted on UAVs, it becomes feasible to map the existing flora (Özgüven, 2018). Additionally, the potential losses in crop yield can be estimated. Studies focusing on NDVI (Normalized Difference Vegetation Index) and similar metrics are conducted as green plants exhibit a heightened sensitivity to infrared wavelengths (Türkseven et al., 2018). UAVs offer a unique advantage in vegetation analysis by acquiring high-resolution aerial imagery. Integrating Triangular Greenness Index (TGI) analysis with UAV technology offers a promising solution for the identification and monitoring of vegetation. The TGI, a visible vegetation index, quantifies the relative abundance of photo synthetically active vegetation and serves as a proxy for vegetation health and dynamics. It is calculated by exploiting the differential reflectance properties of vegetation in the red and green regions of the electromagnetic spectrum.

UAV-based TGI analysis involves capturing aerial imagery using RGB (red, green, blue) digital cameras mounted on UAV platforms.

In the specific context of this study, there is an ongoing issue of fungal disease in pine trees at Harran University Osmanbey Campus. This disease causes the leaves of pine trees to dry up and lose their green color. To address this problem, an approach is being taken to detect the affected trees by generating the TGI from images obtained using UAV technology. By utilizing UAV-based aerial imagery and applying TGI analysis, it is anticipated that the diseased trees can be accurately identified based on distinct changes in greenness observed in their foliage.

This study aims to achieve the following objectives: firstly, to assess the applicability of the TGI obtained from UAV-based aerial images for the detection and monitoring of fungal disease affecting pine trees at Harran University Osmanbey Campus. Secondly, to examine the relationship between TGI values and the severity of the fungal disease, with the goal of establishing a quantitative measure of vegetation health and identifying areas with a high disease prevalence. Lastly, to evaluate the feasibility and effectiveness of utilizing UAV-based aerial imagery and the TGI as a cost-effective and efficient method for early detection and monitoring of fungal disease in pine trees.

2. Material and Methods

The methodology section of this study encompasses the implementation of a data collection, the subsequent image processing, the generation of the TGI, and the accuracy analysis of the obtained results.

2.1. Data Collection

The data collection process using UAVs for acquiring high-resolution aerial images involves planning the flight path and imaging parameters. A photogrammetric flight plan is meticulously designed to ensure comprehensive coverage of the target area and optimize the image acquisition process. Factors such as spatial resolution, image overlap, and flight altitude are carefully considered during the planning stage. The flight plan determines the path that the UAV will follow to capture images of the designated area, often designed in a grid or zigzag pattern with sufficient image overlap. Imaging parameters, including camera settings and image capture intervals, are also determined during the flight planning phase (Uysal et al., 2013; Demirel et al., 2022). These parameters ensure high-quality images with optimal exposure and sufficient overlap for accurate photogrammetric analysis.

During the actual UAV flight, the system follows the predetermined flight plan, capturing images at regular intervals. The onboard camera system captures high-resolution images at specified locations along the flight path. The images are geotagged with GPS coordinates, providing precise location information for each captured image. Geotagging enables accurate spatial referencing and integration of the images into a coordinate system. After data collection, the images undergo post-processing, which includes georeferencing, distortion correction, and image mosaicking. Georeferencing aligns the images with reference points, establishing their accurate geographic location. Distortion correction corrects any lens or perspective distortions, ensuring accurate measurements and analysis. Image mosaicking stitches the individual images together, creating a seamless orthomosaic for a comprehensive view of the target area. This carefully planned and executed data collection process using photogrammetric UAV flights provides high-resolution aerial images with precise geolocation, supporting vegetation analysis, land cover mapping, and environmental monitoring endeavors.

This study was carried out with the DJI Mavic 2 Pro UAV system, which is useful in data collection and has high sensitivity. It is a successful system with features such as an effective range of 8 km, a maximum flight time of 31 minutes, 4K recording with a Hasselblad camera, a 1" CMOS sensor, GPS sensor, 4-way obstacle sensing, automatic return to home, and a weight of approximately 1 kg. The UAV used in the study is depicted in Figure 1.

Figure 1. The UAV system used in the study (URL-1)

2.2. Fungal Monitoring

Vascular wilt diseases represent a significant threat to pine forests on a global scale, inducing swift wilting, discoloration, and eventual demise. These afflictions primarily stem from fungal pathogens infiltrating the xylem, the vital water transport system within trees, disrupting water flow and triggering dehydration, nutrient deficiencies, and ultimately mortality. Common culprits encompass Bursaphelenchus xylophilus, the pin-ewood nematode, often coupled with Bursaphelenchus conicentrus, a fungal symbiont, culminating in pine wilt disease (PWD), and Ceratocystis fagacearum, accountable for Ceratocystis wilt in diverse pine species (Zhou et al., 2017; Costanza et al., 2018). PWD has notably wrought widespread havoc in Asia, decimating millions of hectares of pine forests. Its dissemination is facilitated by insect vectors such as the pine sawyer beetle (Monochamus spp.), which transmit the nematode to uninfected trees. Initial symptoms manifest as wilting and discoloration of needles, escalating to complete crown browning over weeks to months (Kim et al., 2020). A comprehensive understanding of the intricate interplay between fungus, insect vector, and host tree is indispensable for devising effective management tactics. Contemporary strategies are centered around thwarting vector dispersal via insecticide applications and implementing silvicultural measures. Moreover, ongoing research into resilient pine varieties and biological control agents offers promising avenues for future disease mitigation efforts (Kim et al., 2020; Wang et al., 2011).

2.3. Image Processing

The image processing section of this study focuses on the post-processing of UAV-based aerial images using the structure from motion (SfM) algorithm, a widely used technique in photogrammetry (Akca and Polat, 2022, Uysal et al., 2015; Yiğit, 2020). The SfM algorithm plays a crucial role in reconstructing three-dimensional structures by establishing correspondences between common features in a collection of two-dimensional images and estimating camera positions and orientations (Snavely et al., 2008). By applying the SfM algorithm to the captured aerial images, accurate orthomosaics and three-dimensional models can be generated, providing researchers with precise geometric information about the study area. The SfM algorithm examines shared points or features that appear in multiple images and employs intrinsic and extrinsic camera parameters, including focal length, distortion, principal point, camera position, and orientation. By utilizing these parameters, the algorithm calculates the 3D coordinates of the points in the scene, generating a point cloud that represents the scene's structure (Remondino and El-Hakim, 2006). SfM algorithms are grounded in the principles of photogrammetry, computer vision, and machine learning, representing advanced techniques that are widely acknowledged and embraced in the field (Toprak et al., 2019)

The generated orthomosaics and three-dimensional models offer numerous applications, including vegetation analysis, topographic mapping, and infrastructure planning. These representations provide detailed and reliable information about the spatial distribution and characteristics of vegetation, as well as the topography of the area of interest. This information is valuable for assessing vegetation health, quantifying land cover changes, and supporting decision-making processes related to infrastructure development and management.

By utilizing the capabilities of the SfM algorithm and image processing techniques, this study aims to gain insights into various aspects, such as vegetation dynamics, topographic features, and spatial relationships. These findings will contribute to effective environmental monitoring and management practices, enhancing the understanding and decision-making capabilities in relevant fields.

2.4. Triangular Greenness Index (TGI)

Currently, spectral information plays a crucial role in agriculture for distinguishing vegetation types and conducting in-depth analysis of vegetation characteristics. Typically, these analyses are based on spectral indices, which are derived by calculating ratios of different bands or normalizing band differences (Jackson and Huete, 1991). Many of these indices utilize NIR wavelengths, which are sensitive to both chlorophyll content and leaf area index (LAI). Haboudane et al. (2008) introduced the triangular chlorophyll index based on green, red, and red-edge bands to quantify leaf nitrogen levels. Subsequently, red-edge bands have been incorporated into various satellite sensors (Eitel et al., 2007; Herrmann et al., 2011; Ramoelo et al., 2012), thereby enhancing the sensitivity for chlorophyll detection (Gitelson, 2011). However, low-cost multispectral sensors typically lack NIR or red-edge bands and are limited to visible wavelength bands. To address this limitation, a visible-band index known as the TGI was developed (Hunt et al., 2011). The proposed method relies on chlorophyll content as its basis.

TGI is an important vegetation index utilized to assess the greenness and vigor of vegetation using remotely sensed data. It serves as a valuable tool for evaluating vegetation health and dynamics in various applications. The TGI is computed by utilizing three spectral bands, namely the red, green, and blue bands, which are typically extracted from remote sensing imagery. The selection of these bands is contingent upon the particular remote sensing system or sensor employed. In the context of this study, the visible region of the electromagnetic spectrum (RGB) captured by a consumer-grade digital camera is utilized for TGI calculation. TGI is calculated as follows.

$$TGI = (GREEN - (0{,}39 * RED) - (0{,}61 * BLUE) \quad (1)$$

The TGI formula compares the spectral differences between the green band and the red/blue bands, capturing the greenness component of vegetation. Higher TGI values indicate healthier and more vigorous vegetation, reflecting a greater level of greenness. It is worth noting that the choice of spectral bands in the TGI formula may vary depending on the remote sensing system's characteristics and the specific objectives of the analysis.

The calculation of the TGI incorporates key components that contribute to its biological significance in assessing vegetation health. The green band represents the reflectance of green light, which is strongly absorbed by chlorophyll, the primary pigment responsible for photosynthesis. The red band reflects the absorption of red light, and healthy vegetation tends to reflect more green light and absorb more red light due to its high chlorophyll content. The inclusion of the blue band in the TGI formula further emphasizes the greenness component. Herewith, higher TGI values indicate vegetation with higher chlorophyll content and greater greenness, while lower TGI values may suggest stressed or less vigorous vegetation with reduced chlorophyll levels and diminished photosynthetic activity (Hunt et al., 2011).

2.5. Raster Color Slices

The color slice technique is a valuable tool used in image processing to highlight specific data ranges and colors within an image (Yu et al., 2023). By utilizing the raster color slices tool, users can select desired data ranges and assign corresponding colors to visually emphasize certain areas of interest (Harris Geospatial, 2016). The output of this tool is a raster image where pixel values are color-mapped based on the defined ranges and colors. This resultant image can be treated as a classification image in subsequent processing, enabling further analysis and interpretation. The color slices effectively group pixel values into discrete ranges, each represented by a unique color. Overlaying a color slice on an associated image enhances the visualization of image processing results, allowing for a clearer understanding of the spatial distribution and characteristics of the highlighted areas. This technique is particularly useful in applications where specific data ranges or features need to be emphasized and analyzed in the context of the overall image.

2.6. Accuracy Analysis

The methodology for calculating a confusion matrix with ground truth region of interest (ROI) involves comparing predicted and actual class labels. This is done by applying a classification or prediction model to a dataset with labeled instances and comparing the predicted labels with the ground truth labels. The confusion matrix, a tabular representation of the predicted and actual class labels, is constructed based on the counts of instances in each combination. From the confusion matrix, producer accuracy (sensitivity), user accuracy (precision), overall accuracy, and Kappa coefficient can be calculated (Story and Congalton, 1986). Producer accuracy measures the proportion of correctly predicted instances for each class, while user accuracy calculates the proportion of correctly predicted instances based on the predicted labels. Omission errors, also known as false negatives, occur when the model fails to predict instances that belong to a particular class. Commission errors, also known as false positives, occur when the model incorrectly predicts instances to belong to a particular class. These errors can be identified by examining the entries in the confusion matrix. Overall accuracy provides an assessment of the model's accuracy across all classes, taking into account both omission and commission errors. The Kappa coefficient takes into account chance agreement between predicted and actual labels and provides a measure of the model's performance beyond random chance.

To calculate the confusion matrix and associated metrics, appropriate formulas and calculations are applied based on the counts within the matrix. These metrics offer valuable insights into the model's performance, indicating its accuracy in classifying instances and providing an overall assessment of its performance, considering omission and commission errors. By evaluating the producer and user accuracy, overall accuracy, and Kappa coefficient, researchers can gain a comprehensive understanding of the classification model's strengths and weaknesses, enabling further analysis and improvement (Wang et al., 2022).

Errors of commission indicate the proportion of values that were erroneously predicted to belong to a particular class, despite not actually belonging to that class. These errors, often referred to as false positives, can be observed in the rows of the confusion matrix, excluding the values on the main diagonal. On the other hand, errors of omission represent the fraction of values that truly belong to a specific class but were inaccurately predicted to be part of a different class. These errors, known as false negatives, can be found in the columns of the confusion matrix, except for the values along the main diagonal.

Producer accuracy, also known as sensitivity, measures the probability that a value belonging to a certain class is correctly classified as such. It is derived by calculating the ratio of correctly predicted values to the total number of values in that class. User accuracy, also referred to as precision, assesses the likelihood that a predicted value truly belongs to a given class. This probability is determined by evaluating the fraction of correctly predicted values against the total number of values predicted to be in that class.

Overall accuracy, a fundamental metric, is computed by summing the number of correctly classified values and dividing it by the total number of values. The correctly classified values correspond to the elements along the diagonal from the upper-left to the lower-right of the confusion matrix. The total number of values used for this calculation can be obtained from either the ground truth or predicted-value arrays, as they should be of equal size and reflect the entire dataset.

$$OA = \frac{correctly\ classified\ pixels}{total\ number\ of\ pixels} \tag{2}$$

All calculations and ROI selections were performed in Envi software. For detailed information about confusion matrix and associated metrics, please check the (HarrisGeospatial, 2023) resource.

3. Results

In this study, a total of 1,263 aerial images were acquired using a single camera station. The unmanned aerial vehicle (UAV) was flown at an altitude of 50 meters, resulting in a ground resolution of 1.53 centimeters per pixel. The coverage area of the imagery was approximately 0.136 square kilometers. To ensure comprehensive coverage and minimize data gaps, a 70% overlap between adjacent images was maintained during the flight. This overlap ensured sufficient redundancy and allowed for the creation of accurate orthomosaics and three-dimensional models. Additionally, during the processing stage, 323,584 tie points were identified and used to establish precise georeferencing and alignment of the images. The combination of the extensive image dataset, high overlap, and numerous tie points provides a robust foundation for detailed analysis, mapping, and interpretation in this study. As a result of the data processing and analysis, several outputs were obtained for the study area. Firstly, a point cloud was generated, which represents a digital elevation model (DEM) capturing the three-dimensional structure of the terrain. This point cloud provides detailed information about the elevation and topography of the study area (Figure 2).

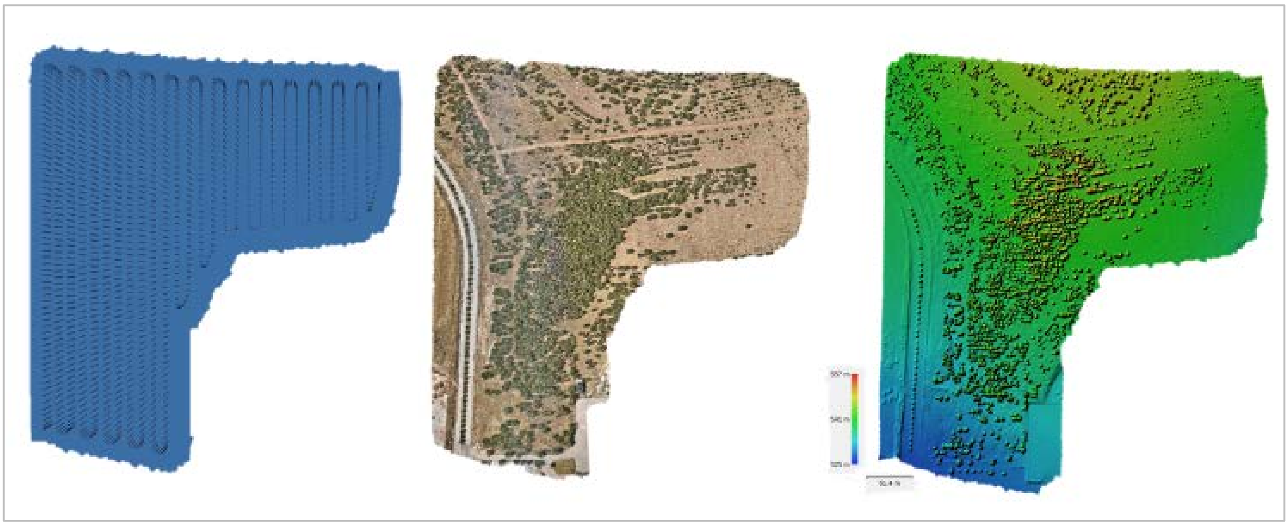

Figure 2. UAV Flight path, dense point cloud and DSM

Additionally, a high-resolution orthophoto was produced, which is an orthorectified image with consistent scale and minimal geometric distortions. This orthophoto accurately represents the study area from a top-down perspective, allowing for visual interpretation and analysis. Figure 3 displays the high-resolution orthophoto, providing a clear and detailed view of the study area and its features.

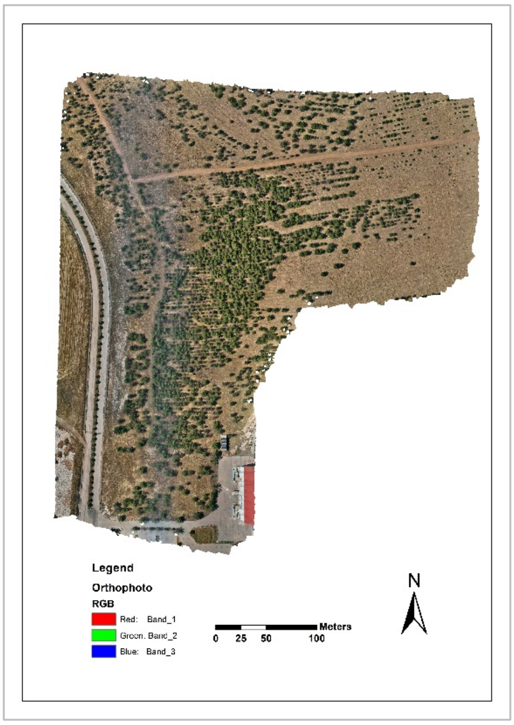

Figure 3. Generated orthophoto

The next step in the study involved generating the TGI using the band math tool in Envi software, based on Equation 1 (Figure 4). The pixel values derived from the color slice operation exhibit a range between -42,9 and 60,46. Figure 4 visually demonstrates that positive pixel values correspond to greener vegetation, indicating higher levels of vigor. Based on the conducted analysis, pixel values equal to or greater than 15.3 are indicative of green vegetation. In contrast, pixel values falling within the range of -5.5 to 15.3 suggest the presence of fungal disease. Negative pixel values represent other elements present in the scene, such as soil and roads. The color slice technique, as illustrated in the figure, facilitates the effective classification and interpretation of the TGI image, allowing for the differentiation and delineation of specific features and components based on their corresponding pixel values.

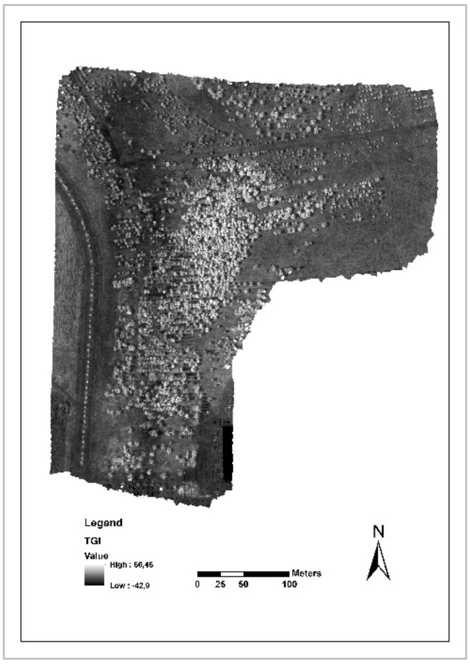

Figure 4. Generated TGI

By considering the defined thresholds for each class, a color slice technique was employed to classify the TGI image, resulting in the delineation of three distinct categories as depicted in Figure 5. These classes include green vegetation, fungal disease, and others. The "other" class encompasses various non-vegetation elements, such as soil, roads, buildings, and shadows, which are not directly related to the vegetation health analysis. Through the successful segmentation and classification of the TGI image, a comprehensive understanding of the spatial distribution and characteristics of different components within the imagery was achieved. This segmentation approach provides a valuable foundation for further analysis and interpretation of the study area, facilitating the identification of specific regions of interest and supporting decision-making processes in vegetation monitoring and management.

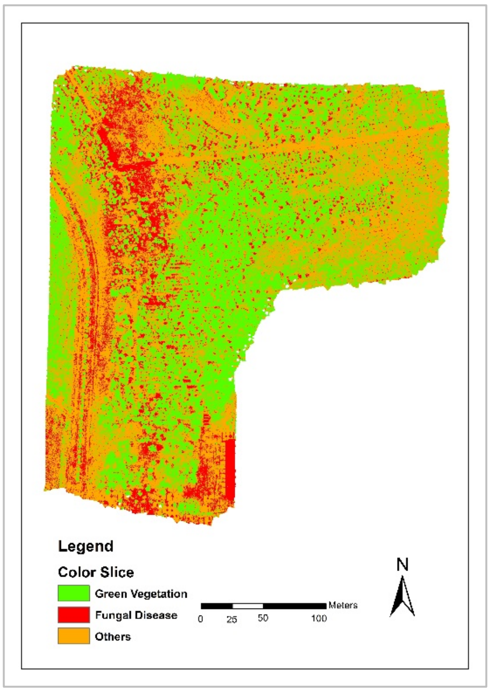

Figure 5. TGI color slice result

Within the scope of the study, a three-class image was generated using TGI color slice. The resulting color slice was initially visually analyzed by comparing it with the orthophoto. Since TGI is sensitive to green color, the accuracy of correctly identifying green pixels representing trees was assessed. The comparative visual representation of three selected sample regions from the area is presented in Figure 6.

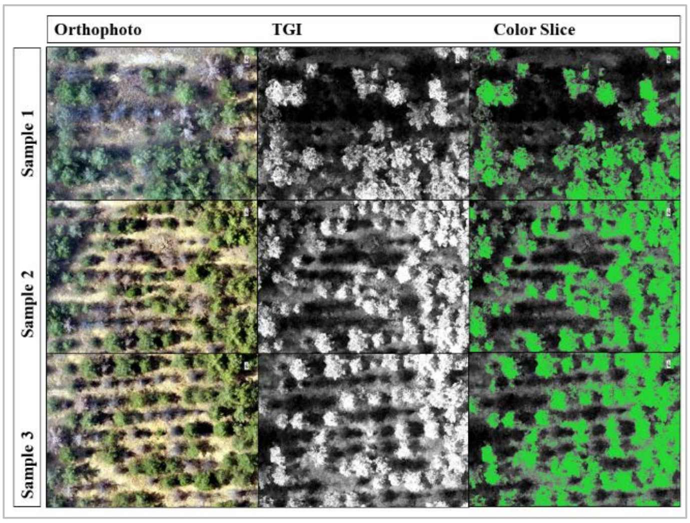

Figure 6. The comparative visual representation of three selected sample regions

It is clear in Figure 6 that TGI is highly successful in detecting green color. Similarly, regions affected by fungal disease are visibly represented as darker shades. Through more detailed visual analysis, it was observed that TGI also performs reasonably well in partially diseased trees. In other words, it provides accurate results for trees that have partially dried due to fungal infection but still have green branches. An example of a partially diseased tree can be seen in Figure 7.

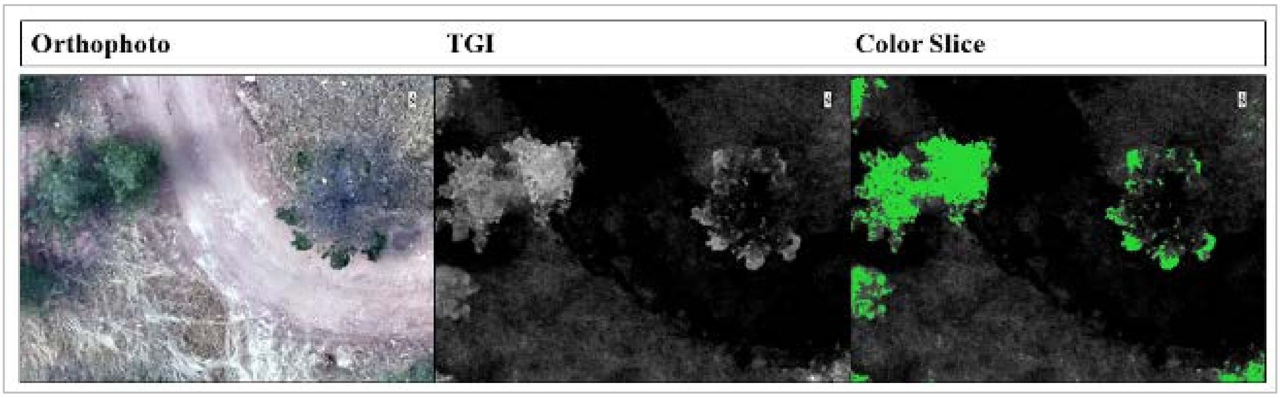

Figure 7. View of a partially diseased tree

In Figure 7, the green branches of the partially diseased tree are clearly visible in the orthophoto. Similarly, these green branches are distinctively separated in the TGI image as well.

To assess the accuracy of the color slice classification, a general accuracy calculation was performed in addition to the visual analysis. In this regard, the confusion matrix was computed depending on the ground truth ROIs, as described in section 2.5. For each class, manual ground truth samples were collected from the field, representing the pixels that truly belonged to each class. Subsequently, using these ROIs, the accuracy of the classified image was calculated. The confusion matrix, generated using the ground truth ROIs, is presented in Table 1.

Table 1
Confusion matrix

Ground Truth Pixels					
		Green Vegetation	Fungal Disease	Soil and others	Total
Predicted Pixels	Green vegetation	4490	9	0	4499
	Fungal Disease	12	3185	74	3271
	Soil and others	56	105	10207	10368
	Total	4558	3299	10281	18138

In the confusion matrix, the diagonal represents the ground truth values of each class and the number of correctly estimated pixels. The horizontal and vertical elements of the matrix indicate commission and omission errors, respectively, which represent the number of pixels that have been misclassified or transitioned between classes. Based on the pixel values in the confusion matrix, Commission and Omission errors for each class, as well as Producer and User Accuracy values, were calculated (Table 2).

Table 2
Producer accuracy and user accuracy

	Green vegetation	Fungal Disease	Others
Errors of Commission	0.002	0.026	0.016
Errors of Omission	0.015	0.035	0.008
Producer Accuracy	0.997	0.974	0.985
User Accuracy	0.985	0.965	0.993

Commission errors, as previously mentioned, indicate the proportion of pixels that were erroneously assigned to a specific class, despite not belonging to that class. Upon reviewing Table 2, it becomes evident that the lowest commission error value is observed in the "Green vegetation" class, indicating a high level of accuracy in correctly classifying pixels as green. On the other hand, omission errors represent the proportion of pixels that truly belong to a particular class but are mistakenly classified as belonging to a different class. Upon examining Table 2, it is observed that the lowest omission error value is found in the "Other" class, indicating the misclassification of pixels that should have been assigned to the "Other" class.

Based on these error values, user accuracy and producer accuracy are calculated. Notably, the lowest user and producer accuracies are observed in the fungal disease class. This outcome is expected due to the significant occurrence of both commission and omission errors in this class. It suggests that pixels associated with fungal disease are less accurately detected and tend to be mixed with other classes. Consequently, to gain further insights into this finding, a visual analysis was conducted, aiming to identify the specific classes with which the fungal disease class was frequently confused and to explore the underlying reasons for this confusion (see Figure 8).

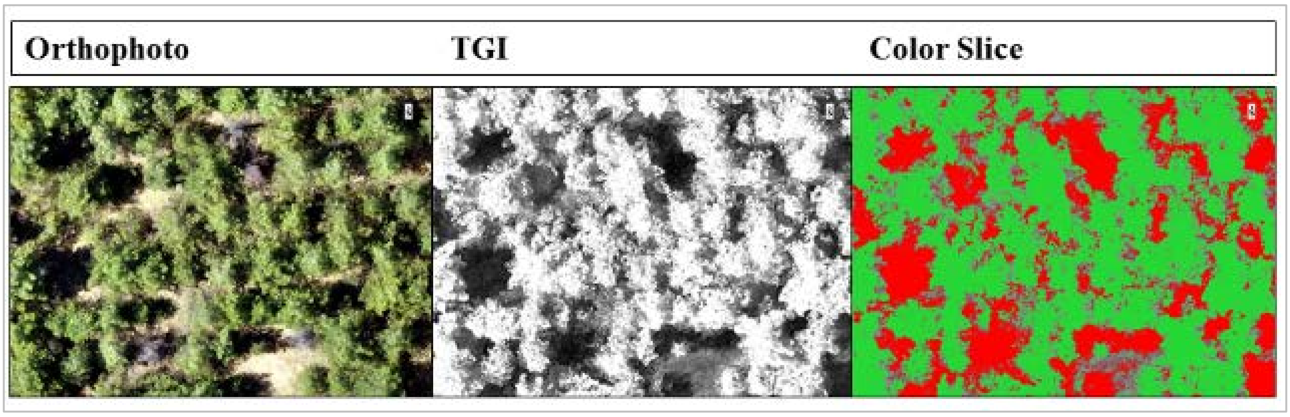

Figure 8. Fungal disease mixed with shadow.

During the analysis, it was observed that shadows, which are included in the "Other" class, were partially mixed with fungal disease. Despite this partial mixing with shadows, it is believed that this index can be utilized for detecting diseased trees. Especially in dense forests and data where the shadow is very little in the orthophoto depending on flight time and weather conditions, it is thought that this index will give higher results. From the perspective of end-users, the "Green vegetation" class achieved a detection rate of 98.5%, while the "Fungal Disease" class achieved a detection rate of 96.5%. The overall accuracy of the study, calculated using equation 2, yielded a general accuracy of 98.6%.

4. Discussions

The results obtained from the application of the TGI using UAV-based aerial imagery for the detection and monitoring of fungal disease in pine trees at Harran University Osmanbey Campus are promising. The TGI analysis effectively identified distinct changes in greenness observed in the foliage of affected trees, enabling accurate detection of diseased vegetation. The integration of UAV technology in data collection enhanced the accuracy and efficiency of TGI calculation, contributing to effective management and conservation strategies in the context of fungal disease detection in vegetation.

The high-resolution aerial images acquired through UAV flights provided detailed information about the study area, allowing for precise vegetation analysis and monitoring. The SfM algorithm was applied to the aerial images for image processing, enabling the generation of accurate orthomosaics and three-dimensional models. These representations facilitated the assessment of vegetation dynamics, topographic features, and spatial relationships, supporting environmental monitoring and management practices.

The TGI, calculated using the red, green, and blue spectral bands from the UAV-based aerial imagery, served as a valuable tool for evaluating vegetation health and dynamics. The TGI formula exploited the spectral differences between the green and red/blue bands, capturing the greenness component of vegetation. Higher TGI values indicated healthier and more vigorous vegetation, while lower values suggested stressed or less vigorous vegetation. By quantifying vegetation greenness, the TGI provided insights into vegetation health, stress, and productivity, supporting various environmental applications such as agriculture, forestry, and ecosystem studies.

The accuracy analysis of the TGI results involved the calculation of a confusion matrix and associated metrics, including producer accuracy, user accuracy, overall accuracy, and the Kappa coefficient. These metrics provided a comprehensive assessment of the classification model's performance, considering both omission and commission errors. By evaluating these metrics, researchers gained insights into the strengths and weaknesses of the classification model and identified areas for improvement.

The successful application of UAV-based TGI analysis in detecting and monitoring fungal disease in pine trees highlights the potential of this integrated approach for vegetation assessment and management. The early detection of diseased trees based on changes in greenness observed in their foliage allows for timely intervention and targeted conservation efforts. The cost-effective and efficient nature of UAV technology, combined with the TGI analysis, offers a practical solution for environmental monitoring and management endeavors.

TGI analysis has several limitations that need to be considered. Firstly, it is sensitive to lighting conditions, and variations in cloud cover or shadows can affect the accuracy of results. Additionally, the effectiveness of the TGI can vary depending on the vegetation type and coverage, as different species may respond differently to the spectral bands used in the analysis. Furthermore, the TGI may have limited sensitivity to factors beyond chlorophyll content, such as nutrient deficiencies or non-chlorophyll-related diseases. Spatial and temporal limitations, as well as the need for ground truth validation, should also be considered. Despite these limitations, addressing them through calibration, validation, and complementary analyses can enhance the utility of the TGI in vegetation assessment and management.

5. Conclusions

This study demonstrated the applicability and effectiveness of the TGI derived from UAV-based aerial imagery for the detection and monitoring of fungal disease in pine trees. The integration of UAV technology in data collection and the utilization of the TGI provided accurate and timely identification of diseased vegetation, enabling effective management and conservation strategies.

The high-resolution aerial images acquired through UAV flights, along with the application of the SfM algorithm, supported precise vegetation analysis, topographic mapping, and spatial relationship assessment. The TGI, calculated using the red, green, and blue spectral bands, served as a valuable tool for evaluating vegetation health and dynamics. The TGI analysis allowed for the quantification of vegetation greenness and provided insights into vegetation stress, productivity, and overall condition.

The successful detection and monitoring of fungal disease in pine trees using UAV-based TGI analysis demonstrate the potential of this integrated approach for vegetation assessment and management. The early identification of diseased trees based on changes in greenness observed in their foliage facilitates targeted conservation efforts and intervention strategies. The cost-effective and efficient nature of UAV technology, combined with the TGI analysis, offers a practical and promising method for environmental monitoring and management in the context of fungal disease detection in vegetation.

Further research can explore the application of the TGI analysis in other vegetation types and disease scenarios, expanding its potential for environmental monitoring and management. Additionally, the integration of other remote sensing such as thermal imaging or multispectral analysis, could enhance the capabilities of the TGI analysis for comprehensive vegetation assessment.

Author Contribution

Nizar Polat: Literature review, in-situ measurement, photogrammetric process, and writing.

Abdulkadir Memduhoğlu: Literature review, in-situ measurement, interpretation of results, and writing.

Yunus Kaya: Literature review, interpretation of results, and writing. All authors read and approved the final manuscript.

Conflict of Interest

The authors declare that they have received no funds and there is no conflict of interest.

References

Akca, S. and Polat, N. (2022). Semantic segmentation and quantification of trees in an orchard using UAV orthophoto. *Earth Science Informatics*, 15(4), 2265-2274.

Aksoy, H. and Kaptan, S. (2020). Simulation of future forest and land use/cover changes (2019-2039) using the Cellular Automata-Markov Model. *Geocarto International*, 1-17, DOI: https://doi.org/10.1080/10106049.2020.1778102.

Bannari, A., Morin, D., Bonn, F. and Huete, A. R. (1995). A Review of Vegetation Indices. *Remote Sensing Reviews*, 13(1), 95- 120.

Bhupathi, P. and Sevugan, P. (2021). Application of hyperspectral remote sensing technology for plant disease forecasting: An applied review. *Annals of the Romanian Society for Cell Biology*, 25(6), 4555-4566.

Blaga, L., Ilieș, D. C., Wendt, J. A., Rus, I., Zhu, K. and Dávid, L. D. (2023). Monitoring Forest Cover Dynamics Using Orthophotos and Satellite Imagery. *Remote Sensing*, 15(12), 3168.

Brovkina, O., Cienciala, E., Surový, P. and Janata, P. (2018). Unmanned aerial vehicles (UAV) for assessment of qualitative classification of Norway spruce in temperate forest stands. *Geo-spatial Information Science*, 21(1), 12-20.

Chowhan, P. and Chakraborty, A. P. (2022). Remote Sensing Technology—A New Dimension in Detection, Quantification and Tracking of Abiotic and Biotic Stresses. In *Plant Stress: Challenges and Management in the New Decade*, 445-457.

Costanza, K. K., Whitney, T. D., McIntire, C. D., Livingston, W. H. and Gandhi, K. J. (2018). A synthesis of emerging health issues of eastern white pine (Pinus strobus) in eastern North America. *Forest Ecology and Management*, 423, 3-17.

d'Oleire-Oltmanns, S., Marzolff, I., Peter, K. D. and Ries, J. B. (2012). Unmanned aerial vehicle (UAV) for monitoring soil erosion in Morocco. *Remote Sensing*, 4(11), 3390-3416.

Demir, S. and Başayiğit, L. (2020). Sorunlu Gelişim Gösteren Bitkilerin İnsansız Hava Araçları (İHA) ile Belirlenmesi. *Türk Bilim ve Mühendislik Dergisi*, 2 (1), 12-22.

Demir, S. and Başayiğit, L. (2021). Kısıtlı Sulama Uygulamalarının İHA Multispektral Algılamaya Dayalı Vejetasyon İndekslerine Etkisi. *Yuzuncu Yıl University Journal of Agricultural Sciences*, 31(3), 629-643.

Demirel, M., Kaya, Y. and Polat, N. (2022). Investigation of the effect of UAV flight altitude in map production. In *Intercontinental Geoinformation Days*, 4, 21-24.

Durkaya, B., Kaptan, S. and Durkaya, A. (2020). Socio-economic and cultural sources of conflict between forest villagers and forest; a case study from Black Sea region, Turkey. *Crime, Law and Social Change*, 74, 155-173.

Eitel, J. U. H., Long, D. S., Gessler, P. E. and Smith, A. M. S. (2007). Using in situ measurements to evaluate the new RapidEyeTM satellite series for prediction of wheat nitrogen status. *International Journal of Remote Sensing*. 28, 4183–4190.

Gitelson, A. A. (2011). Nondestructive estimation of foliar pigment (chlorophylls, carotenoids, and anthocyanins) contents: Evaluating a semianalytical three-band model. *Hyperspectral remote sensing of vegetation*, 141.

Haboudane, D., Tremblay, N., Miller, J. R. and Vigneault, P. (2008). Remote estimation of crop chlorophyll content using spectral indices derived from hyperspectral data. *IEEE Transactions of Geoscience and Remote Sensing*. 46, 423–437.

Harris Geospatial. (2016). Raster Color Slices. https://www.harrisgeospatial.com/docs/ColorSlices.html Accessed 24 June 2023.

Harris Geospatial. (2023). Calculate Confusion Matrices. https://www.l3harrisgeospatial.com/docs/CalculatingConfusionMatrices.html, Accessed 24 June 2023.

Herrmann, I., Pimstein, A., Karnieli, A., Cohen, Y., Alchanatis, V. and Bonfil, D. J. (2011). LAI assessment of wheat and potato crops by VENS and Sentinel-2 bands. *Remote Sensing of Environment*. 115, 2141–2151.

Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X. and Ferreira, L. G., (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment*. 83, 195–213.

Hunt, E. R., Daughtry, C. S. T., Eitel, J. U. H. and Long, D. S. (2011). Remote sensing leaf chlorophyll content using a visible band index. *Agronomy Journal*, 103, 1090–1099.

Jackson, R. D. and Huete, A. R. (1991). Interpreting vegetation indices. *Preventive Veterinary Medicine*. 11, 185–200.

Kaya, Y., Sanli, F. B. and Abdikan, S. (2023). Determination of long-term volume change in lakes by integration of UAV and satellite data: the case of Lake Burdur in Türkiye. *Environmental Science and Pollution Research*, 30, 117729–117747.

Kaya, Y., Şenol, H. İ., Memduhoğlu, A., Akça, Ş., Ulukavak, M. and Polat, N. (2019). Hacim Hesaplarında İHA Kullanımı: Osmanbey Kampüsü Örneği. *Türkiye Fotogrametri Dergisi*, 1(1), 7-10.

Kim, B. N., Kim, J. H., Ahn, J. Y., Kim, S., Cho, B. K., Kim, Y. H. and Min, J. (2020). A short review of the pinewood nematode, Bursaphelenchus xylophilus. *Toxicology and Environmental Health Sciences*, 12, 297-304.

Kusak, L., Unel, F. B., Alptekin, A., Celik, M. O. and Yakar, M. (2021). Apriori association rule and K-means clustering algorithms for interpretation of pre-event landslide areas and landslide inventory mapping. *Open Geosciences*, 13(1), 1226-1244.

Özgüven, M. M. (2018). Hassas Tarım. *Akfon kitap kırtasiye*, 334s. Ankara. ISBN: 978-605-68762-4-0.

Ramoelo, A., Skidmore, A. K., Cho, M. A., Schlerf, M., Mathieu, R. and Heitkönig, I. M. A. (2012). Regional estimation of savanna grass nitrogen using the red-edge band of the spaceborne RapidEye sensor. *International Journal of Applied Earth Observation and Geoinformation*. 19, 151–162.

Remondino, F. and El-Hakim, S. (2006). Image-based 3D modelling: a review. *The Photogrammetric Record*. 21(115), 269-291.

Rouse, J. W., Haas, R. H., Schell, J. A. and Deering, D. W. (1974). Monitoring vegetation systems in the Great Plains with ERTS. *NASA Special Publications*, 351(1), 309.

Roy, P. S., Ramachandran, R. M., Paul, O., Thakur, P. K., Ravan, S., Behera, M. D., Sarangi, C. and Kanawade, V. P. (2022). Anthropogenic land use and land cover changes—A review on its environmental consequences and climate change. *Journal of the Indian Society of Remote Sensing*, 50(8), 1615-1640.

Şin, B. and Kadıoğlu, İ. (2019) İnsansız Hava Aracı (İHA) ve görüntü işleme teknikleri kullanılarak yabancı ot tespitinin yapılması. *Turkish Journal of Weed Science*, 20(2), 211-217

Snavely, N., Seitz, S. M. and Szeliski, R. (2008). Modeling the world from internet photo collections. *International Journal of Computer Vision*. 80, 189-210.

Sohl, T. and Sleeter, B. (2012). 15 Role of Remote Sensing for Land-Use and Land-Cover Change Modeling. *Remote Sensing of Land Use and Land Cover*, 225.

Story, M. and Congalton, R. G. (1986) Remote Sensing Brief Accuracy Assessment: A User's Perspective. *Photogrammetric Engineering and Remote Sensing*, 523, 397–399

Toprak, A. S., Polat, N. and Uysal, M. (2019). 3D modeling of lion tombstones with UAV photogrammetry: a case study in ancient Phrygia (Turkey). *Archaeological and Anthropological Sciences*. 11(5), 1973-1976.

Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment*. 8, 127–150.

Türkseven, S., Kızmaz, M. Z., Tekin, A. B., Urkan, E. and Serim, A. T. (2016). Tarımda dijital dönüşüm, insansız hava araçlarının kullanılması. *Tarım Makinaları Bilim Dergisi*, 12 (4), 267-271.

Türkseven, S., Tekin, B., Kızmaz, M. Z., Urkan, E. and Serim, A. T. (2018). İnsansız hava araçları ile pamukta yabancı ot florasının tespit edilme olanakları. *Türkiye VII. Bitki Koruma Kongresi*, 14-17 Kasım 2018, Muğla Türkiye.

URL-1: https://www.dji.com/global

Uysal, M., Toprak, A. S. and Polat, N. (2013). Photo realistic 3D modeling with UAV: Gedik ahmet pasha mosque in afyonkarahisar. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 40, 659-662.

Uysal, M., Toprak, A. S. and Polat, N. (2015). DEM generation with UAV Photogrammetry and accuracy analysis in Sahitler hill. *Measurement*, 73, 539-543.

Wang, C. Y., Fang, Z. M., Wang, Z., Zhang, D. L., Gu, L. J., Lee, M. R., Liu, L. and Sung, C. K. (2011). Biological control of the pinewood nematode Bursaphelenchus xylophilus by application of the endoparasitic fungus Esteya vermicola. *BioControl*, 56, 91-100.

Wang, L., Li, R., Duan, C., Zhang, C., Meng, X. and Fang, S. (2022) A novel transformer based semantic segmentation scheme for fine-resolution remote sensing images. *IEEE Geoscience and Remote Sensing Letters*, 19,1–5.

Yakar, M. and Doğan, Y. (2018). GIS and three-dimensional modeling for cultural heritages. *International Journal of Engineering and Geosciences*, 3(2), 50-55.

Yakar, M., Ulvi, A., Yiğit, A. Y. and Alptekin, A. (2022). Discontinuity set extraction from 3D point clouds obtained by UAV Photogrammetry in a rockfall site. *Survey Review*, 1-13.

Yiğit, A. Y. (2020). İnsansız hava aracı ile elde edilen veriler yardımıyla yol tespiti, Yüksek lisans tezi, Afyon Kocatepe Universitesi, Fen Bilimleri Enstitüsü, Afyon, Türkiye.

Yilmaz, H. M., Yakar, M., Mutluoglu, O., Kavurmaci, M. M. and Yurt, K. (2012). Monitoring of soil erosion in Cappadocia region (Selime-Aksaray-Turkey). *Environmental Earth Sciences*, 66(1), 75-81.

Yu, L., Li, G., Yu, J., Bao, L., Li, X., Zhang, S. and Yang, J. (2023). Effect of conservation tillage on seedling emergence and crop growth-evidences from UAV observations. *Cogent Food & Agriculture*, 9(1), 2240164.

Zhou, L. F., Chen, F. M., Xie, L. Y., Pan, H. Y. and Ye, J. R. (2017). Genetic diversity of pine-parasitic nematodes Bursaphelenchus xylophilus and Bursaphelenchus mucronatus in China. *Forest Pathology*, 47(4), 12334.