The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLVIII-4/W18-2025
Symposium on GeoSpatial Technologies: Visions and Horizons 2025 (GeoVisions2025), 8–10 October 2025, Çanakkale, Türkiye

Pixel-Based Classification of Olive Trees Using Multi-Spectral UAV Images and Vegetation Indices

Rabia Kemal [1], Mine Afanyalı [1], Zeren Baharoğlu [1], İpek Eryavuz [1], Muhammed Enes Atik[1], Saziye Ozge Atik[1]

[1] Dept. of Geomatics Engineering, Civil Engineering Faculty, Istanbul Technical University, 34469, Maslak Istanbul, Türkiye – kemal21, afanyali21, baharoglu22, eryavuz21, atikm, donmezsaz@itu.edu.tr

Keywords: Photogrammetry, Machine Learning, Vegetation Indices, Classification, Olive Tree, UAV.

Abstract

Olives are one of the world's most important harvested crops and the most studied fruit trees. In this context, studies on olive tree identification using state-of-the-art data acquisition methods are a prominent topic today. In this study, images obtained using an unmanned aerial vehicle equipped with a multi-spectral sensor were processed, and olive tree classification was performed using different methods. Using these methods, vegetation indices were generated using the spectral bands provided by the multispectral sensor, and three other data set combinations were created. The effects of NDVI, SAVI, DVI, and RVI indices on the classification were also investigated. Furthermore, the distinction between the olive tree class and other vegetation, artificial surfaces, and soil classes was also quantitatively examined in each dataset. Accordingly, the highest-performing classification was achieved with an overall accuracy of 91% using the Random Trees method with dataset set-2, which included multi-spectral bands.

1. Introduction

Food production has become strategically important due to climate change, rapid population growth, and depletion of natural resources. The sustainability of agricultural production is currently significantly threatened by global issues like climate change, population expansion, land degradation, and the growing depletion of natural resources. In this regard, contemporary technology-based remote sensing methods and smart agricultural applications are strategically important for optimizing resource use in agricultural production, which will increase efficiency and reduce environmental consequences. In line with Target 2.4 of the UN 2030 Agenda for Sustainable Development, this study aims to promote sustainable production techniques and enhance olive farming efficiency. Sensitive olive tree identification and monitoring in this setting represents a strategic potential area in terms of agricultural production, environmental sustainability, climate change adaptation, and rural development strategies.

The olive tree is one of the oldest species in the Mediterranean region (Besnard et al., 2011). This tree species has spread throughout history and shaped the Mediterranean landscape (Šiljeg et al., 2023). Its resistance to extreme climatic conditions and its adaptability to less fertile soils make the olive tree stand out for its social, ecological, and economic benefits. The sustainability and protection of olive trees are essential for many areas, including industry, forest fire prevention, and tourism. However, performing manual identification and evaluation of olive trees is a time-consuming and labor-intensive process. Advances in image processing have enabled the development of automatic detection and counting systems (Srestasathiern and Rakwatin, 2014). Machine learning learns discriminative rules using training data instead of predetermined arbitrary parameters to classify complex data (Atik et al. 2020). Adding vegetation indices to multispectral UAV data can increase the performance of machine learning algorithms (Atik, 2025). With the development of machine learning methods, research into the rapid, automatic, and accurate classification of land cover classes has increased (Rahman et al., 2020).

The high spatial resolution provided by UAV imagery, combined with computer vision algorithms, has led to significant advances in various fields such as forestry, agriculture, geology, surveillance and traffic monitoring (Jemaa et al., 2023). Aerial images obtained by UAV provide much better spatial-temporal resolution than satellite-based remote sensing images (Minarík and Langhammer, 2016). Recently, with the integration of multi-spectral cameras into UAVs, significant progress has been made in the detection and monitoring of vegetation. The multispectral sensor plays a leading role in precision agriculture applications, mostly due to the possibility of extracting vegetation indices (Avola et al., 2019).

The primary objective of this study is to differentiate between olive and non-olive areas using pixel-based classification, by comparing classification performance based on different combinations of bands and vegetation indices to highlight the most effective inputs. In this study, multispectral UAV images of olive trees were subjected to photogrammetric evaluation, followed by the calculation of typical vegetation indices NDVI, SAVI, RVI, and DVI to support classification processes. Their use enables a more accurate classification of olive trees by increasing the distinction between relevant surface features in the multispectral imagery. The initial phase involves semantic segmentation of the preprocessed data, enabling images to be partitioned into segments. Semantic segmentation will be performed on the preprocessed data, followed by supervised classification using Minimum Distance, Maximum Likelihood, Random Trees, and Support Vector Machine algorithms. The classifications will be evaluated by calculating and comparing accuracy metrics, including overall accuracy, user accuracy, producer accuracy, and confusion matrices.

2. Material and Methods

2.1 Data Collection and Flight Planning

In this study, the research area for this project is a nine-acre olive grove located in Akköy village, within the Thermal District of Yalova, comprising approximately 350 olive trees. Yalova is located in the Marmara region of Türkiye. Despite its small size, Yalova is one of the provinces where olive cultivation is widespread due to its dense concentration of olive trees. The multispectral aerial images were captured by a DJI Mavic 3 Multispectral UAV. The flight height is 50 meters. The overlap and sidelap ratios were selected as 80% and 70%, respectively. Along with RGB values, red-edge and near infrared bands were also obtained. The ground sampling distance (GSD) is 4.2 cm for multispectral images and 2.3 cm for RGB images. A total of 361 multispectral aerial images were captured. The image of the area is given in Figure 1.

Figure 1. Study area.

2.2 Generation of Orthomosaic by Photogrammetric Evaluation

Orthomosaics are geometrically corrected images that are appropriate for precise distance measurements because they remove distortions brought on by topography relief, lens aberrations, and camera location. The Structure from Motion (SfM) technique was used in this study to process images and create orthomosaics. Structure-from-Motion (SfM) is a computer vision method that calculates 3D space coordinates using 2D images taken from different angles and with a certain coverage ratio (Bozkurt et al., 2024). SfM starts by employing strong feature detectors, like the Scale-Invariant Feature Transform (SIFT), which guarantee consistency in the face of scale, rotation, and lighting changes, to identify distinguishable keypoints across overlapping images. Outlier removal algorithms and ratio tests are two techniques used to filter matched keypoints for geometric consistency. The camera pose and scene geometry are simultaneously reconstructed by automatically detecting similar features in various images (Arkali and Atik, 2025). A sparse 3D point cloud is then produced by estimating camera postures via bundle adjustment. To create a comprehensive 3D model that forms the foundation for the creation of orthomosaic and digital elevation models, the last stage entails densifying the precise sparse point cloud using Multi-View Stereo (MVS) (Deliry and Avdan, 2021). In this study, the SfM algorithm was applied with Pix4Dmapper.

2.3 Extraction of Vegetation Indices from Multispectral Orthomosaic

A variety of spectral bands are used to create vegetation indices, which include data on biomass, leaf area, and plant health. By using these indices for species and density analysis, this study seeks to enhance classification algorithms. Standard indices include the RENDVI and GNDVI for monitoring plant nitrogen status and early stress detection, the NDVI for evaluating vegetation vigor, the EVI for accounting for soil and atmospheric influences, and the SAVI for sparse vegetation by mitigating the effects of soil brightness (Giovos et al., 2021; Interstate Technology & Regulatory Council, 2019). The list of indices to be used is given in Table 1.

Indices	*Equation*
$NDVI$	$\frac{NIR - RED}{NIR + RED}$
$SAVI$	$\frac{NIR - RED}{NIR + RED + L} \times (1 + L)$
RVI	$\frac{RED}{NIR}$
DVI	$NIR - RED$

Table 1. Vegetation indices used in the study

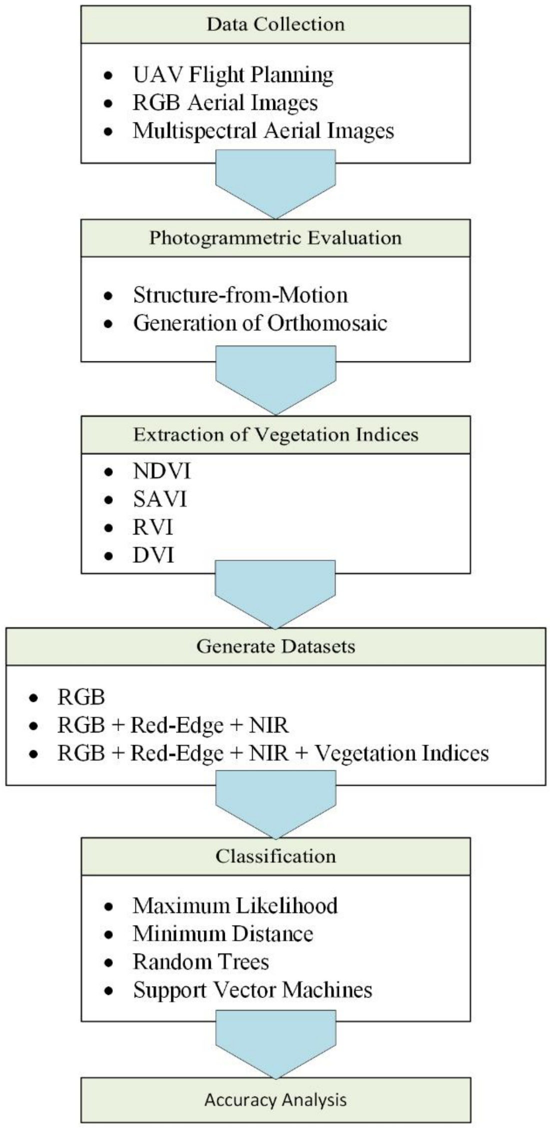

Figure 2. General flow of the study

2.4 Maximum Likelihood Classification

Maximum Likelihood is a supervised classification method which is based on the Bayes theorem. It makes use of a discriminant function to assign pixel to the class with the highest likelihood. Class mean vector and covariance matrix are the key inputs to the function and can be estimated from the training pixels of a particular class. (Ahmad & Quegan ,2012).

2.5 Minimum Distance Classification

Minimum distance classifiers belong to a family of classifiers referred to as sample classifiers. In such classifiers the items that are classified are groups of measurement vectors (e.g. all measurement vectors from an agricultural field), rather than individual vectors as in more conventional vector classifiers (Wacker and Landgrebe,1972).

2.6 Support Vector Machines

Vapnik's Support Vector Machines for regression and classification are among the most used supervised machine learning algorithms. They are a machine learning-based pattern classification method with a strong theoretical background, drawing on statistical learning theory and structural risk minimization strategies. The fundamental purpose of support vector machines is to identify a function in a multidimensional space that can split training data based on known class labels (Harman, 2021). The classification outcome is significantly impacted by the parameters chosen when using the SVM algorithm. Accuracy is directly impacted by the choice of C constant or whether the kernel type is linear or rbf (Arkalı et al., 2025).

2.7 Random Trees

Random Trees classifiers are ensemble methods that involve random selection of training data and features, and use decision trees to generate multiple unrelated trees. This randomization is particularly useful for noisy and high-dimensional datasets because it helps reduce overfitting and maintains strong classification accuracy (Belgiu and Drăguţ, 2016). In the field of remote sensing and object-based image analysis (OBIA), Random Trees are often applied to tasks such as tree crown detection and vegetation mapping. The final classification is determined by a majority vote from the predictions made by each tree within the ensemble. Using both spectral and structural information obtained from multispectral UAVs, Random Trees have shown exceptional effectiveness in identifying individual olive tree canopies in studies focusing on olive groves (Karydas et al., 2023; Elsayed et al., 2023). These classifiers are appropriate for traditional olive groves where trees may be irregularly spaced since they are computationally efficient and can handle varied environments.

2.8 Evaluation Metrics

Accuracy assessment of classifications was determined by means of a confusion matrix (sometimes called error matrix), which compares, on a class-byclass basis, the relationship between reference data and the corresponding results of a classification (Lillesand et al., 2004). Producer accuracy is form is a measure of the accuracy of a particular classification scheme and shows the percentage of a particular ground class that is correctly classified (Story and Congalton,1986). Procuder Accuracy (PA) can be calculating with using Equation (1).

$$Producer\ Accuracy\ (PA) = c_{aa} \times 100\% c_{.a} \qquad (1)$$

where, c_{aa}= element at position a^{th} row and a^{th} *column*, $c_{.a}$=column sums.

User Accuracy is a measure of how well the classification is performed. It indicates the percentage of probability that the class which a pixel is classified to on an image actually represents that class on the ground (Story and Congalton,1986). Equation (2) presents the user accuracy calculation.

$$User\ Accuracy\ (UA) = c_{ii} \times 100\% c_{i.} \qquad (2)$$

where, $c_{i.}$= *row sum.*

A measure of overall behaviour of the classification can be determined by the overall accuracy. Equation (3) demonstrates the overall accuracy formula.

$$Overall\ Accuracy\ (OA) = \frac{\sum_{a=1}^{U} c_{aa}}{Q} \times 100\% \qquad (3)$$

where Q and U are the total number of pixels and classes, respectively (Scepan,1999).

3. Results and Discussion

In this study, machine learning methods for the classification of olive trees in multispectral orthomosaic images were comparatively analyzed. Classification methods used in this study were Maximum Likelihood, Minimum Distance, Support Vector Machine, and Random Trees. Three datasets with different band combinations were created for classification.

1. **Dataset 1:** RGB
2. **Dataset 2:** RGB + Red-edge + NIR
3. **Dataset 3:** RGB + Red-edge + NIR + 4 vegetation indices

For training, 80 regions for each class were selected within the study area (Figure 3). A similar number of samples were selected from each class to prevent bias in model training. Test data was distributed homogeneously across the study area and selected to include 25 pixels from each class (Figure 4). Training and testing were performed using ArcGIS Pro software.

https://doi.org/10.5194/isprs-archives-XLVIII-4-W18-2025-195-2026 | © Author(s) 2026. CC BY 4.0 License.

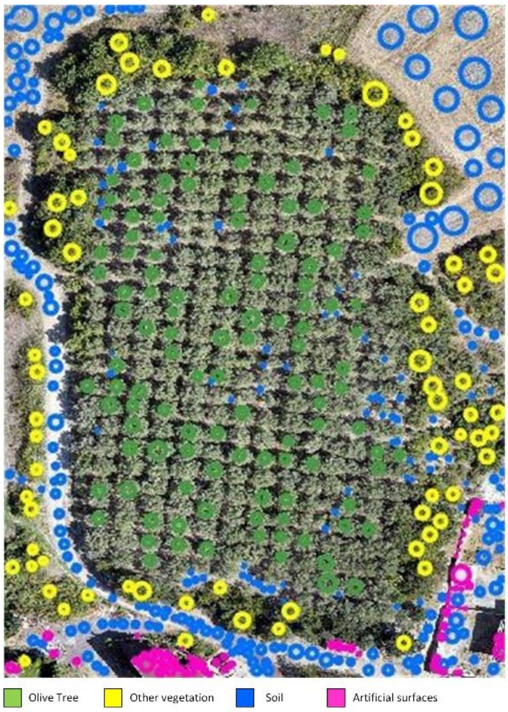

Figure 3. Train samples selected from the study area.

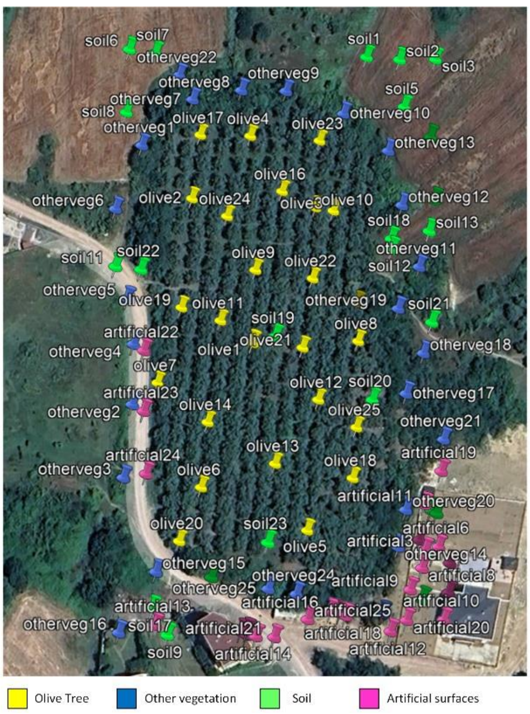

Figure 4. Test samples selected from the study area.

At first, just four approaches were applied to three-band RGB, with the Random Trees method yielding the highest accuracy of 87%. Four algorithms gave results for five-band RGB-RE-NIR that were typically better than the other band combinations; However, the Random Trees approach stood out with a 91.0% accuracy. When applied to Dataset 3, the Maximum Likelihood method achieved the highest overall accuracy with 90.0%. However, some confusion was observed between the soil and artificial areas. This method struggled most on the Dataset 1 image, where spectral similarity between classes limited classification success. In this case, the spectral similarity between olive trees and other vegetation confused classification. For all methods, classification using only RGB bands resulted in notable confusion, especially between olive trees and artificial structures. Among all twelve classification scenarios, the most accurate classification of olive trees was obtained using Maximum Likelihood and Random Trees. Using vegetation indices improved the distinction between vegetated surfaces, enhancing the model's ability to identify olive trees correctly. Results are shown in Table 2.

Datasets	Maximum Likelihood	Minimum Distance	Random Trees	SVM
Dataset 1	74.0	66.0	87.0	62.0
Dataset 2	88.0	85.0	**91.0**	85.0
Dataset 3	90.0	66.0	69.0	67.0

Table 2. Classification result of using all different band combinations (The OA values are shown as a percentage).

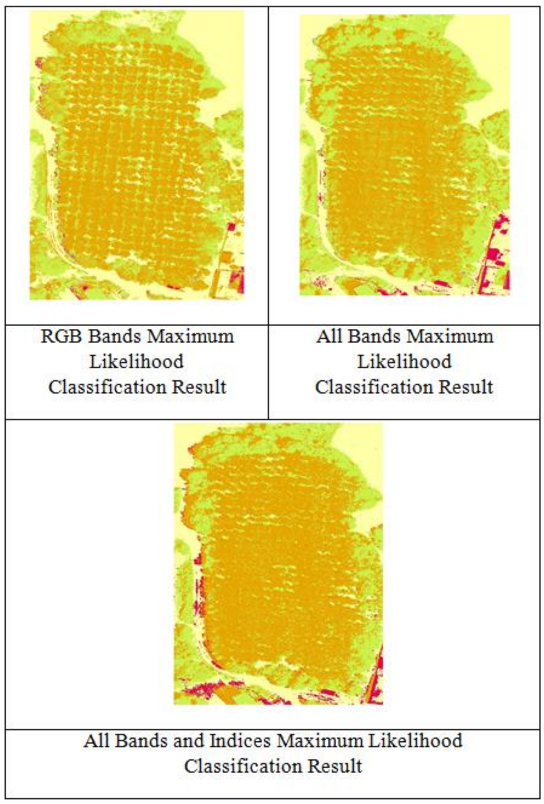

Figure 5. Maximum likelihood classification results.

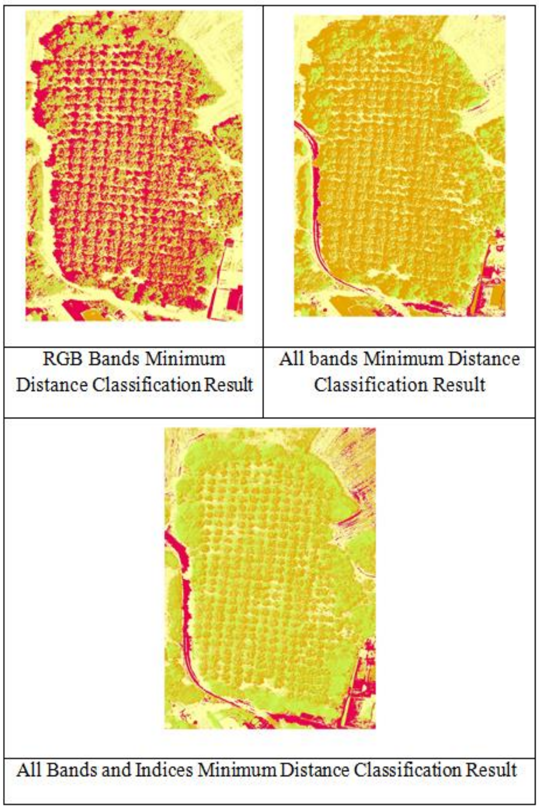

Figure 6. Minimum distance classification results.

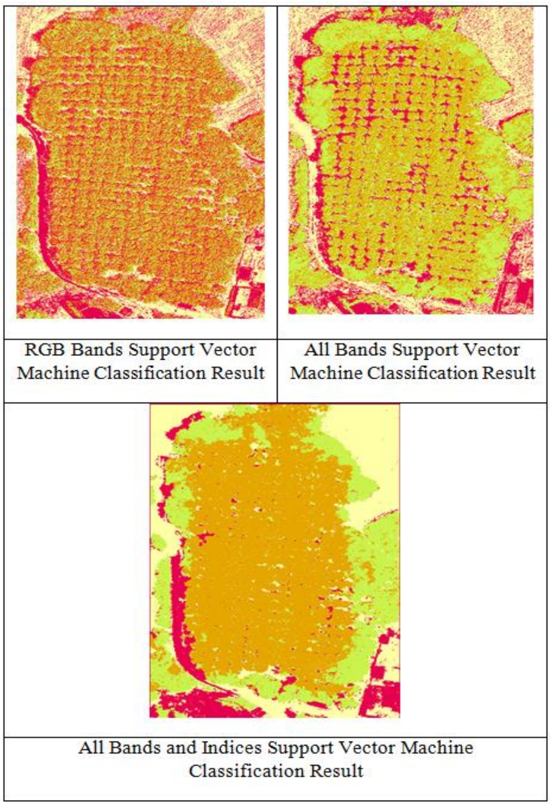

Figure 7. Support Vector Machines classification results.

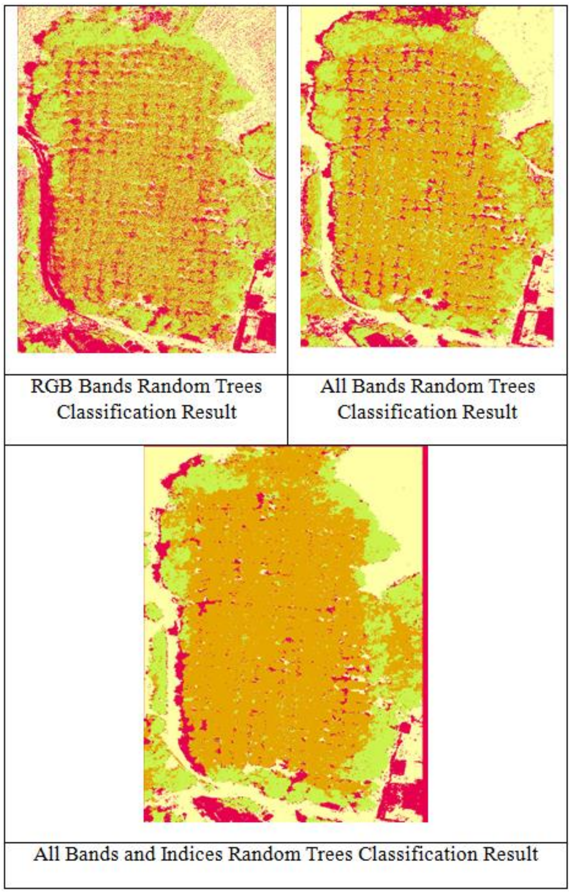

Figure 8. Random Trees results.

Classification results are presented on a class-by-class according to UA and PA metrics (Table 3). According to the results, adding RE and NIR bands significantly improves the performance of the classifiers. Since the study focuses on olive trees, Maximum Likelihood almost completely correctly identifies olive trees in Dataset-2 and Dataset-3, according to the classification results. The minimum distance method, however, produces incorrect predictions for olive trees in Dataset-1. Adding vegetation indices to a multispectral image does not guarantee a positive increase in all classes. Particularly, adding vegetation indices to the soil class negatively impacts classifier performance. The Random Trees method successfully detects olive trees in Dataset-1. This means that Random Trees achieves high success with a small number of input features.

Dataset-1								
	Maximum Likelihood		Minimum Distance		SVM		Random Trees	
Class	UA	PA	UA	PA	UA	PA	UA	PA
Olive tr.	67.9	76.0	40.0	8.0	80.0	64.0	95.0	92.0
Oth. veg.	73.1	76.0	95.7	88.0	94.0	68.0	95.0	88.0
Soil	69.7	92.0	63.9	92.0	83.0	60.0	100	72.0
Art. surf.	100	52.0	42.1	64.0	54.0	96.0	68.0	96.0
Dataset-2								
Olive tr.	96.2	100	88.5	92.0	91.0	88.0	92.0	92.0
Oth. veg.	95.8	92.0	85.2	92.0	91.0	88.0	91.0	84.0
Soil	74.2	92.0	72.4	84.0	86.0	80.0	96.0	96.0
Art. surf.	90.0	72.0	95.0	76.0	72.0	84.0	85.0	92.0
Dataset-3								

Olive tr.	100	100	58.3	28.0	76.0	92.0	78.0	88.0
Oth. veg.	96.2	100	57.5	92.0	88.0	64.0	84.0	64.0
Soil	74.2	92.0	65.5	76.0	71.0	68.0	74.0	80.0
Art. surf.	94.4	68.0	97.7	72.0	75.0	84.0	81.0	84.0

Table 3. Class-based classification results by using all datasets. (The values are shown as a percentage).

4. Conclusions

This study investigated the classification performance of machine learning in olive tree detection using RGB and multispectral aerial photographs obtained with a UAV. In addition to olive trees in the designated region, other tree species, soil, and artificial surfaces were also classified.

The study results indicate that while the Random Trees method yields successful results only with RGB images, Maximum Likelihood stands out when multispectral and vegetation indices are used. This highlights the need to select a method based on the dataset. In addition, optimal band selection for machine learning tasks affects the performance of the algorithms (Atik and Atik, 2024). Furthermore, the high spatial resolution of UAV imagery makes it possible to obtain detailed information about olive trees from orthomosaics. Analyzing the yield status of identified trees and monitoring their health will be key areas of focus for future studies.

Acknowledgements

This research was funded by the The Scientific and Technological Research Council of Türkiye (TÜBİTAK), grant number 1919B012474501. This research was supported by the Istanbul Technical University Scientific Research Projects Office (BAP), grant number MGA-2024-45734.

References

Ahmad, A., & Quegan, S., 2012. Analysis of maximum likelihood classification on multispectral data. *Applied Mathematical Sciences*, 6(129), 6425–6436.

Arkalı, M., Atik, M. E., and Atik, Ş. Ö., 2025. Machine Learning-Based Supervised Classification of Sentinel-2 MSI and Landsat-8 OLI Imagery in Marguerite Bay of Antarctic Peninsula. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., XLVIII-M-6-2025, 45–52, https://doi.org/10.5194/isprs-archives-XLVIII-M-6-2025-45-2025, 2025.

Atik, M. E., & Arkali, M., 2025. Comparative Assessment of the Effect of Positioning Techniques and Ground Control Point Distribution Models on the Accuracy of UAV-Based Photogrammetric Production. *Drones*, *9*(1), 15. https://doi.org/10.3390/drones9010015

Atik, Ş. Ö., 2025. Classification of Urban Vegetation Utilizing Spectral Indices and DEM with Ensemble Machine Learning Methods. *International Journal of Environment and Geoinformatics*, *12*(1), 43-53.

Atik, S. O., & Atik, M. E., 2024. Optimal band selection using explainable artificial intelligence for machine learning-based hyperspectral image classification. *Journal of Applied Remote Sensing*, *18*(4), 042604-042604.

Belgiu, M., & Drăguţ, L., 2016, Random forest in remote sensing: A review of applications and future directions. *ISPRS Journal of Photogrammetry and Remote Sensing*, 114, 24–31. https://doi.org/10.1016/j.isprsjprs.2016.01.011

Bozkurt, S.; Atik, M.E.; Duran, Z. Improving Aerial Targeting Precision: A Study on Point Cloud Semantic Segmentation with Advanced Deep Learning Algorithms. *Drones* **2024**, *8*, 376.

Deliry, S. I., & Avdan, U., 2024. Accuracy assessment of UAS photogrammetry and structure from motion in surveying and mapping. *International Journal of Engineering and Geosciences*, 9(2), 165–190.

Elsayed, M. M., El-Shirbeny, M. A., & Gad, A., 2023. Extraction of olive tree canopy using UAV multispectral data and object-based image analysis. Remote Sensing Applications: Society and Environment, 32, 101046. https://doi.org/10.1016/j.rsase.2023.101046

Giovos, R., Tassopoulos, D., Kalivas, D., Lougkos, N., & Priovolou, A., 2021. Remote sensing vegetation indices in viticulture: A critical review. *Agriculture*, 11(5), 457.

Harman, G., 2021. Prediction of diabetes mellitus using support vector machines and naive bayes classification algorithms. European Journal of Science and Technology(32), 7–13. https://doi.org/10.31590/ejosat.1041186

Interstate Technology & Regulatory Council. (2019). Implementing advanced site characterization tools. Interstate Technology & Regulatory Council.

Karydas, C. G., Gewehr, S., Iatrou, M., Mourelatos, S., et al., 2023. Olive plantation mapping on a sub-tree scale with object-based image analysis of multispectral UAV data: Operational potential in tree stress monitoring. *Journal of Imaging*, 3(4), 57. https://doi.org/10.3390/jimaging3040057

Lillesand, T. M., Kiefer, R. W., & Chipman, J. W., 2004. Remote Sensing and Image Interpretation. John Wiley & Sons.

Scepan, J., 1999. Thematic validation of high-resolution global land-cover data sets. *Photogrammetric Engineering and Remote Sensing*, 65, 1051–1060.

Story, M., & Congalton, R., 1986. Accuracy assessment: a user's perspective. *Photogrammetric Engineering and Remote Sensing*, 52, 397–399.

Wacker, A. G., & Landgrebe, D. A., 1972. Minimum Distance Classification in Remote Sensing. LARS Technical Reports, Paper 25. http://docs.lib.purdue.edu/larstech/25