Detection of Hazelnut Orchards with Sentinel-2 imagery and machine learning classification algorithms

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Abstract

Hazelnut (*Corylus avellana L.*) is an economically important crop in Turkey, with Sakarya being a major cultivation region. Effective large-scale monitoring of hazelnut orchards can be achieved using remote sensing and machine learning techniques. In this study, field surveys were conducted in approximately 150 hazelnut orchards in Sakarya to provide training data. Multi-temporal Sentinel-2 imagery from six acquisition dates capturing key phenological stages was stacked for the classification of hazelnut orchards and other land use/land cover (LULC) types. Vegetation indices including NDVI, AVI, SAVI, and EVI were applied to enhance class separability. Supervised classification was performed using Random Forest (RF) and Extreme Gradient Boosting (XGBoost) algorithms, with hyperparameters optimized via RandomizedSearchCV and cross-validation. Both models achieved high performance in detecting hazelnut orchards; however, RF yielded better overall results in quantitative metrics and visual assessments. These findings demonstrate that integrating multi-temporal Sentinel-2 data, vegetation indices, and machine learning enables accurate large-scale mapping of hazelnut orchards in Sakarya.

1. Introduction

Hazelnut (*Corylus avellana L.*) is a highly preferred agricultural product due to their rich nutritional value and widespread use across various industries. Turkey, with its climate and geography in the Black Sea region, provides ideal conditions for hazelnut cultivation and holds a leading position globally. According to Food and Agricultural Organization data for 2023, Turkey ranked first in both hazelnut production and exports, accounting for approximately 58% of global production (FAO, 2025). This has made hazelnut a valuable economic commodity for Turkey, prompting the implementation of various policies aimed at increasing productivity. In particular, the increase in regularly maintained and newly established orchards in Sakarya has significantly improved yield levels, positioning the province as the third-largest hazelnut-producing region in the country with 12.7% in 2023 (TEPGE, 2024). Due to the vast areas involved in hazelnut cultivation, remote sensing technologies have not only become a practical tool but also a necessity for monitoring and analyzing production areas effectively.

Remote sensing technologies, such as multispectral imagery, have brought new opportunities to the sustainable agriculture sector and land use/land cover (LULC) classification. To effectively analyze the large volume and complexity of remote sensing data, advanced computational techniques are required. In this context, machine learning methods are commonly used to detect agricultural areas and to assess the health and density of trees and crops. These advantages not only facilitate large-scale monitoring but also enhance the ability to distinguish specific crop types, such as hazelnut, based on their unique spatial and spectral characteristics. Sentinel-2 with 12 spectral bands, providing a 10 meters spatial resolution for visible bands (Red, Green, Blue), 20 meters for infrared and some other bands, and 60 meters for atmospheric bands. This multi-band capability, coupled with its high temporal resolution, offering acquisition as frequent as 5 days, makes Sentinel-2 particularly valuable for multi-temporal analysis (Wang et al., 2016). It is highly effective for monitoring agricultural areas, as it captures detailed changes over time and allows for precise differentiation between various land cover types, including crops like hazelnut. Furthermore, Vegetation indices such as NDVI (Altieri et al., 2022), Soil Adjusted Vegetation Index (SAVI), Enhanced Vegetation Index (EVI), and Advanced Vegetation Index (AVI) (Nicolás et al., 2023) can highlight differences in spectral reflectance, enabling a clearer distinction between target crops and other land cover types.

Machine learning methods are widely applied in remote sensing tasks such as crop type identification, vegetation health monitoring, and land cover classification. In particular, algorithms like Random Forest (RF) and Extreme Gradient Boosting (XGBoost) are frequently employed in the literature for distinguishing between different crop types and mapping agricultural areas (Lodato et al., 2024). Moreover, when ground-based data is limited due to constraints such as restricted fieldwork time or inaccessibility of the region, machine learning becomes one of the most suitable approaches for accurate analysis. These methods are preferred due to their strong performance in handling complex datasets, enabling the extraction of valuable information from remote sensing imagery (Aksoy et al., 2023; Sasso et al., 2024).

Several studies have investigated the use of remote sensing and machine learning techniques for detecting and monitoring hazelnut orchards, employing different data sources and classification strategies. The study (Tumer et al., 2024) employed object-based classification of very high-resolution aerial photographs using Support Vector Machines (SVM), Bayesian classifier, Random Forest, and K-Nearest Neighbors

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to accurately detect hazelnut orchards in Sakarya, Türkiye, achieving the highest Hazelnut F1-Score with SVM using the Radial Basis Function (RBF) kernel (98.92% in Paralı) and Bayes (97.39% in Açmabaşı). In another recent study, Sasso et al. (2024) integrated optical and radar remote sensing data from Sentinel-1 and Sentinel-2 to map hazelnut orchards in Italy, comparing multiple machine learning algorithms and identifying Random Forest as the best generalizing model, with 96% overall accuracy and a 91% Hazelnut F1-Score across diverse test areas. Another recent researches on hazelnut monitoring highlights different optimal approaches, with Morisio et al. (2025) achieving the highest accuracy (66%) and lowest false negative rate (13%) using logistic regression on UAV-based multispectral indices, Vinci et al. (2023) obtaining over 90% accuracy with object-based classification of UAV imagery using Random Forest, and Lodato et al. (2024) reaching 96% accuracy by integrating multi-source satellite data with Random Forest. Collectively, these studies demonstrate that both data source selection and algorithm choice play a critical role in optimizing classification accuracy for hazelnut orchard mapping and monitoring.

In this study, machine learning-based supervised classification approaches were applied to identify the spatial distribution of hazelnut orchards and optimum hyperparameter settings are determined. Furthermore, Stacked Sentinel-2 images were used to distinguish between different land use and land cover (LULC) classes. The stacked images, which include a total of 72 bands from six different dates, were selected based on fieldwork conducted during various phenological periods, with 150 hazelnut orchards visited at specific times of the year. In particular, the unique phenological stages and spectral reflectance characteristics of hazelnut orchards were considered to effectively separate them from other land use types. Sample polygons for training data were carefully selected from these field observations. The classification process and model development were performed using the Random Forest (RF) and XGBoost algorithms, with the processing carried out on platforms such as Google Earth Engine (GEE) and Kaggle. The accuracy of the results was evaluated using various performance metrics, such as overall accuracy, F1-score and user's, producer's accuracy. This approach enables more systematic and reliable monitoring of large-scale hazelnut cultivation areas.

2. Study Area & Fieldwork

The study area focusing on Sakarya Province, which ranks third in hazelnut production in Turkey, with 789,000 decares of land and 98,000 tons of production in 2023 (Bars, 2023). During the fieldwork, approximately 150 hazelnut orchards, representing various phenological stages, were visited and analyzed in selected regions of Sakarya (Figure 1). Based on this field data, the most optimal temporal intervals for hazelnut cultivation were determined by considering the phenological stages and biophysical parameters, as examined through vegetation indices such as NDVI, SAVI, EVI, and AVI. These indices have proven to be particularly effective in differentiating 12 land use and land cover (LULC) classes in the study area that are determined depending on the CORINE class nomenclature, including the hazelnut class (Figure 2).

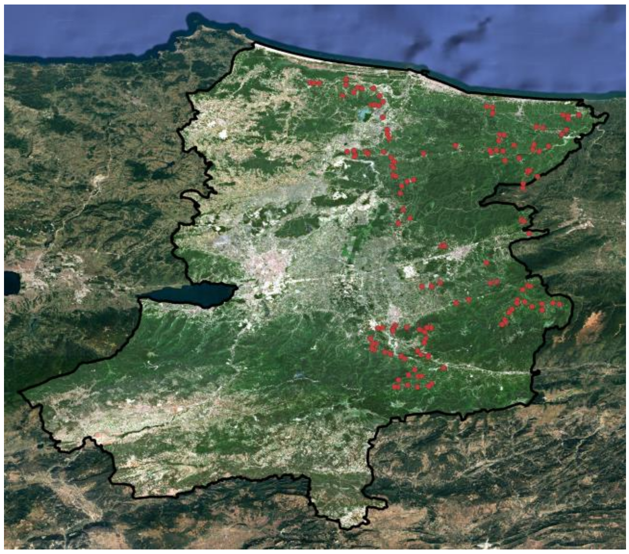

Figure 1. Sakarya boundry for Sentinel-2 image and distribution of fieldwork hazelnut parcels (Basemap: Google Satellite).

Figure 2. LULC classes depending on the CORINE nomenclature and related RGB Codes (Basemap: Google Satellite)

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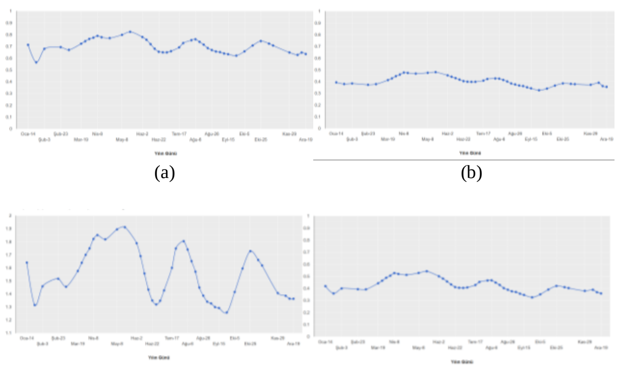
3. Sample Collection & Data pre-processing

Considering the phenological stages (Bektaş & Çil, 2023) and the results of the field survey, six acquisition dates were selected from atmospherically clear and radiometrically stable Sentinel-2 imagery (25 December 2023, 19 March 2024, 12 June 2024, 22 July 2024, 16 August 2024, 5 October 2024). Within the Google Earth Engine (GEE) environment, all 12 spectral bands of the Sentinel-2 datasets were resampled to a uniform spatial resolution of 10 meters. Subsequently, date-specific images corresponding to the identified phenological stages were multi-temporally stacked, yielding a 72-band composite dataset. Based on the CORINE land cover classification and, in particular, the orchards visited during the field survey, hazelnut orchards were specifically identified using index values, and polygons were collected as samples for each class.

Phenological Stages	Period
Male Flowering	January - February
Female Flowering	January - February
Pollination	January - February
Female Flower Shedding	March
Leaf Emergence	March - April
Fertilization	May -June
Nut Cluster Shedding	June
Harvest	August - September
Leaf Fall	November - December

Table 1. Phenological stages of hazelnut



(a) (b) (c) (d)

Figure 3. Time series of spectral indices in 2025 for hazelnut orchards (a)NDVI, (b)AVI, (c)EVI, (d)SAVI

The seasonal profiles of NDVI, AVI, EVI, and SAVI for the hazelnut orchard align well with its phenological stages, showing low values during winter dormancy, a steady rise from late February to peaks in May–June during full leaf development, and a gradual decline through fruit maturation and harvest. While NDVI and SAVI display smoother trends, EVI shows greater sensitivity with higher amplitude, and AVI maintains lower absolute values but follows a similar seasonal pattern.

4. Methodology

4.1 Machine Learning Algorithms

Two widely used supervised machine learning algorithms Extreme Gradient Boosting (XGBoost), and Random Forest (RF) are employed to perform the classification task. Extreme Gradient Boosting (XGBoost) is an advanced gradient boosting algorithm that efficiently handles sparse data, incorporates weighted quantile computation, and uses memory and disk access optimizations to scale to very large datasets while maintaining high accuracy and efficiency (Chen & Guestrin, 2016). In this study, XGBoost is employed due to its scalability, ability to manage high-dimensional data, and strong predictive performance. Its further benefits from built-in regularization mechanisms that help prevent overfitting and allow for more effective hyperparameter optimization (Aksoy et al., 2023). Random Forest, on the other hand, is an ensemble machine learning method that combines many decision trees built from randomly selected input variables, and determines the final class of a sample based on majority voting (Ustuner & Simsek, 2025; Rodriguez-Galiano et al. 2012; Akar and Güngör 2015). Its robustness and ease of implementation make it a widely adopted algorithm in various classification and regression tasks.

4.2 Accuracy Assessment

Accuracy assessment is essential for evaluating the performance and reliability of classification methods and for guiding the selection of the most appropriate approach for specific applications. Compared to point-based approaches, polygon-based accuracy assessment offers advantages by better representing the actual shape and variability of agricultural fields, thereby providing results that are more consistent with real-world conditions. Common accuracy metrics such as overall accuracy (OA), user's accuracy (UA), producer's accuracy (PA), and the F1-score are derived from the confusion matrix, which summarizes how well predicted classes correspond to actual ones. To enhance the robustness of evaluations, it is common to integrate diverse reference data sources, including field surveys and high-resolution imagery. However, interpreting these metrics requires careful consideration of factors such as class imbalance and data quality. In this study, we applied the method proposed by Olofsson et al. (2013), which uses stratified random sampling to calculate OA, UA, and PA while adjusting area estimates to reduce bias from classification errors (Karimi et al., 2025). A comprehensive accuracy assessment ensures that classification outcomes are both scientifically sound and practically applicable for decision-making.

5. Experiments & Results

Model training was conducted on the Kaggle platform using scikit-learn and XGBoost libraries. The dataset was split into 70% training, 20% validation, and 10% test sets through stratified sampling. Owing to the large study area (11,998 × 9,915 pixels) and high feature dimensionality, RandomizedSearchCV was applied to a subset of 50,000 training samples for efficient hyperparameter optimization. For both Random Forest (RF) and XGBoost (XGB), optimal parameters were identified via 3-fold cross-validation with the macro-averaged F1-score as the selection criterion. The best XGB model incorporated 400 trees, depth 8, learning rate 0.1, subsample ratio 1.0, and column subsample ratio 0.7, while the optimal RF employed 300 trees, depth 40, and a balanced class weight strategy. Using these parameters, the final models were trained and evaluated with overall accuracy, precision, recall, F1-score, and weighted IoU. The trained RF and XGB models were subsequently applied to the full scene, and prediction masks were exported as GeoTIFFs for further spatial analysis. Both models achieved robust performance in detecting hazelnut orchards, with RF demonstrating marginally superior results across all classes.

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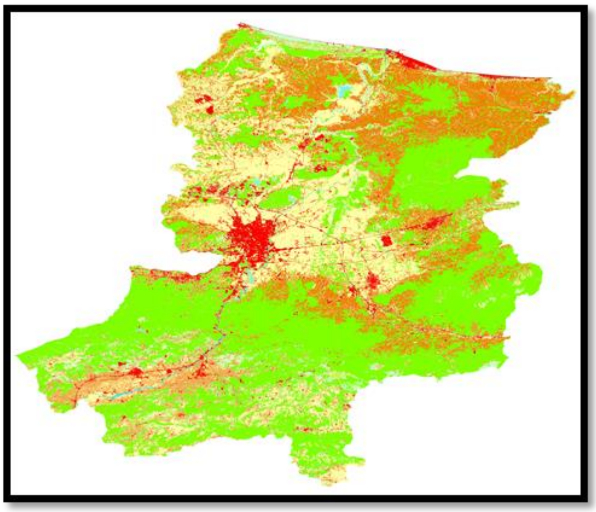
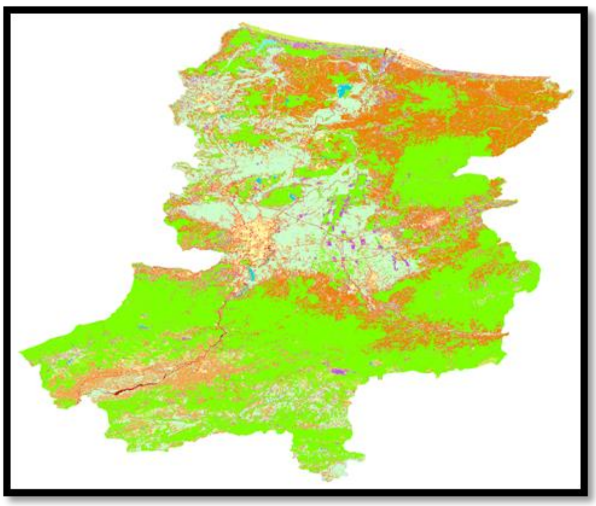
Overall, Random Forest delivers stronger performance than XGBoost both globally and on the key hazelnut class. Overall accuracy is 96.32% for Random Forest versus 80.74% for XGBoost, and weighted IoU is 97.45% versus 87.69%. For the hazelnut class, Random Forest attains 98.24% producer's accuracy, 97.52% user's accuracy, and a 98.36% F1 score, while XGBoost reaches 93.22%, 94.92%, and 94.06%, respectively (Table 2). The hazelnut class likely scores well in both models because it is the most prevalent class, whereas several less represented classes are harder and appear to pull XGBoost's overall accuracy down. Random Forest not only keeps hazelnut performance high but also handles the rarer classes more reliably, which explains its higher OA and weighted IoU and suggests it generalizes better under class imbalance. As shown in the prediction masks (Figure 4), although both models yield comparable outcomes for Hazelnut and Forest classes, RF demonstrates clear superiority over XGB, particularly in discontinuous urban fabric and arable land areas.

Random Forest Prediction Mask



XGBoost Prediction Mask



Hazelnut	Disc. Urban Fabric	Perm. Copland	Forest
Grassland	Sparsely Veg. Areas	Arable Land	Greenhouse
Water Courses	Road and rail networks..	Water Bodies	Wetland

Figure 4. Prediction masks for RF and XGBoost with legend.

Metric	Random Forest	XGBoost
OA (%)	96.32	80.74
Weighted IoU (%)	97.45	87.69
Hazelnut producer's accuracy (%)	98.24	93.22
Hazelnut user's accuracy (%)	97.52	94.92
Hazelnut F1-score (%)	98.36	94.06

Table 2. Accuracy Assessment

6. Conclusion

This study demonstrates the effectiveness of combining field surveys, vegetation indices, and multi-temporal Sentinel-2 imagery for mapping hazelnut orchards in Sakarya. Fieldwork allowed detailed sampling for the hazelnut class, and the use of key phenological periods enabled the creation of stacked imagery capturing critical growth stages. Optimal hyperparameters were determined for both Random Forest and XGBoost, enabling RF to outperform XGB in overall classification, particularly for hazelnut and other minority classes. While dominant classes such as hazelnut and forest were reliably classified, classes with limited spatial distribution, including permanent cropland, remain challenging due to spectral similarities. Future studies incorporating higher-resolution imagery and targeted analysis of underrepresented classes could further improve classification accuracy and support sustainable agricultural monitoring.

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