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Land Cover and Crop Types Classification using Sentinel 2A-Derived Vegetation Indices and an Artificial Neural Network

Abstract.

Developments in remote sensing data acquisition capabilities, data processing, and interpretation of ground-based, airborne, and satellite observations have made it possible to couple remote sensing technologies and precision crop management systems. Land cover and crop type classification is a fundamental task in remote sensing and is crucial in various environmental and agricultural applications. Accurate and timely information on land cover and crop types is essential for land management, land-use planning, environmental monitoring, and food security assessment. Remote sensing data, such as satellite imagery, provides a valuable source of information for characterizing the Earth's surface by capturing the spectral and spatial properties of different land cover and crop types. With the advancements in artificial intelligence and machine learning algorithms, land cover and crop type classification automation has become more efficient and accurate. Most studies have focused on classifying land cover and crop types at the same sites. Training sets and test sets are often selected from a unique study area. The main objective of this study is to develop an approach for land cover and crop type classification in different sites located in distinct districts using Sentinel 2A-derived vegetation indices and an Artificial Neuron Network (ANN). Fourteen vegetation indices calculated from six Sentinel-2A images were used to classify Maize and Forage plants. The Multi-Layer Perceptron (MLP) algorithm model was calibrated on a specific geographical location and validated on another geographical location. The ANN algorithm utilizes the power of deep learning to automatically learn complex patterns and relationships in the input data, enabling it to classify crop types based on the provided features effectively. The results show that the studied crops are classified with an overall accuracy ranging between 66.1% and 88.4% on the first site and between 73.1% and 88.1% on the second site. The present study can advance research on using high spatial resolution satellite remote sensing data for classification using machine learning approaches and offers a promising approach to effectively classifying land cover and crop types in different geographical areas.

Keywords.
Artificial Neural Network, classification, crop types, Multi-Layer Perceptron, remote sensing, Sentinel 2A, vegetation indices

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Introduction

Land cover and crop type classification are essential tasks for various applications such as agricultural monitoring and land management. As the global population increases, the need for efficient land use and sustainable agricultural practices has become increasingly important. Remote sensing technology, coupled with advanced machine learning techniques, offers a powerful solution by enabling large-scale and timely analysis of Earth's surface. Sentinel-2A satellite imagery, known for its high spatial resolution and multispectral capabilities, has become a valuable resource for such classification. Utilizing vegetation indices derived from Sentinel-2A data and artificial neural networks (ANN) can significantly enhance the accuracy of land cover and crop type classifications (Hu et al. 2022). Previous studies have demonstrated the effectiveness of integrating different satellite data sources for land cover classification. For example, the successful mapping of land use and land cover in various regions has been achieved through the integration of Sentinel-2 optical data (Tavares et al. 2019). The popularity of employing advanced classification algorithms with Sentinel-2 data has increased because of its superior spatial resolution compared with other satellite images. Researchers have chosen Sentinel-2A data for land use/land cover classification in studies ranging from wetland monitoring to urban greenspace analysis (Priyadarshini et al. 2018). Furthermore, the fusion of Sentinel-2A data with UAV imagery has been utilized to achieve finer crop classification at a spatial scale, ensuring the precise mapping of crop distribution (Li-cheng et al. 2019).

Numerous studies have focused on the classification of crop types and land cover using datasets obtained from the same locations (Vijayasekaran 2019; Jia et al. 2014; Wu et al. 2017; Jagadeeswaran 2018; Valcarce-Diñeiro et al. 2019; Fernández and Morales 2019). Therefore, the literature examined demonstrates the significance of employing machine learning and classification algorithms and integrating remote sensing data with crop models to classify crop types. Hyperspectral imaging and deep learning algorithms have been identified as viable methods for crop classification. In previous studies, the training and test datasets were usually selected from the same study sites in the literature. However, few studies have explored classification approaches using different datasets (Khan et al. 2021). Further research is required to develop effective crop-type classification approaches using high-resolution remote sensing data and advanced machine-learning algorithms.

The aim of the present study is to evaluate the capability of well vegetation indices, including the normalized difference vegetation index (NDVI), normalized difference water index (NDWI), green normalized difference vegetation index (GNDVI), atmospherically resistant vegetation index (ARVI), soil adjusted vegetation index (SAVI), optimized soil-adjusted vegetation index (OSAVI), modified soil-adjusted vegetation index (MSAVI), visible atmospherically resistant index (VARI), structure insensitive pigment index (SIPI), simple ratio (SR), red edge chlorophyll index (ReCI), green chlorophyll index (GCI), Green Leaf Index (GLI), and green ratio vegetation index (GRVI), to classify maize and forage crops in two distinct agricultural areas. The classification was performed using the ANN algorithm. The model was trained at a specific location and validated at another location.

Materials and Methods

Study site

This study was conducted in two different villages in Bursa province in northwest Turkey, which lies approximately between latitudes 40°5'26.39"N and 40°11'19.03"N and longitudes 28°21'35.43"E and 28°29'25.84"E (Fig. 1). The study site included two villages, Tepecik and Ormankadı, located in the Mustafakemalpaşa district, with areas of 13.08 km^2 and 17.60 km^2, respectively.

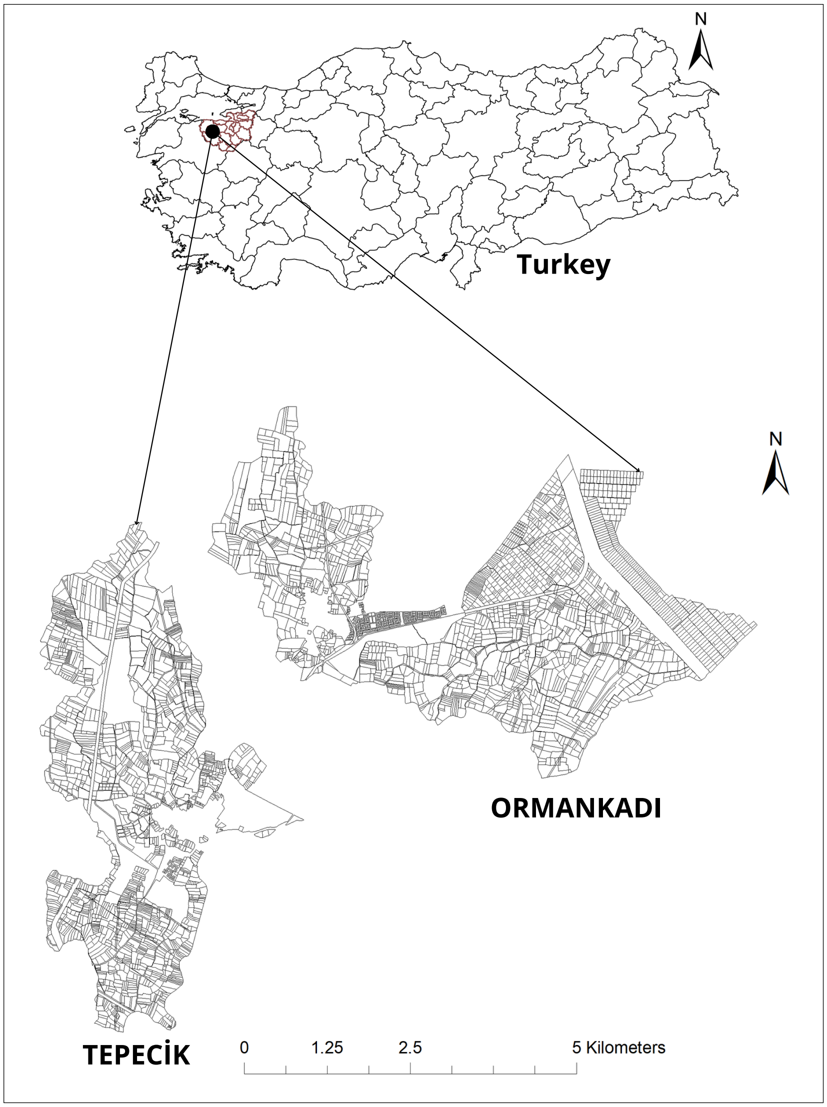


Fig. 1 Location and a view of the investigated sites

The climate in the study area is characteristic of a Marmara transitional Mediterranean climate. Precipitation occurs mostly during spring and winter. Precipitation during the winter typically occurs in the form of snow. The coldest month of the year is generally February, and the hottest month is July. Although the vegetation covering the soils of the study area provides the general characteristics of the Marmara Region, regions close to the sea and rural areas show differences. The soils in the study area are alluvial calcareous brown, red-brown Mediterranean, and large Rendzina soil groups formed in situ (Bantchina et al. 2017). Maize, pulses, tomatoes, forage plants, orchards, sugar beets, meadows, and pastures are generally cultivated in the study area, with minor changes from year to year. This study focuses on maize and forage crops.

Methodology

In this study, Sentinel-2A-derived spectral indices (NDVI, NDWI, GNDVI, ARVI, SAVI, OSAVI, MSAVI, VARI, SIPI, SR, ReCI, GCI, GLI, and GRVI) and an ANN machine-learning algorithm were selected to assess the feasibility of accurate maize and forage crop classification. The overall methodology and steps used in this study are illustrated in Fig. 2.

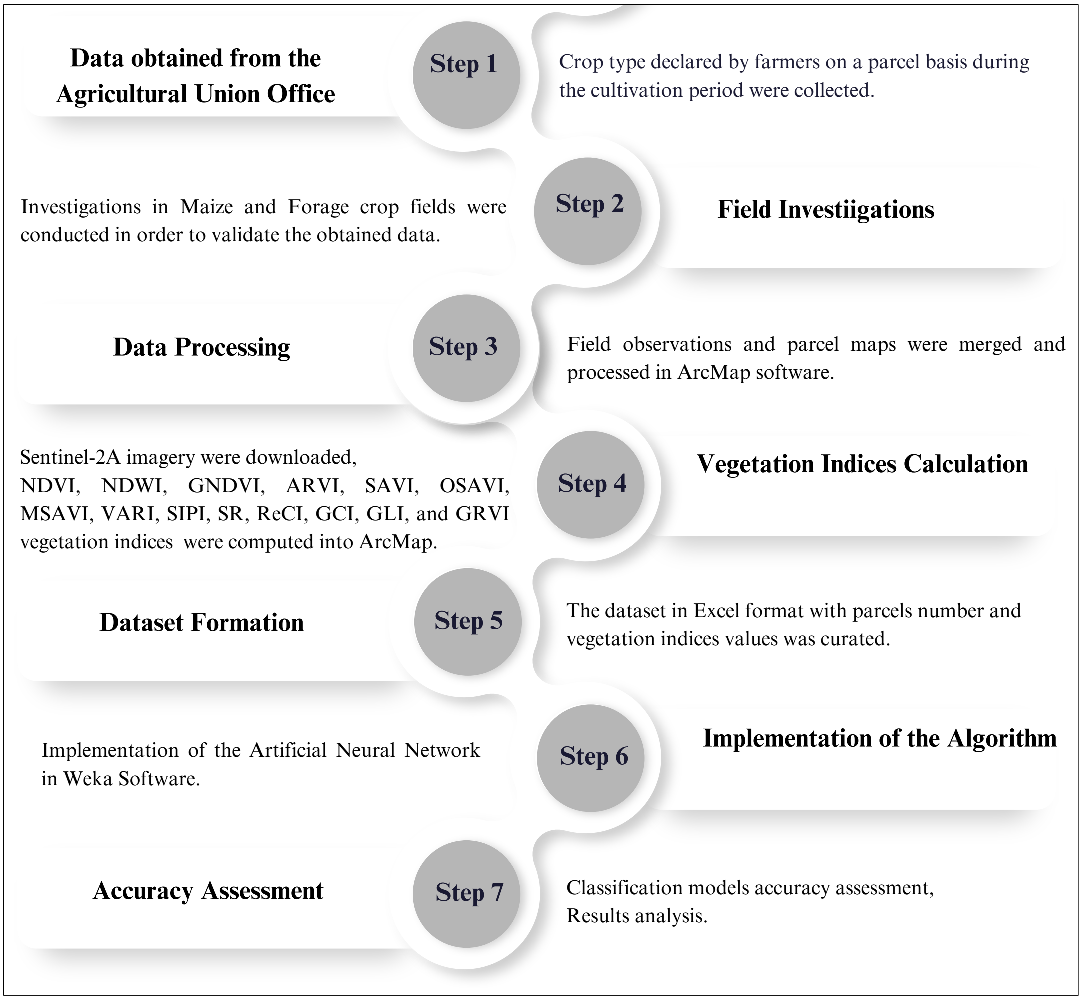


Fig. 2 Study methodology flowchart

Ground Truth

This study used data obtained from Mustafakemalpaşa and Karacabey Irrigation Unions, where crop types declared by farmers on a parcel basis during the cultivation period were collected. These declarations were cross-referenced with onsite observations to validate their accuracy. The field investigations were conducted during the 2022 crop season. Plots with maize and forage crops were investigated in the villages of Tepecik and Ormankadı in the Mustafakemalpaşa district. A total of 2000 parcels were investigated. Field investigations demonstrated accurate data from the Mustafakemalpaşa and Karacabey Irrigation Unions.

The established crop patterns from field observations and parcel maps were processed using ArcGIS ArcMap 10.8 (ESRI Redlands, California, USA) software. The vector-based data were further transformed into raster pixels for the analysis. After the pre-processing steps, 988 parcels were considered in each village (Ormankadı and Tepecik). The data were exported in an Excel worksheet format, with each row containing information on a distinct pixel and each column encompassing the parcel number. The dataset was labeled into two classes, maize and forage. The index values were averaged per parcel and a dataset with 988 parcels/rows was curated for both training and testing purposes.

Sentinel 2A-Derived Spectral Indices

Sentinel-2A data were used in this study. The Sentinel fleet of satellites was designed to deliver remote sensing data to the European Commission's Copernicus program. The Sentinel-2A satellite was launched by the European Space Agency on June 23, 2015, and operates in a sun-synchronous orbit with a 10-day repeat cycle.

Sentinel 2A-derived vegetation indices have a significant utility in agricultural and environmental monitoring. These indices are valuable tools for evaluating the health, growth, and overall productivity of the vegetation. In this study, Sentinel-2A imagery was used to derive the vegetation indices. The images were downloaded from https://scihub.copernicus.eu/dhus/#/home in bottom-of-atmosphere L2A format. Six images from May 12, June 18, July 18, August 10, September 16, and October 09, 2022, covering the study area, all atmospherically corrected and cloudless, were selected. These six images were selected by considering one image per month to cover the phenological stages of the maize crop. The number of images was chosen to evaluate whether it was possible to achieve a high accuracy with few images. In the study area, maize and forage crops are generally seeded in May and harvested in October or November.

In this study, fourteen (14) well-known and commonly used vegetation indices (VIs) were selected. These indices have been used in many studies and have been recognized to improve the accuracy of crop-type classification (Thenkabail 2000; Li, et al. 2010; Agilandeeswari et al. 2022). VIs using bands with a 10 m resolution were used to obtain high-resolution data. For each scene, 10 m spatial resolution bands (2, 3, 4, and 8, respectively, Blue, Green, Red, and NIR spectral bands) were selected. The VIs and formulae used in this study are listed in Table 1.

Table 1. Sentinel-2A-derived VIs used in this study

VIs	Description	Formula	Reference
NDVI	Normalized Difference Vegetation Index	(Band8 - Band4) / (Band8 + Band4)	(Tucker 1979)
NDWI	Normalized Difference Water Index	(Band3 - Band8) / (Band3 + Band8)	(Gao 1996)
GNDVI	Green Normalized Difference Vegetation Index	(Band8 - Band3) / (Band8 + Band3)	(Gitelson 1996)
ARVI	Atmospherically Resistant Vegetation Index	[Band8 - (2*Band4) + Band2] / [Band8 + (2*Band4) + Band2]	(Kaufman and Tanre, 1992)
SAVI	Soil Adjusted Vegetation Index	[(Band8 - Band4) / (Band8 + Band4 + 0.5)]*(1 + 0.5)	(Huete 1988)
OSAVI	Optimized Soil Adjusted Vegetation Index	(Band8 - Band4) / (Band8+ Band4 + 0.16)	(Rondeaux 1996)
MSAVI	Modified Soil-Adjusted Vegetation Index	[2 * Band4 + 1- sqrt((2 * Band4 + 1)^2 - 8 * (Band4 -Band3))]/2	(Qi 1994)
VARI	Visible Atmospherically Resistant Index	(Band3 - Band4) / (Band3 + Band4 - Band2)	(Gitelson et al. 2002)
SIPI	Structure Insensitive Pigment Index	(Band8 - Band2) / (Band8 - Band4)	(Penuelas et al. 1995)
SR	Simple Ratio	Band8 / Band4	(Birth and McVey 1968)
ReCI	Red Edge Chlorophyll Index	(Band8 / Band4) - 1	Gitelson and Merzlyak (1994)
GCI	Green Chlorophyll Index	(Band8 / Band3) - 1	(Gitelson et al. 2003)
GRVI	Green Ratio Vegetation Index	Band8 / Band3	(Sripada et al. 2006)
GLI	Green Leaf Index	[(Band3- Band4) + (Band3– Band2)] / [(2* Band3) + Band4 + Blue]	(Gobron et al. 2000)

Artificial neural network (*ANN*)

In this study, a multilayer perceptron (MLP) was used to classify the crop types. MLP is a type of artificial neural network (*ANN*) that has been extensively applied in various domains, including computer science (LeCun et al. 1998), artificial intelligence (Rumelhart et al. 1986), statistics (Pham et al. 2019), and geophysics (Hajian et al. 2011). The MLP was trained using a back-propagation algorithm, which is a successful gradient-based learning technique (Haykin and

Kosko 2009). It is one of the simplest forms of neural network and serves as a foundational building block for more complex architectures. Fig. 3 presents a breakdown of the key components and functions of the MLP.

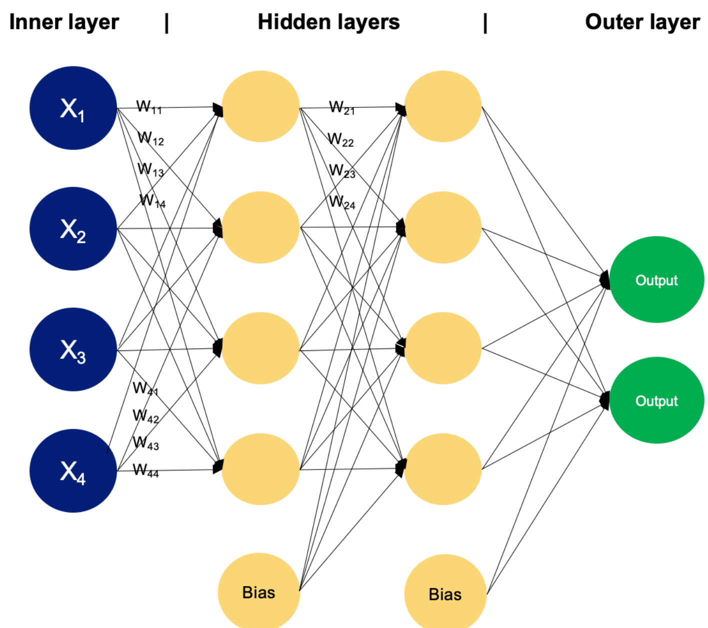


Fig. 3 Structure of a typical artificial neural network

Input Layer: This layer consists of neurons that receive input features. Each neuron represents a feature of the input data. Hidden Layers: MLPs contain one or more hidden layers that transform the inputs into something that the output layer can use. Each neuron in these layers applies a nonlinear transformation to the values received from the previous layers. The complexity and capacity of a MLP depend largely on the number of hidden layers and the number of neurons in each layer. Output Layer: The final layer that produces the output of the network. The function of the output layer depends on the type of prediction or classification required (e.g., binary classification, multiclass classification, and regression).

Neurons in the hidden layers and sometimes in the output layer apply activation functions to introduce nonlinearity into the model, enabling it to learn more complex patterns. Common activation functions include the sigmoid, Hyperbolic Tangent (Tanh), ReLU (Rectified Linear Unit).

During the learning process, the input data are passed through the network, from the input layer through the hidden layers, and finally to the output layer, where a prediction is made. Once a prediction is made, the error (difference between the predicted output and the actual label) is calculated, and this error is propagated back through the network to update the weights. This process was performed using a gradient descent method.

Classification Models Implementation

The Waikato Environment for Knowledge Analysis (Weka), a popular open-source machine learning software toolkit that provides a wide range of tools and algorithms for data mining and machine learning tasks, was used to perform the classification tasks (Hall, et al. 2009). The dataset was split into training and test sets by using a 70:30 partition. The hyperparameters were set before the learning process to determine the optimal combination for each class. The hyperparameters for each algorithm used in this study are listed in Table 2.

Table 2. The hyperparameters used for modeling in this study

Model	Hyperparameters	Values
ANN	Number of fully connected layers	2, 3
	First layer size	100
	Second layer size	100
	Optimizer	Adam
	Dropout rate	0, 0.1, 0.2
	Number of epochs	80, 120
	Batch size	8, 16, 32
	Activation Function	Sigmoid

Model Accuracy Assessment

Assessing the accuracy of machine learning models for crop-type classification is crucial for understanding how well the model performs and whether it is suitable for classification tasks. The evaluation metrics used to assess the performance of the classification models were True Positives (TP), overall accuracy, precision (P), recall (R), F1-score, Matthews correlation coefficient (MCC), Receiver Operating Characteristic Area (ROC Area), and Precision-Recall Curve Area (PRC Area). The formulae for the performance metrics are listed in Table 3.

Table 3. Model Performance Evaluation Metrics

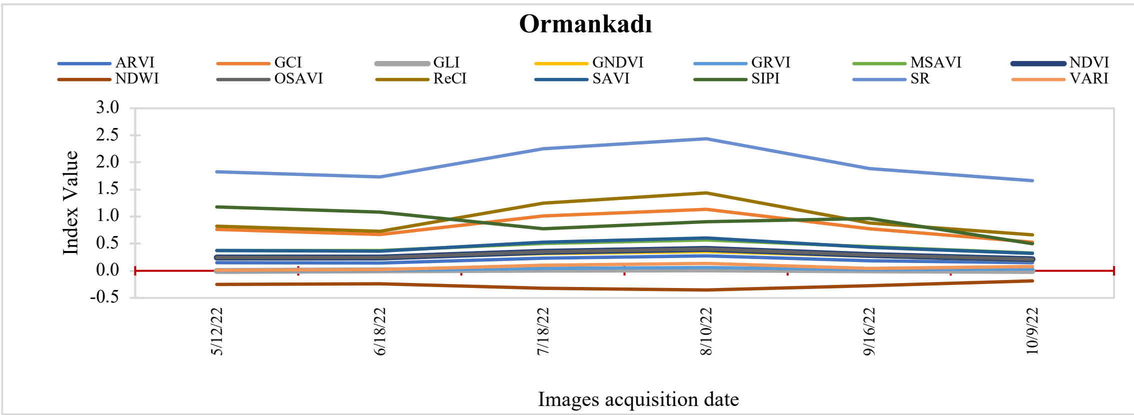
Performance Evaluation Metrics	*Formula*
Overall Accuracy (OA)	$\frac{TP + TN}{(TP + TN + FP + FN)}$
Precision (P)	$\frac{TP}{(TP + FP)}$
Recall (R)	$\frac{TP}{(TP + FN)}$
F1-Score	$2 * \frac{P * R}{(P + R)}$
MCC	$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$
ROC Area	$ROC\ Area = \int_0^1 True\ Positive\ Rate\ d(False\ Positive\ Rate)$
PROC Area	$PROC\ Area = \int_0^1 Precision\ d(Recall)$

TP, True Positives; TN, True Negatives; FP, False Positives; FN, False Negatives; MCC, Matthews Correlation Coefficient; ROC Area, Receiver Operating Characteristic Area; PRC Area, Precision-Recall Curve Area

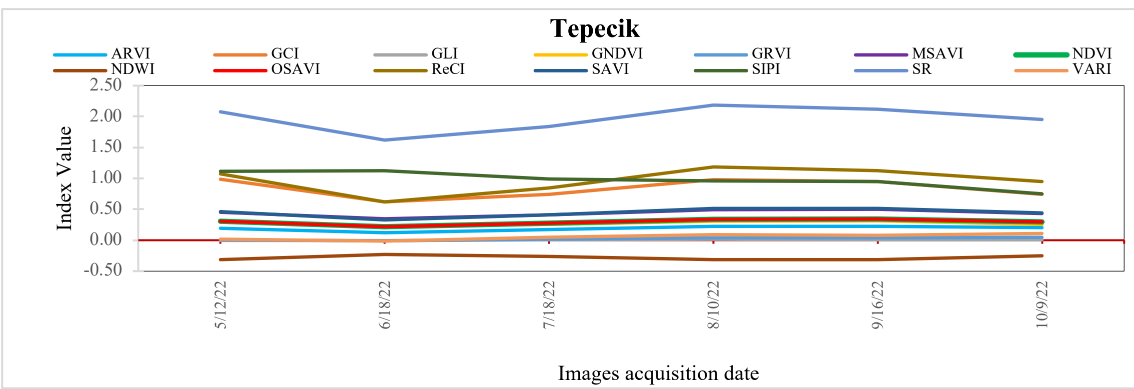
Results

Spatiotemporal Distribution of the Studied Vegetation Indices

Temporal analysis of vegetation indices using Sentinel 2 data provides valuable insights into crop types and their temporal dynamics. The temporal analysis of Sentinel 2A-derived vegetation indices used in this study is shown in Fig. 4. The vegetation indices had higher values during the growing stage and lower values during the early and late stages of the maize crop.



(a)



(b)

Fig. 4 Temporal distribution of used Sentinel 2A-derived VIs in Ormankadı (a) and Tepecik (b) for Maize and Forage

ANN Classification Model Accuracy Results

This section presents the quantitative results of the ANN classification algorithms used to classify maize and forage in the Tepecik and Ormankadı sites. The results are presented in terms of high values of OA, TP Rate, Precision, Recall, F1-Score, MCC, ROC Area, and PRC Area and low values of FP Rate.

The ANN model exhibited good accuracy in maize and forage classification when calibrated on Tepecik and validated on Ormankadi sites (Table 4). During the calibration phase, the model achieved an OA of 88.4%, with a True Positive Rate of 83.1% for maize and 92.9% for forage crops, indicating a high proportion of accurately identified maize and forage crop parcels. The low False Positive Rate of 7.1% for maize and 16.9% for forage underscored the model's proficiency in minimizing misclassifications. Precision, at 90.8% for maize, and 86.7% for forage reflected the model's precision in labeling instances as maize and forage, whereas a Recall of 83.1% for maize and 92.9% signified its ability to capture a substantial portion of actual maize and forage occurrences, respectively. The F1-Score of 86.8% for maize and 89.7% for forage indicated a harmonious balance between Precision and Recall. A MCC of 94.3% highlighted the performance of the model, considering both false positives and false negatives. The ROC and PRC Area values of 94.3% and 92.8%, respectively, for maize, and 94.3% and 95.0%, respectively, for forage, affirmed the model's discriminative capacity and Precision-Recall trade-off. The overall accuracy for maize and other crops was 89.9%.

The model validation on Ormankadı maintained the model's performance by achieving an OA of 66.1%, with high TP Rate (61.2%), Precision (91.1%), Recall (61.2%), F1-Score (73.2%), and MCC (36.4%) values, indicating its resilience across diverse datasets for maize crops. For forage crops, the model demonstrated an accuracy of TP Rate (81.3%), Precision (40.2%), Recall (81.3%), F1-Score (53.8%), and MCC (36.4%). The ROC Area and PRC Area values achieved accuracies of 76.8% and 49.1%, respectively.

Furthermore, the ANN model consistently demonstrated robust performance in crop type classification when Ormankadı and Tepecik were used as the calibration and validation sets, respectively. Training on Ormankadı yielded a high OA of 88.1%. For maize classification, the accuracies were the TP Rate (95.0%), Precision (90.2%), Recall (95.0%), F1-Score (92.5%), and MCC (63.8.0%), showing the model's ability to effectively capture the intricacies of maize patterns at this study site. For forage classification, the accuracies were the TP Rate (64.0%), Precision (78.7%), Recall (64.0%), F1-Score (70.6%), and MCC (63.8.0%).

Subsequently, the validation of the model on Tepecik maintained the accuracy of the model with 73.1% OA. For maize crop extraction, the validation model maintained the model's performance by achieving high TP Rate (93.8%), Precision (64.0%), Recall (93.8%), F1-Score (76.1%), and MCC (52.3%) values, indicating its resilience across diverse datasets. The ROC Area and PRC Area values achieved accuracies of 77.0% and 65.8%, respectively. The model demonstrated moderate accuracy in classifying forage with a TP Rate of 55.6%, Precision of 91.4%, Recall of 55.6%, F1-Score of 69.1%, and MCC of 52.3%. The ROC Area and PRC Area values achieved accuracies of 77.0% and 84.6%, respectively.

Table 4. Performance metrics of the ANN model

ANN Model	TP Rate (%)	FP Rate (%)	Precision (%)	Recall (%)	F1-Score (%)	MCC (%)	ROC Area (%)	PRC Area (%)	Crop Type
Tepecik Training	83.1	7.1	90.8	83.1	86.8	76.7	94.3	92.8	Maize
	92.9	16.9	86.7	92.9	89.7	76.7	94.3	95.0	Forage
	88.4	12.4	88.6	88.4	88.3	76.7	94.3	94.0	OA
Testing on Ormankadı	61.2	18.8	91.1	61.2	73.2	36.4	76.8	89.0	Maize
	81.3	38.8	40.2	81.3	53.8	36.4	76.8	49.1	Forage
	66.1	23.6	78.7	66.1	68.5	36.4	76.8	79.3	OA
Ormankadı Training	95.0	36.0	90.2	95.0	92.5	63.8	94.4	98.4	Maize
	64.0	5.0	78.7	64.0	70.6	63.8	94.4	80.1	Forage
	88.1	29.1	87.6	88.1	87.6	63.8	94.4	94.4	OA
Testing on Tepecik	93.8	44.4	64.0	93.8	76.1	52.3	77.0	65.8	Maize
	55.6	6.2	91.4	55.6	69.1	52.3	77.0	84.6	Forage
	73.1	23.7	78.9	73.1	72.3	52.3	77.0	76.0	OA

Qualitative Classification Results

The map presented in Fig. 5 visually represents the classification outcomes of the ANN model in Tepecik and Ormankadı and offers insights into the spatial distribution and arrangement of crop types. The qualitative interpretation of the classified crop map substantiates the effectiveness of our machine-learning-based approach in accurately distinguishing between crops. The spatial patterns captured in these maps validated the accuracy of the classification models and highlighted the feasibility of leveraging machine learning techniques for precise crop type identification.

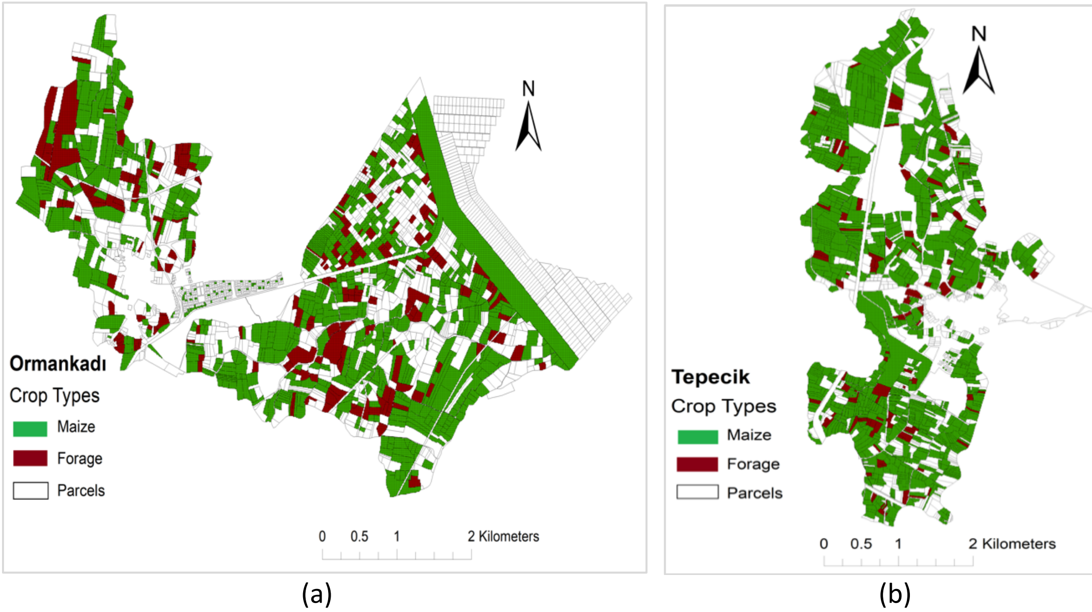


Fig. 5 ANN model-based classified crop type maps for Ormankadı(a), and Tepecik (b)

Discussion

Land cover and crop type classification using remote sensing data and machine learning techniques has recently gained considerable attention in the scientific community. This study aimed to explore a new approach to enhance remote sensing research using high-resolution satellite-derived vegetation indices and machine-learning methods. The present study underscores the commendable performance consistently exhibited by an artificial neural network for maize and forage crop classification across the two study regions. The model calibrated on Tepecik and validated on Ormankadı maintained its accuracy, with an overall accuracy ranging from 66.1% to 88.4%. Furthermore, the model consistently demonstrated robust performance when Ormankadı served as the calibration set and Tepecik as the validation set, with overall accuracies of 73.1% and 88.1%, respectively.

The ANN model used in the two scenarios demonstrated similar results in terms of model performance. The findings are acceptable as they align comparably with the results documented in the relevant literature. For instance, in their investigation of deep learning for crop type classification, Khan et al. 2021 reported a 70.0% overall classification accuracy achieved by models trained on one geographical area and subsequently validated it in other areas within Nebraska (United States).

The integration of machine learning algorithms with Sentinel-2-derived spectral indices has emerged as a focal point of interest in remote sensing and agricultural research. Numerous studies have provided valuable insights into the utilization of machine learning for crop classification and mapping (Bantchina and Gundogdu 2024; Muntean 2023; Hudait and Patel 2022; Ibrahim et al. 2021; Moumni and Lahrouni 2021; Arias et al. 2020). These researchers achieved a higher accuracy using a common approach (calibration and validation in the same study area).

To the best of our knowledge, few studies using the approach proposed in this study are available in the literature. The proposed approach is unique because it suggests exploring alternative methods other than common techniques of crop type classification. The vegetation indices used and the chosen number of images covering all phenological stages showed that it is possible to achieve acceptable accuracy in maize and forage crop classification.

Conclusion

In conclusion, the utilization of Sentinel-2A-derived vegetation indices in conjunction with artificial neural networks offers a robust approach for land cover and crop type classification. The objective of the present study was to develop an approach for classifying maize and forage crops across heterogeneous agricultural areas. The ANN model demonstrated its ability to classify crops accurately and effectively across different geographical areas. The use of Sentinel 2A-derived vegetation indices in conjunction with an advanced artificial neural network algorithm achieved good results. Further studies are expected to be performed using other crops, more remote data, and deep learning techniques to improve classification accuracy. In future research, it may be necessary to conduct studies using synthetic-aperture radar data and images taken only at specific phenological stages. Thus, crop-type classification could be performed without following all phenological stages to investigate whether the classification accuracy improved. These additional research efforts should help understand the factors contributing to suboptimal classification performance within specific test areas for other crop types within the same geographical region.

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