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Crop Type Classification using Sentinel 2A-Derived Normalized Difference Red Edge Index (NDRE) and Machine Learning Approach

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Abstract: Satellite remote sensing (*RS*) enables the extraction of vital information on land cover and crop type. Land cover and crop type classification using RS data and machine learning (*ML*) techniques have recently gained considerable attention in the scientific community. This study aimed to enhance remote sensing research using high-resolution satellite imagery and a ML approach. To achieve this objective, ML algorithms were employed to demonstrate whether it was possible to accurately classify various crop types within agricultural areas using the Sentinel 2A-derived Normalized Difference Red Edge Index (NDRE). Five ML classifiers, namely Support Vector Machines (*SVM*), Random Forest (*RF*), Decision Tree (*DT*), K-Nearest Neighbors (*KNN*), and Multi-Layer Perceptron (*MLP*), were implemented using Python programming on Google Colaboratory. The target land cover classes included cereals, fallow, forage, fruits, grassland-pasture, legumes, maize, sugar beet, onion-garlic, sunflower, and watermelon-melon. The classification models exhibited strong performance, evidenced by their robust overall accuracy (*OA*). The RF model outperformed, with an OA rate of 95% and a Kappa score of 92%. It was followed by DT (88%), KNN (87%), SVM (85%), and MLP (82%). These findings showed the possibility of achieving high classification accuracy using NDRE from a few Sentinel 2A images. This study demonstrated the potential enhancement of the application of high-resolution satellite RS data and ML for crop type classification in regions that have received less attention in previous studies.

Keywords: Classification, Crop Type, Machine Learning, NDRE, Remote Sensing, Sentinel 2A.

[1] This study did not require approval from the ethics committee. The article was prepared in accordance with research and publication ethics.

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Sentinel 2A Uydu Görüntüsünden Normalleştirilmiş Fark Kırmızı Kenar İndeksi (NDRE) Kullanılarak Tarımsal Ürünlerin Makine Öğrenme Yöntemleri ile Sınıflandırılması

Öz: Uzaktan algılama, arazi örtüsü ve bitki türleriyle ilgili kritik bilgilerin edinilmesini sağlayarak tarım alanındaki araştırmalara önemli katkılar sunmaktadır. Son zamanlarda, uzaktan algılama verileri ve makine öğrenimi algoritmaları aracılığıyla arazi örtüsü ve ürün türlerinin sınıflandırılması konusu büyük ilgi çekmektedir. Bu çalışmanın ana amacı, yüksek çözünürlüklü uydu görüntüleri ve makine öğrenimi yaklaşımını kullanarak uzaktan algılama araştırma alanını geliştirmektir. Bu hedefe ulaşmak adına, Sentinel 2A'dan elde edilen Normalleştirilmiş Fark Kırmızı Kenar İndeksi (*NDRE*) ile tarım alanlarındaki çeşitli ürün türlerinin etkili bir şekilde sınıflandırılmasının mümkün olup olmadığını değerlendirmek amacıyla çeşitli makine öğrenimi yöntemleri kullanılmıştır. Karar Ağaçları (KA), Destek Vektör Makineleri (DVM), Rastgele Orman (RO), K-En Yakın Komşular (KEYK) ve Çok Katmanlı Algılayıcı (ÇKA) dahil olmak üzere beş makine öğrenimi sınıflandırıcı algoritması uygulanmıştır. Analizde değerlendirilen hedef arazi örtüsü sınıfları arasında tahıllar, nadas, yem bitkileri, meyveler, çayır-mera, baklagiller, mısır, şeker pancarı, soğan-sarımsak, ayçiçeği ve karpuz-kavun bulunmaktadır. Elde edilen sınıflandırma modelleri, yüksek doğruluk oranları ile güçlü bir performans sergilemiştir. RF modeli %95'lik genel doğruluk (*OA*) oranı ve %92'lik Kappa skoru ile en yüksek performans göstermiştir. Bunu sırasıyla %88, %87, %85 ve %82 OA ile KA, KEYK, DVM ve ÇKA takip etmiştir. Bu bulgular, az sayıda Sentinel 2A görüntüsünden NDRE kullanılarak yüksek sınıflandırma doğruluğu elde edilebileceğini göstermektedir. Bu çalışma, yüksek mekânsal çözünürlüğe sahip uydu uzaktan algılama verileri ve makine öğrenimi algoritmalarının, mahsul türü sınıflandırması için potansiyel bir gelişim sağlayabileceğini doğrulamıştır.

Anahtar Kelimeler: Makine Öğrenme, NDRE, Sınıflandırma, Tarımsal Ürünlerin, Sentinel 2A, Uzaktan Algılama.

Introduction

The incorporation of cutting-edge technologies into agriculture is essential for accurate and effective crop management. The emergence of remote sensing, specifically the Sentinel and Landsat satellites, has provided opportunities for detailed research using high-resolution imagery. The use of remote sensing data and machine learning techniques for the classification of crop types has gained considerable interest in recent years. Scientists have investigated the utilisation of Sentinel-2 data for crop mapping and vegetation monitoring. Sentinel imagery time series, characterised by a brief return time and superior spatial resolution, has demonstrated significant promise in crop classification, particularly in areas prone to frequent cloud cover (Cuenca et al., 2020). Several studies have investigated the application of various machine learning algorithms to classify land use/land cover and crop types. Machine learning techniques, such as k-nearest neighbors (KNN), random forest (RF), support vector machine (SVM), and deep recurrent neural network approaches, have been investigated for land cover classification using remote sensing data (Zhou et al., 2017; Ndikumana et al., 2018; Sitokonstantinou et al., 2018; Mustak et al., 2019; Yang et al., 2019; Abubakar et al., 2020). These studies have emphasised the significance of classification algorithms and the capacity of machine learning approaches to achieve precise crop mapping by utilising remote sensing data (Sonobe et al., 2018; Sonobe, 2019; Yang et al., 2019; Ren et al., 2020; Mashaba-Munghemezulu et al., 2021). These approaches have contributed to the early mapping of crops (Tian et al., 2021) and land cover mapping (Pech-May et al., 2022).

Furthermore, the use of deep learning models and ensemble learning techniques has been proposed for fine crop classification and identification, demonstrating their potential for accurate and detailed crop mapping (Li et al., 2020; Lu et al., 2022; Liu et al., 2022; Mazarire et al., 2022) in heterogeneous agricultural landscapes.

Therefore, the examined literature demonstrates the significance of employing machine learning and classification algorithms and integrating remote sensing data with crop models to classify crop types accurately. Hyperspectral imaging and deep learning algorithms have been identified as viable methods for crop classification. Numerous technologies and methodologies exist for accurately mapping crops using remote sensing data. Nevertheless, additional studies are required to integrate dense time series of remote sensing data, categorise a wide array of crop varieties on a larger scale, and offer a comprehensive understanding of classification certainty and effectiveness during the cultivation period. Additional research is required, particularly in numerous regions of the world, which have yet to receive much scrutiny from researchers.

In addition, vegetation indices derived from the spectral reflectance of crops captured by high-resolution remote sensing offer a wealth of information regarding plant health, growth, and composition (Gündoğdu & Bantchina, 2018). The complex subtleties of these indices function as excellent indicators for differentiating between different crop varieties, offering a non-intrusive method for monitoring large-scale agricultural landscapes. Incorporating machine learning algorithms into this framework signifies a fundamental change in agricultural classification approaches.

Different remote sensing approaches can be used for monitoring vegetation and primary production dynamics. The aim of the present study was to evaluate the capability of Sentinel-2A-derived Normalized Difference Red Edge Index (*NDRE*) to classify crop type accurately using seven imagery and machine learning algorithms agricultural land. The studied crops included cereals, fallow, forage, fruits, grassland-pasture, legumes, maize, sugar beet, onion-garlic, sunflower, and watermelon-melon. The classification performance of various ML classifiers, including Random Forest (*RF*), Support Vector Machines (*SVM*), K-Nearest Neighbours (*KNN*), Decision Tree (*DT*), and Multi-Layer Perceptron (*MLP*) classifiers, were investigated.

Materials and Methods

Study site

This study was conducted in Uluabat Village, located in the Karacabey District of Bursa Province, northwest Turkey. The study site covers an area of 16.01 km^2 and lies between latitudes 40°11'4.28"N and 40°12'1.46"N and longitudes 28°23'27.20"E and 28°27'266"E (Figure 1). The climate of the study area has characteristics of a Marmara transition-typ e Mediterranean climate. Precipitation occurs mainly during spring and in the form of snow during winter. The coldest month of the year is 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. Alluvial soils generally exist in and around Karacabey (Bantchina et al., 2017). In the study area, maize, pulses, tomatoes, fodder crops, orchards, sugar beets, meadows, pastures, and fruits are cultivated with minor changes yearly.

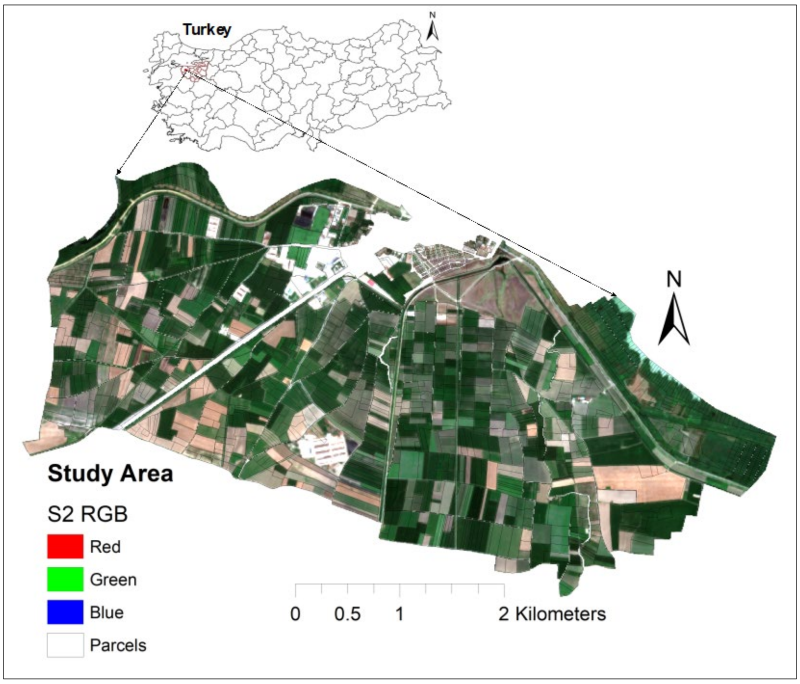


Figure 1. *Sentinel 2A RGB imagery of the study area*

Ground truth data

The data used in this study were obtained from the Karacabey Irrigation Union, where the 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. Field investigations were conducted during the 2022 crop season. During the field investigation, the coordinates of the samples and the crop types were recorded. The established crop patterns from the field observations and parcel maps were processed using ArcGIS ArcMap 10.8 (ESRI, Redlands, California, USA) software. After preprocessing, 1233 fields with different crop types were considered. The final dataset with parcel numbers and the distribution of pixel numbers for the different crops are listed in Table 1.

Table 1. Parcels and pixels number per crop type

Crop Types	Number of Parcels	Number of Pixels
Cereals	69	7719
Fallow	114	9954
Forage	87	8875
Fruits	3	133
Grassland - Pasture	22	6984
Legumes	169	19424
Maize	694	63641
Onion-Garlic	23	1810
Sugar Beet	4	357
Sunflower	12	1522
Watermelon-Melon	36	10236
Total	**1233**	**130655**

Sentinel 2A-Derived Normalized Difference Red Edge Index (*NDRE*)

Sentinel-2A imagery was used in this study. Sentinel-2A provides high-resolution optical imagery of Earth's surface. These scenes were downloaded from https://scihub.copernicus.eu/dhus/#/home. This study used seven images of 29 April, 12 May, 18 June, 18 July, 10 August, 16 September, and 09 October 2022 covering the study area, all atmospheric corrected and cloudless. These seven images were selected by considering one per month to demonstrate if a small number of images could achieve good classification accuracy.

Vegetation indices (*VIs*) derived from Sentinel-2A data are widely used in remote sensing and environmental monitoring to assess vegetation health, growth, and productivity. The Normalized Difference Red Edge Index (NDRE) was used in this study. NDRE (Hardisky et al., 1983) is a vegetation index commonly used in remote sensing to assess plant health and monitor crop productivity. Unlike traditional vegetation indices that rely on red and near-infrared (*NIR*) bands, NDRE is calculated using NIR and red-edge (*RE*) spectral bands, which are sensitive to changes in plant chlorophyll content and leaf structure. In this study, 10 m spatial resolution bands (band 8, NIR) and 20 m resolution bands (band 8A, RE) were selected for each scene. To maintain consistency, bands with distinct 20 m resolutions were resampled (downscaled) to a uniform 10 m resolution for NDRE calculation using SNAP. The formula for NDRE is as follows:

$$NDRE = \frac{(NIR - RE)}{(NIR + RE)}$$

Where:

- NIR is the reflectance in the near-infrared spectral band
- RE is the reflectance in the red-edge spectral band

NDRE values range from -1 to 1, with higher values indicating healthier and more photosynthetically active vegetation.

The established crop patterns from field observations were integrated into the attribute table of the parcel map using ArcGIS ArcMap 10.8 (ESRI, Redlands, California, USA). Vector-based data were further transformed into a raster pixel format. The NDRE values were calculated using the Python window in ArcMap 10.8 software using spectral bands, as shown in Figure 2.

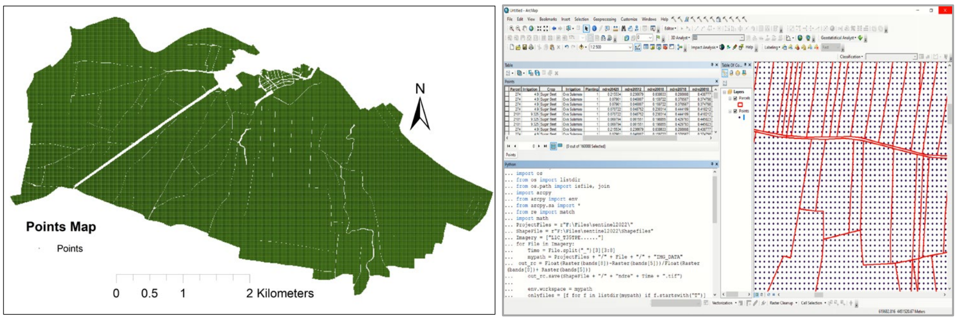


Figure 2. *Data processing into ArcGIS ArcMap software*

The data were exported in an Excel worksheet format, with each row containing information on a distinct pixel and column encompassing the parcel number. The final dataset, with 130655 rows/pixels, was curated for training and testing purposes by using the ML algorithms.

Machine Learning Classifier Algorithms

In this study, five machine learning classifier algorithms, namely, Random Forest (*RF*), Decision Tree (*DT*), Support Vector Machines (*SVM*), K-nearest Neighbors (*KNN*), and Multi-Layer Perceptron (*MLP*), were used for classification. The five classifier algorithms were as follows:

Random Forest (*RF*)

RF is a machine learning technique that utilises an ensemble of decision trees to generate predictions (Arora et al., 2022). Every decision tree in RF is trained on a random subset of the training data and a random subset of the input features (Strobl et al., 2007).

Decision Tree (*DT*)

DT is used for regression and classification tasks. These are intuitive and interpretable models that make predictions by recursively partitioning the feature space based on the values of input features (Izza et al., 2022).

Every internal node of a tree is a decision based on a specific feature, and every leaf node is a predicted value or class label (Mahynski et al., 2022).

Support Vector Machines (*SVM*)

SVM is a powerful and widely used supervised machine learning algorithm for classification tasks. SVMs have been particularly effective in handling high-dimensional data with limited training samples, making them suitable for applications such as hyperspectral image classification (Ghamisi et al., 2017).

K-Nearest Neighbors (*KNN*)

KNN is a simple yet effective method that determines the class of a query example by identifying its nearest neighbors in the training dataset (Cunningham & Delany, 2021). The KNN algorithm assigns the class label of most of its k-nearest neighbors to the query example, where k is a parameter defined by the user (Jensen & Cornelis, 2008).

Multi-Layer Perceptron (*MLP*)

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 is trained using a back-propagation algorithm, which is a successful gradient-based learning technique (Haykin & Kosko, 2009).

Classification Models Implementation

The classification models were trained using Python programming on Google Collaboratory. The dataset was split into training and test sets using an 80:20 partition. Hyperparameters were set before the learning process began. When tuning the hyperparameters, a grid search technique was used to determine the optimal combination for each crop type classification. The hyperparameters for each classifier algorithm used in this study are listed in Table 2.

Table 2. ML hyperparameters used for modelling in this study

ML Models	Best hyperparameters used
Random Forest	*{'criterion': 'gini', 'max_depth': 75, 'min_samples_leaf': 2, 'min_samples_split': 10, 'n_estimators': 50}*
Support Vector Machines	*{'C': 1, 'degree': 2, 'gamma': 'scale', 'kernel': 'linear', 'probability': True, 'shrinking': True}*
K-Nearest Neighbors	*{'metric': 'euclidean', 'n_neighbors': 10, 'weights': 'distance'}*
Decision Tree	*{'criterion': 'entropy', 'max_depth': 10, 'min_samples_leaf': 10, 'min_samples_split': 5}*
Multi-Layer Perceptron	*{'activation' : 'tanh', 'alpha' : 0001, 'hidden_layer_sizes' : (100,), 'learning_rate' : 'constant', 'solver' : 'adam'}*

Models Accuracy Assessment

Assessing the accuracy of machine learning models in crop type classification is crucial for understanding how well the model performs and whether it suits the classification task. Statistical tools were used to evaluate the accuracy of the classification models. The evaluation metrics used were as follows:

Confusion Matrix is a tool used in machine learning and classification to assess the performance of a classification model. It provides a way to visualise the performance of a model by summarising the results of its predictions on a dataset, particularly in the context of binary (two-class) classification problems. A confusion matrix was built based on the concepts of true positives, true negatives, false positives, and false negatives. True Positives (*TP*): These are instances that are correctly predicted as positive by the model. In other words, the model correctly identifies instances from the positive class. True Negatives (*TN*): These are instances that are correctly predicted as negative by the model. The model correctly identifies instances from the negative class. False Positives (*FP*): These are instances that are incorrectly predicted as positive by the model but actually belong to the negative class. False Negatives (*FN*): These are instances that are incorrectly predicted as negative by the model but actually belong to the positive class. A confusion matrix is usually presented in tabular form with two classes, "positive" and "negative," along with the actual and predicted labels (Table 3).

Table 3. Confusion Matrix format

	Actual Positive	*Actual Negative*
Predicted Positive	*TP*	*FP*
Predicted Negative	*FN*	*TN*

From this confusion matrix, performance metrics such as accuracy, precision, recall, and F1-score were calculated to evaluate the performance of the classification models. **Overall Accuracy (*OA*)** measures the proportion of correctly classified instances among all instances. **Precision (*P*)** measures the number of predicted positive instances that are actually positive. **Recall (*R*)** indicates how well the model captures all positive instances. **F1-Score** is the harmonic mean of Precision and Recall, providing a balanced measure between the two. The **Kappa score (*K*)**, also known as Cohen's Kappa coefficient, has been widely used as an inter-rater reliability metric in machine learning and is particularly valuable in evaluating the performance of classification models. Collectively, these metrics help understand the strengths and weaknesses of the classification model used in this study and make informed decisions about its performance and potential improvements (Muntean & Militaru, 2023). The formulae for the performance metrics are listed in Table 4.

Table 4. Model performance evaluation metrics

Performance 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	$2*\frac{P*R}{(P+R)}$

True Positives (TP), True Negatives (TN), False Positives (FP), False Negatives (FN)

Results and Discussions

Quantitative Classification Performance Results

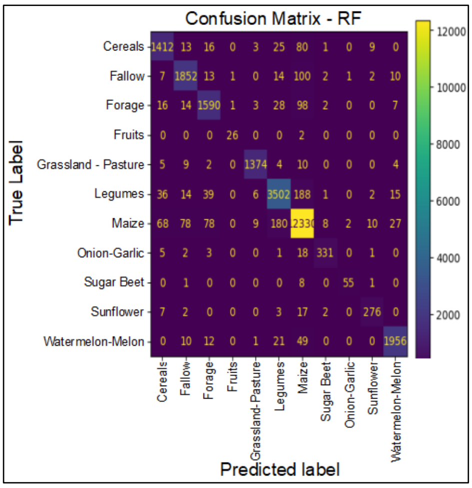
Quantitative results for the five machine learning classifiers used in this study to classify cereals, fallow, forage, fruits, grassland-pasture, legumes, maize, sugar beet, onion-garlic, sunflower, and watermelon-melon in Uluabat village are presented in this section. Quantitative results are summarised using the performance metrics Precision, Recall, F1-score, Overall Accuracy (*OA*), and Kappa score (*K*). The confusion matrix and its significance in evaluating the performance of the models are presented.

Random Forest Classifier (*RF*) Model Accuracy

The Random Forest (RF) model demonstrated remarkable accuracy by achieving an OA of 95%. The highest performance in terms of Precision was observed in the Grassland-Pasture fields with 98% Precision. This model exhibited a robust capability to classify all crop types correctly by exhibiting strong performance, particularly in terms of Precision, Recall, F1-score, and Kappa score (92%). Table 5 shows the accuracy of the RF model for the studied crops.

Table 5. Performance metrics of the RF model

Crop Type	*Precision (%)*	*Recall (%)*	*F1-score (%)*
Cereals	91	91	91
Fallow	93	93	93
Forage	91	90	91
Fruits	93	93	93
Grassland - Pasture	98	98	98
Legumes	93	92	92
Maize	96	96	96
Onion-Garlic	95	92	94
Sugar Beet	95	85	89
Sunflower	92	90	91
Watermelon-Melon	97	95	96
accuracy			**95**
macro avg.	94	92	93
weighted avg.	95	95	95
Kappa Score	***92***		

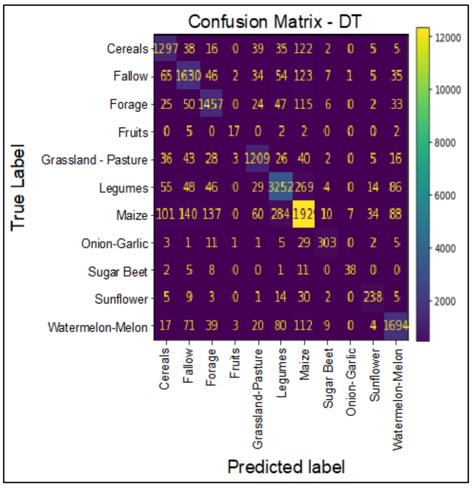


Decision Tree Classifier (*DT*) Model Accuracy

The DT model demonstrated an overall accuracy of 88%. The DT model achieved accuracy values ranging from 63% to 93%, 61% to 93%, and 62% to 93% for the Precision, Recall and F1-score, respectively, implying moderate to good accuracy. A kappa score of 84% was achieved. The accuracy results of the DT model are listed in Table 6.

Table 6. Performance metrics of the DT model

Crop Type	*Precision (%)*	*Recall (%)*	*F1-score (%)*
Cereals	81	83	82
Fallow	80	82	81
Forage	81	83	82
Fruits	63	61	62
Grassland-Pasture	86	86	86
Legumes	86	86	86
Maize	93	93	93
Onion-Garlic	88	84	86
Sugar Beet	83	58	68
Sunflower	79	76	77
Watermelon-Melon	86	83	84
accuracy			**88**
macro avg.	82	80	81
weighted avg.	88	88	88
Kappa Score	**84**		

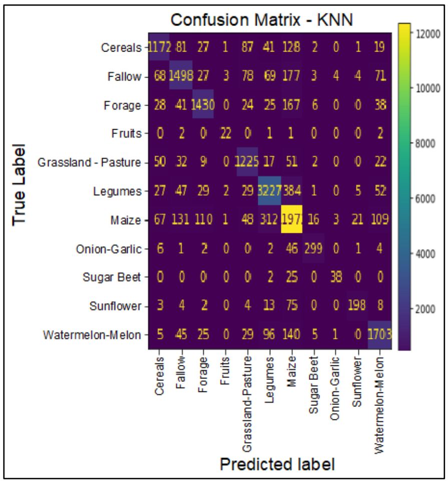


K-Nearest Neighbors Classifier (*KNN*) Model Accuracy

KNN demonstrated an overall accuracy of 87%, achieving accuracy values ranging from 76% to 91%, 58% to 94%, and 68% to 92% for Precision, Recall, and F1-score, respectively. The kappa score of the KNN classifier was 82%. The accuracy results of the KNN model are presented in Table 7.

Table 7. Performance metrics of the KNN model

Crop Type	*Precision (%)*	*Recall (%)*	*F1-score (%)*
Cereals	82	75	79
Fallow	80	75	77
Forage	86	81	84
Fruits	76	79	77
Grassland-Pasture	80	87	84
Legumes	85	85	85
Maize	91	94	92
Onion-Garlic	90	83	86
Sugar Beet	83	58	68
Sunflower	86	64	74
Watermelon-Melon	84	83	84
accuracy			**87**
macro avg.	84	79	81
weighted avg.	87	87	87
Kappa Score	**82**		

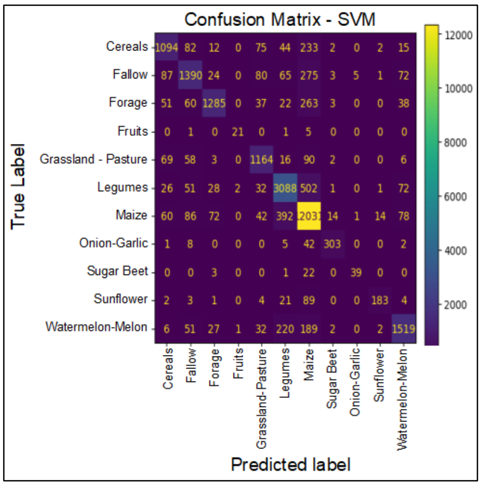


Support Vector Machines Classifier (*SVM*) Model Accuracy

The SVM demonstrated an overall accuracy of 85%, achieving accuracy values ranging from 78% to 92%, 60% to 94%, and 71% to 91% for the Precision, Recall, and F1-score, respectively. The Kappa score of the SVM classifier was 78%. The accuracy results for the SVM model are presented in Table 8.

Table 8. Performance metrics of the SVM model

Crop Type	*Precision (%)*	*Recall (%)*	*F1-score (%)*
Cereals	78	70	74
Fallow	78	69	73
Forage	88	73	80
Fruits	88	75	81
Grassland - Pasture	79	83	81
Legumes	80	81	80
Maize	88	94	91
Onion-Garlic	92	84	88
Sugar Beet	87	60	71
Sunflower	90	60	72
Watermelon-Melon	84	74	79
accuracy			**85**
macro avg.	85	75	79
weighted avg.	85	85	84
Kappa_Score	**78**		

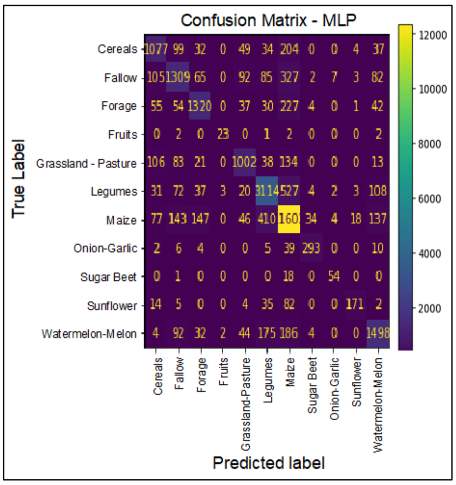


Multi-Layer Perceptron Classifier (*MLP*) Model Accuracy

The MLP model exhibited an overall accuracy of 82%. The model achieved accuracy values ranging from 70% to 87%, 55% to 92%, and 66% to 89% for Precision, Recall, and F1-score, respectively. The kappa score of the MLP classifier was 75%. The Model accuracy results are presented in Table 9.

Table 9. Performance metrics of the MLP model

Crop Type	*Precision (%)*	*Recall (%)*	*F1-score (%)*
Cereals	73	70	72
Fallow	70	63	66
Forage	80	75	77
Fruits	82	77	79
Grassland - Pasture	77	72	74
Legumes	79	79	79
Maize	87	92	89
Onion-Garlic	86	82	84
Sugar Beet	81	74	77
Sunflower	85	55	67
Watermelon-Melon	78	74	76
accuracy			**82**
macro avg.	80	74	76
weighted avg.	82	82	82
Kappa Score	**75**		



Qualitative Classification Results

The map presented in Figure 3 visually represents the classification outcomes of the Random Forest model (the outperformed model with 95% overall accuracy) and offers insights into the spatial distribution and arrangement of the 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.

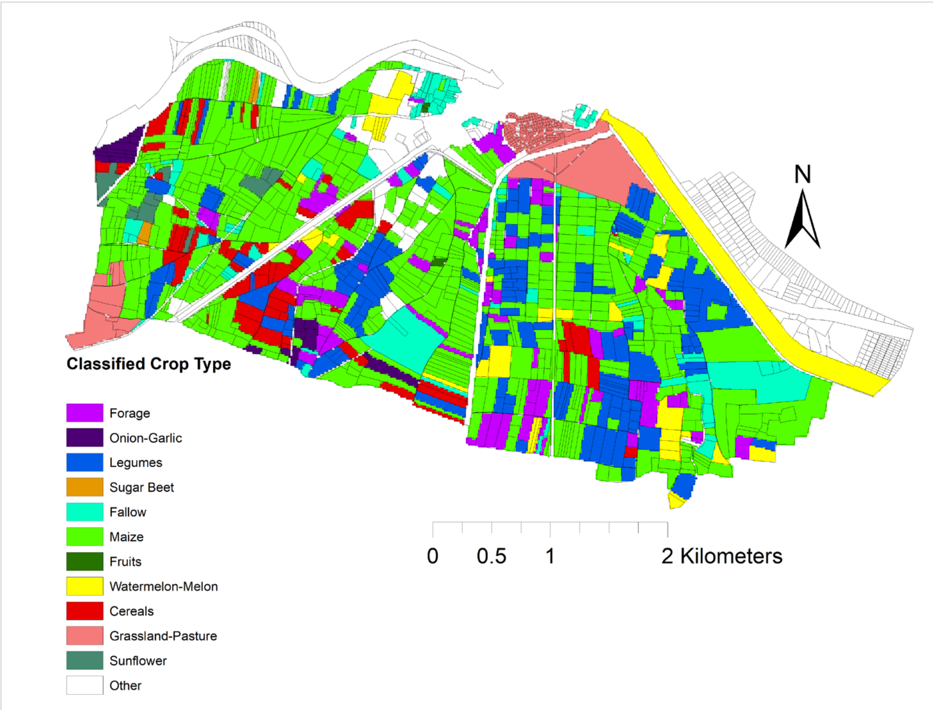


Figure 3. *Random Forest model-based classified crop type map*

In summary, in terms of Overall Accuracy, the best model to classify different crops in Uluabat was Random Forest (95%), followed by Decision Tree (88%), K-Nearest Neighbors (87%), Support Vector Machine (85%), and Multi-Layer Perceptron (82%). The Kappa score ranged between 75% and 92%. All the models performed well by displaying robust accuracy, making them suitable for diverse crop classifications in the study area. These models, characterised by robust accuracy, are viable tools for crop science research in diverse regional contexts. Although the models reflected a high level of accuracy, low accuracy for some crops (e.g., cereals and fruits) may be observed because of factors such as varying soil conditions, land management practices, and natural variations in vegetation health. This underscores the need to refine and adapt the classification models to consider these nuanced differences in future studies. The findings are acceptable as they align comparably with the results documented in the relevant literature. For instance, Sonobe (2019) highlighted the effectiveness of RF and SVM as the most effective classification approaches for identifying vegetation types using remote sensing data, with an overall accuracy of 92.1%. Abubakar et al. (2020) achieved overall accuracies of 96.93% and 97.44% for maize classification using Random Forest, Support Vector Machines, Simple Bayes, machine learning algorithms, and Sentinel 2-derived vegetation indices. Fan et al. (2021), in their study on crop type classification, achieved the highest overall accuracy of 96–98%, using Sentinel 2 and Random Forest algorithm. Furthermore, Lu et al. (2022) achieved a classification accuracy of 91.2% with a kappa coefficient of 0.882 using deep learning for fine crop classification.

Furthermore, using RapidEye imagery on crop type classification, Ustuner et al., 2014 found that NDRE has the highest contribution to classification accuracy compared to NDVI and GNDVI. Nevertheless, Kang et al., 2021 demonstrated that the NDVI time series was more conducive to improving the overall classification accuracy of crops, and NDRE can assist NDVI in improving the crop classification accuracy.

The results of the present study revealed the capability of the Sentinel 2A-derived Normalized Difference Red Edge Index (*NDRE*) and machine learning approach for crop type classification and could contribute valuable insights for crop classification and mapping at the parcel level.

Conclusion

This study investigated the performance of various machine learning models for classifying crop types using the Normalized Difference Red Edge Index (*NDRE*). Notably, the ML models demonstrated high accuracy in Uluabat village, reflecting their robust capability for crop type classification. The implications of accurate land cover and crop type classification are wide-ranging, encompassing applications such as monitoring land use changes, assessing crop health, estimating yields, and facilitating precision agriculture. The present study confirmed the importance of NDRE in agricultural monitoring and assessment of crop type and vegetation dynamics. By harnessing the synergy between high-resolution remote sensing data and advanced machine learning algorithms, stakeholders, including policymakers, researchers, and practitioners, can make informed decisions and implement effective land management strategies. This study offers a comprehensive overview of the methodologies employed in such a classification, contributes to the existing body of knowledge, and provides insights into sustainable land management practices.

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