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Investigating the Effect of Spectral Bands and Vegetation Indices Selection on Agricultural Crop Classification (Especially for Double Cropping Regions)

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ABSTRACT

In this study, a classification study was carried out using multi-temporal Sentinel-2 imagery and datasets generated from different vegetation and spectral indices, and the effects on the classification result were investigated. As the study area has very fertile soils, suitable climate and temperature conditions and irrigated land, it is possible to grow more than one crop on the same plot during a production season. Wheat_maize (winter_wheat+summer_maize), wheat_cotton (winter_wheat+summer_cotton), lentil_cotton (winter_lentil+summer_cotton), lentil_maize (winter_lentil+summer_maize) are the crops included in the classification study, except for double crops; maize, cotton, wheat and lentils are also included. Time series of vegetation indices can be used to capture information on plant phenology and can be used as reference information in crop classification. Time series curves of different vegetation indices were constructed and compared for all crops, especially for double crops with the same phenological periods. In addition to the vegetation indices, the variation of the time series reflectance values of each spectral band was also observed for all crops and the effect of different indices and bands on the classification result was investigated. The study generated 16 different data sets using conventional vegetation indices, NDVI, SAVI, EVI and NDRE vegetation indices and all other bands of the Sentinel-2 satellite except the 60m bands. While single crops with different time series (maize, cotton, lentil, wheat) had an accuracy of over 90% in each dataset, double crops could not exceed 81% accuracy by mixing with each other in the DS-5 (R-G-B-NIR) dataset. In the DS-1 (NDVI time series) dataset, the overall accuracy for double crops is in the range of 84-85%. Classification with DS-2 (NDRE time series) increased the overall accuracy for double crops to 90%. When comparing the time series reflectance values of each spectral band for all crop types, except the crop indices, it was observed that the B6 (Red Edge-2) and B11 (SWIR-1) bands were separated from the other bands and increased the classification result by 2% when included in the dataset. Especially in the classification studies carried out on products with close phenological periods, the Red Edge band (especially Red Edge-2) and the indices (NDRE) generated from these bands will improve the classification result by preventing confusion between classes, and the B11 (SWIR-1) band also has a positive effect on classification. This study has fully demonstrated the application potential of red edge bands and the indices constructed from them. It also promotes the use of red edge band optical satellite data in agricultural remote sensing.

Key words: crop, classification, random forest, sentinel-2, spectral band, vegetation index

Spektral Bantların ve Bitki Örtüsü İndeks Seçiminin Tarımsal Ürün Sınıflandırmasına Etkisinin Araştırılması (Özellikle Çift Ekim Yapılan Alanlarda)

ÖZ

Bu çalışmada, çok zamanlı Sentinel-2 görüntüleri ile farklı bitki örtüsü ve spektral indekslerden oluşturulan veri setleri kullanılarak bir sınıflandırma çalışması gerçekleştirilmiş ve sınıflandırma sonucu üzerindeki etkileri araştırılmıştır. Çalışma alanı çok verimli topraklara, uygun iklim ve sıcaklık koşullarına ve sulanan arazilere sahip olduğundan, bir üretim sezonu boyunca aynı parselde birden fazla ürün yetiştirmek mümkündür. Buğday_mısır (kışlık_buğday+ yazlık_mısır), buğday_pamuk (kışlık_buğday+yazlık_pamuk), mercimek_pamuk (kışlık_mercimek+yazlık_pamuk), mercimek_mısır (kışlık_mercimek+yazlık_mısır) sınıflandırma çalışmasına dâhil edilen ürünlerdir, çift ürünler dışında; mısır, pamuk, buğday ve mercimek de dahil edilmiştir. Bitki örtüsü indekslerinin zaman serileri, bitki fenolojisi hakkında bilgi yakalamak için kullanılmakta olup ve ürün sınıflandırmasında referans bilgi olarak kullanılmaktadır. Farklı bitki örtüsü indekslerinin zaman serisi eğrileri oluşturulmuş ve tüm ürünler için, özellikle de aynı fenolojik dönemlere sahip çift ürünler için karşılaştırılmıştır. Bitki örtüsü indekslerine ek olarak, her bir spektral bandın zaman serisi yansıma değerlerinin değişimi de tüm ürünler için gözlemlenmiş ve farklı indeks ve bantların sınıflandırma sonucu üzerindeki etkisi araştırılmıştır. Çalışmada geleneksel vejetasyon indeksleri, NDVI, SAVI, EVI ve NDRE vejetasyon indeksleri ve Sentinel-2 uydusunun 60m bantları hariç diğer tüm bantları kullanılarak 16 farklı veri seti oluşturulmuştur. Farklı zaman serilerine sahip tek ürünler (mısır, pamuk, mercimek, buğday) her veri setinde %90'ın üzerinde doğruluğa sahipken, DS-5 (R-G-B-NIR) veri setinde çift ürünler birbirleriyle karıştırılarak %81 doğruluğu geçememiştir. DS-1 (NDVI zaman serisi) veri setinde, çift mahsuller için genel doğruluk %84-85 aralığındadır. DS-2 (NDRE zaman serisi) ile sınıflandırma, çift mahsuller için genel doğruluğu %90'a çıkarmıştır. Ürün indeksleri hariç tüm ürün türleri için her bir spektral bandın zaman serisi yansıma değerleri karşılaştırıldığında, B6 (Red Edge-2) ve B11 (SWIR-1) bantlarının diğer bantlardan ayrıştığı ve veri setine dahil edildiğinde sınıflandırma sonucunu %2 oranında artırdığı görülmüştür. Özellikle fenolojik dönemleri yakın olan ürünler üzerinde yapılan sınıflandırma çalışmalarında Red Edge bandı (özellikle Red Edge-2) ve bu bantlardan üretilen indekslerin (NDRE) sınıflar arası karışıklığı önleyerek sınıflandırma sonucunu iyileştireceği, B11 (SWIR-1) bandının da sınıflandırma üzerinde olumlu etkisi olduğu görülmüştür. Bu çalışma, kırmızı kenar bantlarının ve bunlardan oluşturulan indekslerin uygulama potansiyelini tam olarak ortaya koymuştur. Ayrıca, kırmızı kenar bantlı optik uydu verilerinin tarımsal uzaktan algılamada kullanımını teşvik etmektedir.

Anahtar kelimeler: bitki, sınıflandırma, sentinel-2, spektral bant, rastgele orman, vejetasyon indeksi

INTRODUCTION

Remote sensing has a wide range of applications, from environmental monitoring and climate change studies to agricultural and geological applications. It has the advantage of providing data at different temporal, spatial and spectral resolutions. Recent technological developments in Earth observation satellites and the increasing number of satellites have made access to information on land cover/use, agricultural crop patterns and changes at local and global scales faster, cheaper and more accessible (Khatami et al. 2016). A notable example of this progress is the Copernicus programme, which includes Sentinel satellites with different characteristics. Among these, the Sentinel-2 satellite stands out as a passive sensor satellite. Its wide range of bands, its ability to provide images with different spatial resolutions and its frequent acquisition intervals are a significant advantage for monitoring areas with a continuous dynamic structure, such as agriculture.

Satellite imagery allows the observation, identification, mapping and evaluation of dynamic agricultural areas with at different temporal and spatial resolutions. The most common method used in agricultural crop type detection with satellite imagery is image classification. Classification accuracy depends on the classification method used (pixel or object based) and the characteristics of the satellite image (low, medium or high spatial resolution; multispectral or hyperspectral), as well as the design and characteristics of the training/test data (number of pixels, statistical distribution of selected samples, etc.) and the selection of the appropriate number of images and bands (Lu and Weng 2018;Kavzoglu 2009).

Due to the complexity and diversity of crop types and the small spectral differences between different crops, crop classification using a single time-phased remote sensing image is prone to the phenomena of "same object with different spectra" and "different objects with the same spectrum", resulting in misclassification and mixed classification, and the classification accuracy is difficult to improve (Conese and Maselli 1991;Gomez et al. 2016). Agricultural crops are grown in different phenological periods according to crop variety, topography and climatic conditions, as well as in similar or very close phenological periods. For this reason, it is necessary to use multi-temporal images in classification studies to detect crops in close or different phenological periods. Crop type classification studies can be performed from a single image or multiple images, but when applied to time series images, they have been shown to perform better than single date mapping methods (Gomez et al. 2016). Time series remote sensing data are widely used in the field of agricultural remote sensing, as they can reflect differences in the growth status of different crops, show different phenological characteristics, and improve separability and classification accuracy (Murty et al. 2003;Zhong et al. 2019).

Table1. Literature review of crop type classification

Ref.	Study area	Satellite	Feature	Method	Classses	Subject
Kobayashi et al. 2020	Hokkaido, Japan	Sentinel-2	Spectral bands 91 Vegetation indices	RF	Beans,beetroot,grass, maize,potato, wheat	Crop classification using spectral indices derived from Sentinel-2A imagery
Kang et al. 2021	Hebei, China	Sentinel-2	10 Red edge Indices	RF	Wood, orchard,minor crop, cotton,spring maize, winter wheat-summer maize, greenhouses,water body, cities	Land Cover and Crop Classification Based on Red Edge Indices Features
Stern et al. 2023	Iowa, USA	Landsat	NDI5,NDI7,NDTI, STI,NDSVI	SVM MINDIST MAXLI RANDTR SAM	Corn, soybean, other	Comparison of Five Spectral Indices and Six Imagery Classification Techniques for Assessment of Crop Residue Cover Using Four Years of Landsat
Pasternak and Filipiak 2002	Lower Silesian, Poland	Sentinel-2	12 Vegetation indices PCA	RF	Beetrooot,maize,wheat,canola sunflower,potato, rye	The Evaluation of Spectral Vegetation Indexes Accuracy of Crop Type Detection
Sun et al. 2019	Yangzi, China	Sentine-1 Sentinel-2 Landsat-8	NDVI,EVI,TVI, NDWI,NDTI Texture	ANN RF SVM	Forest,maize,rape, urban,water,wheat	Using of Multi-Source and Multi-Temporal Remote Sensing Data Improves Crop-Type Mapping in the Subtropical Agriculture Region
Zhang et al. 2020	Heilongjiang China	Sentinel-2	NDVI,PMI,NDSVI NDRI,NDTI	SVM RF CART	Rice,corn,water, soybean,potato, beet,forest,building	Accessing the temporal and spectral features in crop type mapping using multi-temporal Sentinel-2 imagery
Vuolo 2018	Marchfeld lower, Austria	Sentinel-2	Spectral bands	RF	Carrot,maize,onion,pumpkin,soybean, sugarbeet,sunflower, winter cereal	How much does multi-temporal Sentinel-2 data improve crop type classification?
Üstüner et al. 2015	Aydın Türkiye	RapidEye	Spectral bands, NDRE	SVM	Maize, cotton, soil, water	The effect of spectral band and plant index selection on crop pattern classification accuracy: Comparative analysis
Şimşek et al. 2016	Harran Plain Türkiye	Landsat	NDVI	Rule Based Classification	Wheat, maize,cotton	Controlling of product declarations of farmers using remote sensing techniques: the Harran Plain case
Teke and Y. Çetin 2021	Harran Plain Türkiye	Sentinwl-2	NDVI, SAVI,EVI	VDTW	Maize, cotton	Multi-Year VDTW Based Crop Mapping

Additional data (such as texture filters, vegetation indices and digital elevation models) are sometimes used to improve the distinguishability of the products to be classified, and vegetation indices are one of these additional data (Song et al. 2015;Kim and Yeom 2015). Specifically, Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), and Enhanced Vegetation Index (EVI) are used to monitor vegetation systems or ecological responses to environmental change (Song et al. 2015). Normalized Difference Red Edge (NDRE), The NDRE index includes a red edge band and plays a very important role in vegetation monitoring, providing valuable information on plant health, species differentiation, stress detection and other factors. Its sensitivity to chlorophyll content and reduced susceptibility to atmospheric interference make it a key component in remote sensing applications for agriculture, forestry and ecosystem monitoring. The use of multi-temporal remote sensing data to construct Normalized Difference Vegetation Index (NDVI) and other vegetation index time series, combined with the seasonal rhythms and phenological differences of different crops, has been widely used in crop classification, which has improved the accuracy of crop classification (Kang et al. 2021). In addition to the characteristics of remote sensing data, classification algorithms are important to improve the classification accuracy of crop maps. Recently, Random Forest (RF) is a widely used machine learning algorithm consisting of an ensemble of decision trees, and it has been a highly successful machine learning algorithm for classification and regression methods (Biau and Scornet 2016). Random forest algorithms have been used to map land cover over large areas using high-resolution satellite imagery time series, with successful results (Pelletier et al. 2016).

There are many studies in the literature on crop type classification using different satellites, different indices and bands. In these studies using different algorithms, the effects of different indices and bands on the classification results have also been investigated and compared Table 1.

Most of the studies in the literature are on single crops. In this study, not only were double crops with very close phenological periods studied, but also the changes in the temporal curves of these crops in different vegetation and spectral bands were monitored and compared. The changes in the time series curves of these crops with close phenological periods and the time curves of different vegetation indices were studied and the effects of the index data causing these changes on the classification result were investigated. In addition to the index data, the effect of the spectral bands on the classification accuracy was also investigated.

STUDY AREA AND MATERIALS

Study Area

The study area was located in the Harran Plain, Şanlıurfa, Turkey (36° 47'-39° 15' E, 36° 40' 37° 41' N) at an altitude between 350 and 500m (Fig.1). The Harran Plain, with a total area of 225,000 ha, is the third largest plain in Turkey and has great agricultural potential. The Harran Plain has a continental climate with mild winters and high summer temperatures. These climate and temperature conditions, together with the increase in irrigated areas in recent years, have led to the cultivation of double crops (two types of crops: wheat_maize (winter_wheat + summer_maize), wheat_cotton (winter_wheat + summer_cotton), lentil_cotton (winter_lentil + summer_cotton), lentil_maize (winter_lentil+summer_maize), during the production season (Bozkurt and Aybek 2016). The main crops grown in the region, including wheat, barley, lentil, cotton and maize, cover 95% of the Harran Plain. As these products are not homogeneously distributed within the boundaries of the plain, and considering the plain as a whole, the study area includes the boundaries of the plain.

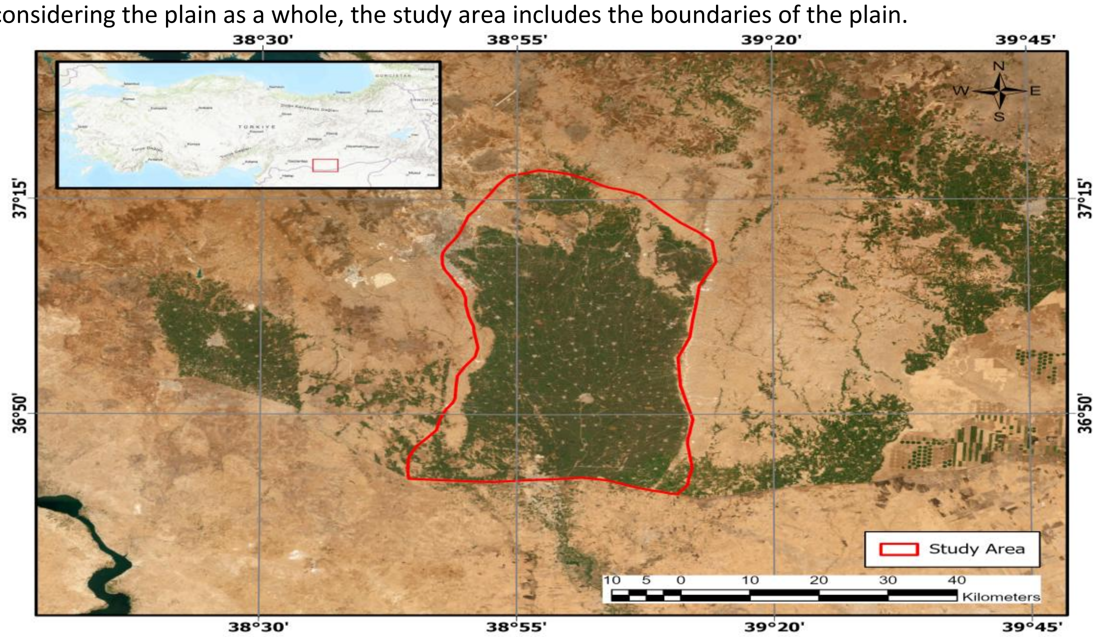

Fig.1. Study area

Sentinel-2

Sentinel-2A and Sentinel-2B are constellation satellites launched by the European Space Agency (ESA) under the European Commission's (EC) Copernicus programme. Each identical satellite is equipped with a multispectral sensor covering 13 spectral bands with a spatial resolution of 10 m to 60 m and a radiometric resolution of 12 bits. Sentinel-2A was launched in June 2015, followed by Sentinel-2B in March 2017. Information on the spectral bands and reflectance values of the Sentinel-2 satellite images is given in Table 2.

Table2. Spectral bands of Sentnel-2 images

Description	Bands	Wavelength (µm)	Resolution (m)
Aerosol	B1	458-523	60
Blue	B2	458-523	10
Green	B3	543-578	10
Red	B4	650-680	10
Red-Edge-1	B5	698-713	20
Red-Edge-2	B6	733-748	20
Red-Edge-3	B7	773-793	20
NIR	B8	785-900	10
Veg. Red Edge	B8a	885-875	10
Water Vapour	B9	935-955	60
Cirrus	B10	1360-1390	60
SWIR-1	B11	1565-1655	20
SWIR-2	B12	2100-2280	20

All bands except B1-B9-B10 were used in this study. However, the three atmospheric bands were not used in this study as they are mainly used for atmospheric corrections and cloud screening. (Drusch et al. 2012). The fact that Sentinel-2 imagery contains a large number of spectral bands, and in particular has a temporal resolution of 5 days, provides a significant advantage for monitoring agricultural areas, detecting crop patterns and analyzing changes. (Şimşek and Durduran 2023). As the study area is predominantly covered by crops with closely aligned phenological periods, 23 observations were made by Sentinel-2A between March and September 2016. After June, the selected images were cloud-free, while before June, images with a low cloud fraction were selected and cloudy areas were detected and masked. The acquisition dates of the Sentinel-2 satellite images are shown in Table 3.

Table 3. Acquisition time of Sentinel-2

Day of Year (DOY)	Acquisition Time	Day of Year (DOY)	Acquisition Time
37	29 March 2022	212	29 March 2022
57	5 April 2022	220	5 April 2022
87	5 May 2022	230	5 May 2022
102	20 May 2022	240	20 May 2022
117	6 June 2022	252	6 June 2022
132	14 July 2022	262	14 July 2022
152	11 August 2022	272	11 August 2022
167	7 September 2022	282	7 September 2022
177	2 October 2022	292	2 October 2022
192	17 October 2022	317	17 October 2022
202	27 October 2022	302	27 October 2022

Ground Truth Data

Two field studies were carried out in April for wheat, barley and lentil crops and in August for maize and cotton crops. Given the large area of the plain (225,000 ha), the number of samples could not reach the desired level due to time and cost constraints. In addition to field data, parcels declared by farmers were used as ground truth data in the study. 3145 agricultural parcels (cotton: 610, maize: 105, lentil: 340, wheat: 520, lentil_maize: 250, lentil_cotton: 380, wheat_maize: 413, wheat_cotton: 527) were used in the classification study.

The Farmer Declaration Parcels (FDP) in Turkey, also known as the Farmer Registration System (FRS), is a government initiative aimed at registering and tracking agricultural activities and farmers in the country (Aydoğdu et al. 2011). This system was introduced to improve the efficiency and transparency of agricultural practices and to provide various benefits to registered farmers. The FRS requires farmers to register themselves and their farming activities. This registration process involves providing personal information and details of the land they farm. The parcels of agricultural activity registered by farmers in the system are called FDPs. In addition to the geometric information of the parcels, the system also contains information on the province, district, parcel number, agricultural parcel number, information on the products grown, area, surface, cadastral area, date of cultivation and date of harvest of each parcel. (Şimşek and Durduran 2023). When the FDPs were examined, it was found that there were systematic and non-systematic differences between the geometry and attribute information of the parcels and the parcels in the field. Because of these differences, a number of processing steps were applied to the FDPs, and at the end of these steps, ground truth data were produced from the FDPs and used in the classification study together with the data collected in the field. The agricultural calendar for the crops grown in the plain was obtained and is presented graphically (Fig. 3.). The calendar provides information on the sowing, growing, dense vegetation and harvesting periods of crops grown in the region. The exact dates of sowing and harvesting vary between plots and farmers. In some cases, there may be a difference of up to 1-3 weeks between the categorized crops; wheat and barley crops are included in the wheat class.

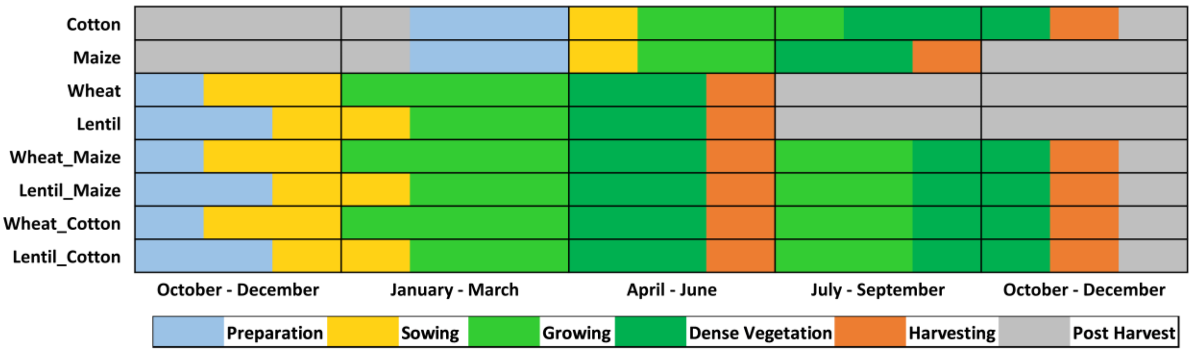

Fig.3. Approximate crop calendar in the region.

Looking at the phenological period of the crops, it is observed that maize and cotton are separated from each other with a dense vegetation stage, while wheat and lentil are in close phenological stages. It was observed that double crops (wheat_maize, lentil_maize, wheat_cotton, lentil_cotton) were in close phenological stages. The calendar shows that the phenological periods of both single and double crops are very close and different indices and bands should be used to distinguish these crops in the classification study.

METHODOLOGY

General Architecture Overview

After acquiring 23 Sentinel-2 images, the cloudy areas and the shadow areas caused by the clouds were masked. The bands were resampled from 20 m to 10 m. Four different spectral indices were calculated for each Sentinel-2 image, and spectral curves were created for each crop by overlapped these indices with ground truth data. The spectral index curves and spectral bands were then compared for each crop type. Classification studies using the RF algorithm were carried out with different datasets generated from different indices and bands, and the effect of bands and indices on the classification results was compared. Fig. 4. shows the flowchart used in this study.

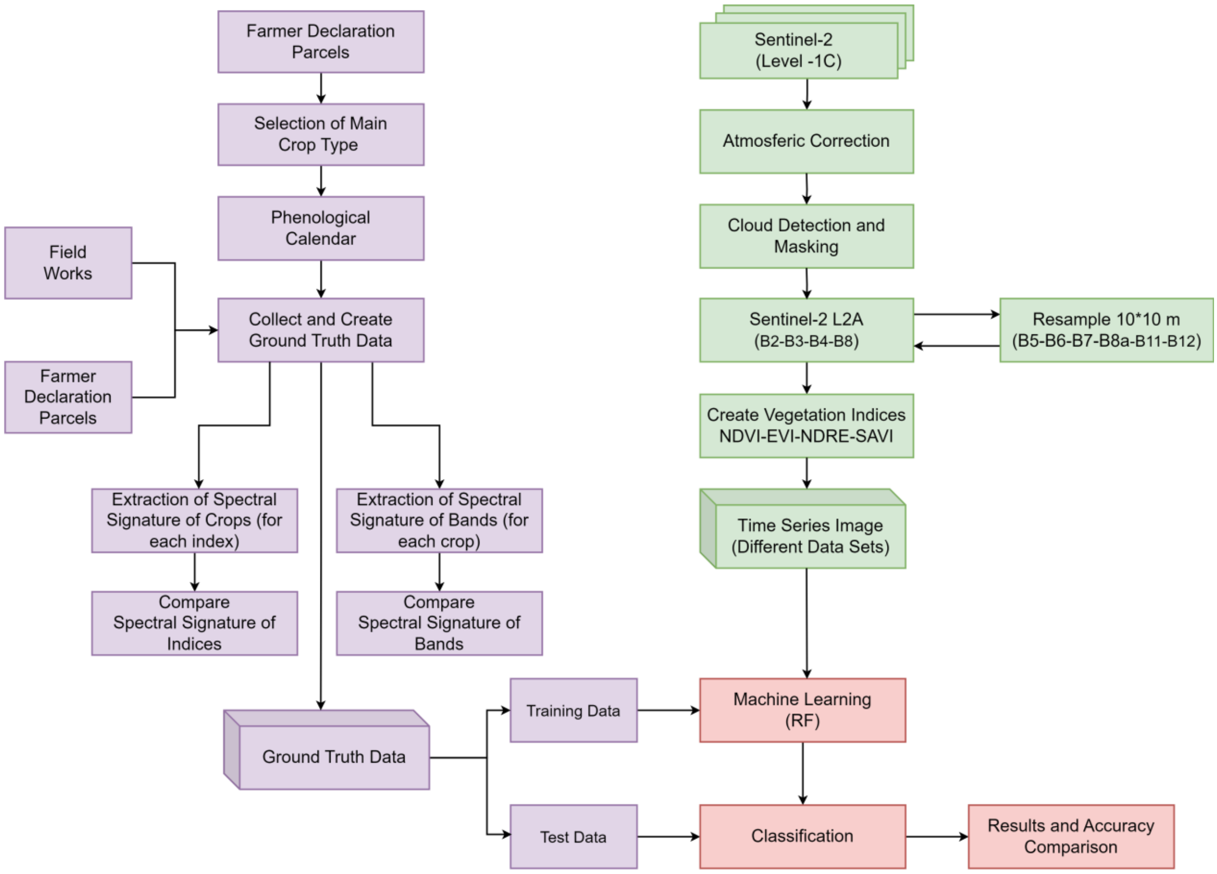

Fig.4. Workflow of study

Satellite Image Processing

In data processing, no further geometric correction of the L1C products is required, only atmospheric correction and spatial resolution resampling. (Zheng et al. 2007). Sentinel-2 images are provided in Level 1C format and contain above-atmospheric reflectance values. To calculate the actual reflectance values of plants in a classification study, top-of-atmosphere (TOA) values should be converted to bottom-of-atmosphere (BOA) reflectance values (Wilm 2017). Atmospheric effects were eliminated by converting TOA values to BOA values using the Sen2cor plugin. After Sen2Cor processing, the L1C TOA reflectance values were converted to Level 2A (L2A) BOA reflectance values (Wilm et al. 2013). The conversion of Sentinel-2 data from L1C to L2A improves the accuracy of derived vegetation indices such as NDVI by accounting for atmospheric effects, ensuring that observed changes in NDVI and other indices are more closely related to actual variations in vegetation health. Clouds and cloud shadows in satellite imagery are the main sources of noise that cause problems in image analysis (Kalkan and Maktav 2016). Brightness caused by clouds and shadows can affect data analysis and lead to changes in NDVI and other indices. (Zhu and Woodcook 2012). Cloud-covered areas cause anomalies in the image bands as well as in the pixel values of the indices created from these bands, which adversely affects the classification results (Karslen et al. 2021). To eliminate this situation, clouds and shadow areas caused by clouds have been detected and masked by the Sen2core software (Fig.5.) . The cloud screening and classification part of Sen2Cor is available as source code in the distributed (Skakun et al. 2022). Potentially cloudy pixels are subjected to a series of filters based on spectral band thresholds, ratios and index calculations - Normalized Difference Snow Index (NDSI). After atmospheric correction and cloud masking, B5-B7-B8a-B11-B12 were resampled from 20m to 10m.

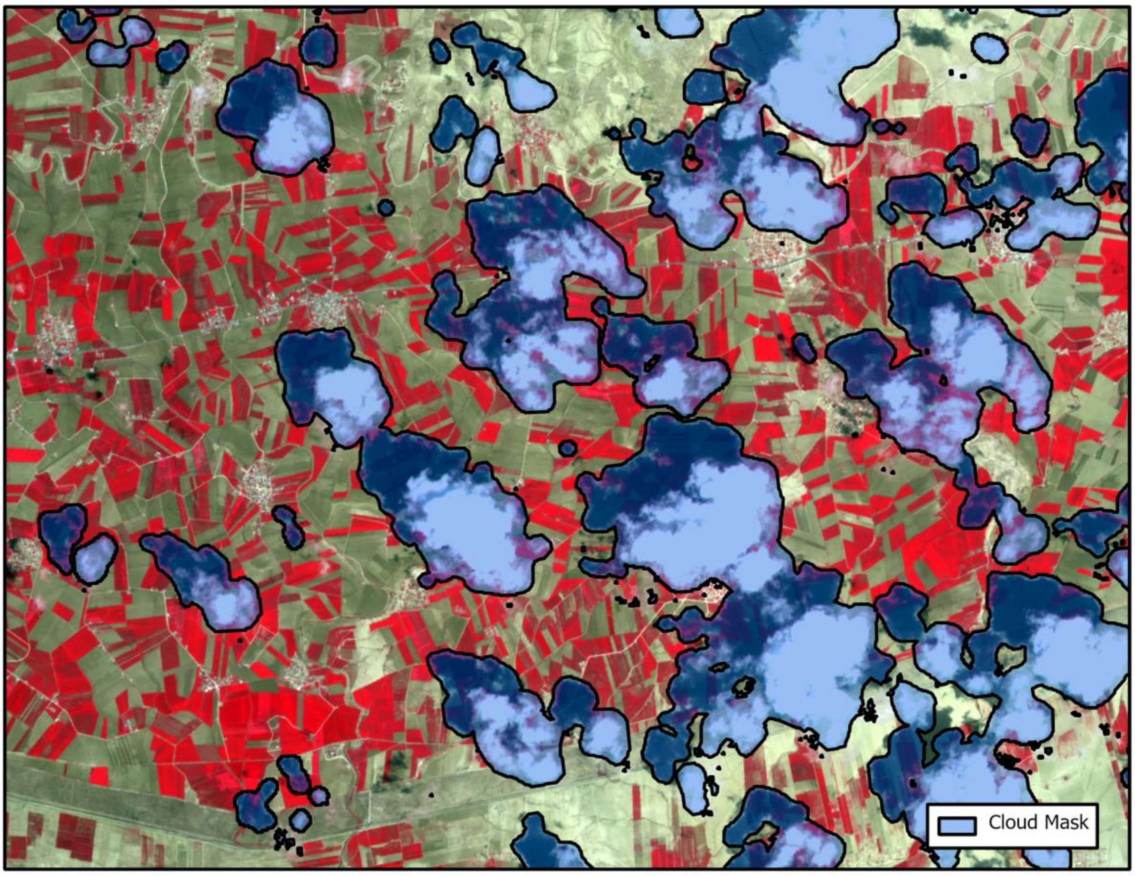

Fig.5. Cloud detection and masking.

Vegetation Indices and Spectral Band Analysis

As can be seen from the phenological calendar in Figure 3, the single and double crops in the study area have very close phenological periods. The seasonal rhythm and phenological characteristics of different crops can be reflected by the difference in the spectrum or vegetation index of multi-temporal remote sensing data (Gomez et al. 2016). NDVI is widely used for crop type identification (Gumma et al. 2020). The NDVI index provides information on plant health and development (Morsy and Hadı 2022). In order to see this phenological closeness on a crop by crop basis, time series NDVI plots were first created. Each plot was overlapped with multi-temporal NDVI images and the median NDVI values of each plot in the time series were calculated. After this process, the vegetative development and change of each plot was determined and the characteristics of the NDVI curves showing the variability over time were revealed. The characteristic NDVI curves for each crop were checked against the phenological calendar and the spectral reflectance values of each crop collected during the field study. When analysing the NDVI time series curves of each crop, it can be seen that lentils and wheat, which are winter crops, are separated from each other, while maize and cotton, which are summer crops, show new different time curves (Fig. 6). With the NDVI index, these four crops (lentil, wheat, maize, cotton) have different reflectance values on the same dates and their temporal curves are separated from each other. Therefore, no studies have been carried out with different vegetation indices in single crops.

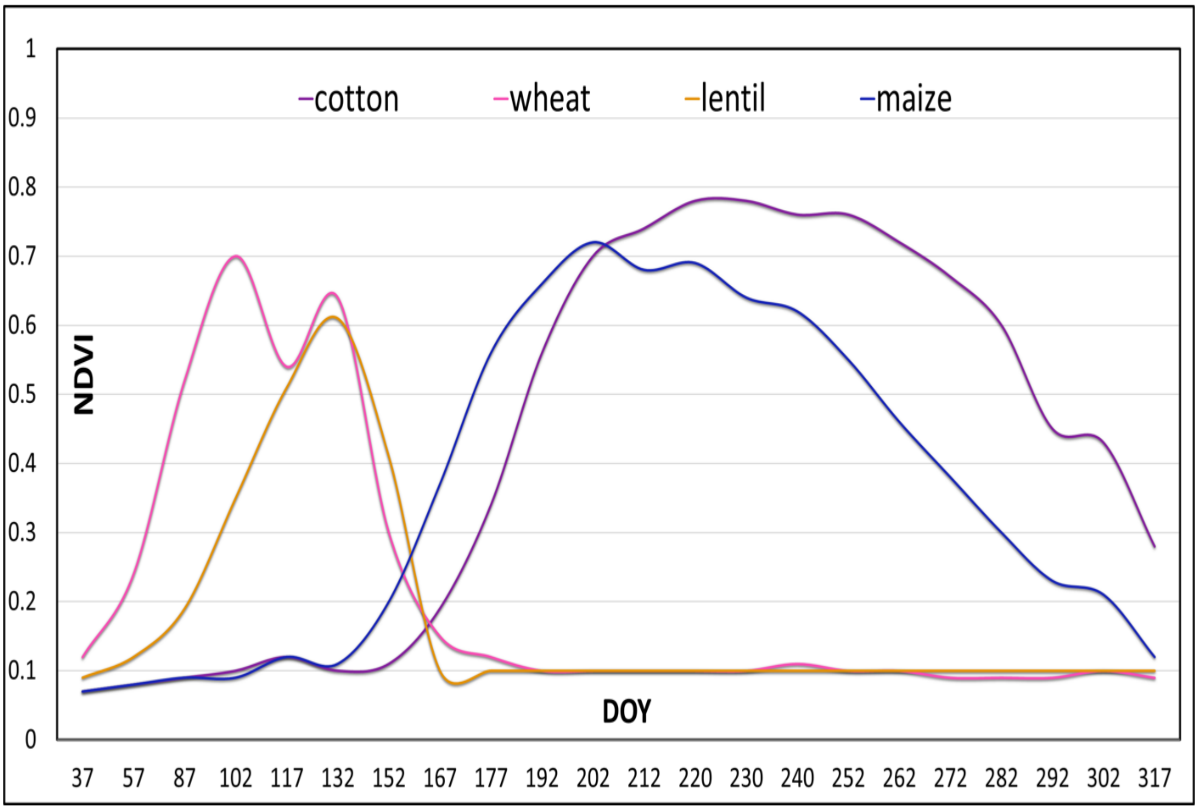

Fig.6. NDVI times series of single crops

When analyzing the NDVI time series curves, wheat_maize-wheat_cotton crops and lentil_maize-lentil_cotton crops differ from each other between day 57. and day 132. However due to the later sowing of lentil, but it can be seen that the reflectance values for all crop types are very close to each other between day 220. and day 317. Fig 7.

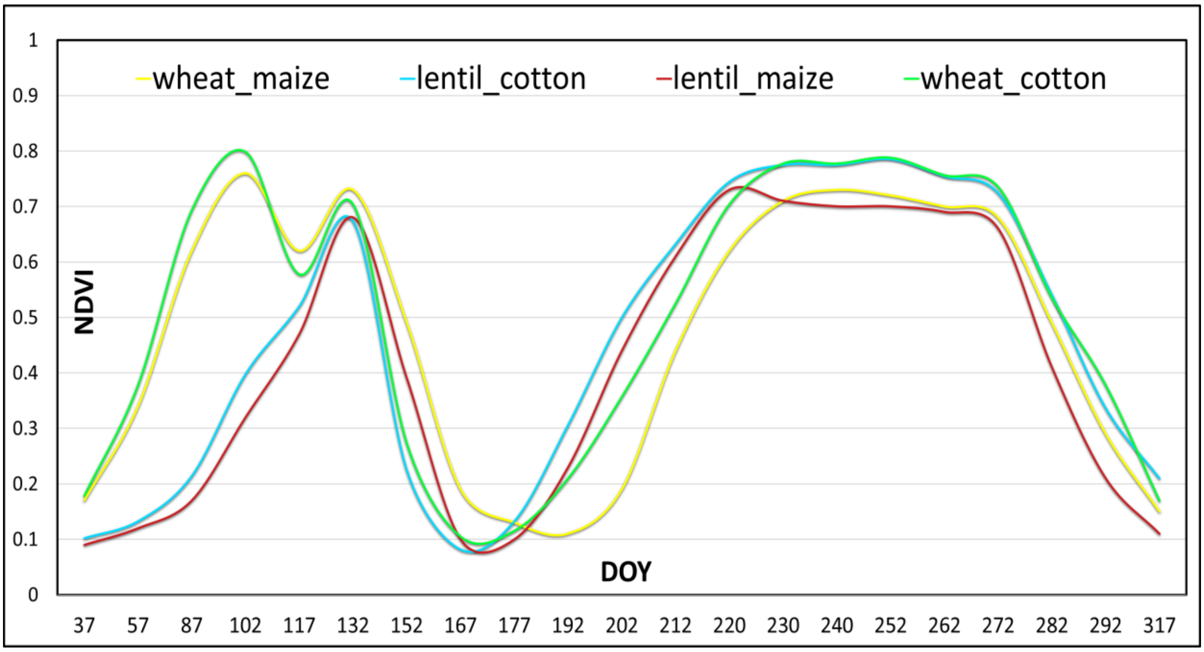

Fig.7. NDVI time series of double crops

It was observed that the NDVI time series curves were similar for both crops, especially in the second period of the year. The effect of different vegetation indices on the time series curves of the crops and the classification results were investigated in this study. There are nearly 100 vegetation indices in the literature. In this study, NDVI, NDRE, SAVI and NDRE indices, which are traditional vegetation indices, were used Table 4.

Table 4. Acquisition time of Sentinel-2

Spectral Index	Full Name	Formula	Description	Reference
NDVI	Normalized Difference Vegetation Index	(NIR - R)/(NIR + R)	Commonly used for assessing overall vegetation health and density	Tucker 1979
EVI	Enhanced vegetation index	2.5*(NIR - R)/(NIR + 6*R-7.5*B+1)	Similar to NDVI but designed to minimize atmospheric influences and improve sensitivity in high biomass regions	Huete et al. 2002
SAVI	Soil-Adjusted Vegetation Index	(NIR - R)/(NIR + R + L)*(1 + L)	Designed to minimize soil background influences in the vegetation index	Huete 1988
NDRE	Normalized Difference Red Edge	(NIR – Redge2)/(NIR + Redge2)	Particularly sensitive to changes in chlorophyll content, making it valuable for detecting early signs of stress	Barnes 2000

Comparing the NDVI, SAVI and NDRE time series curves of lentil_maize and lentil_cotton, it is observed that the curves are close to each other as in the case of NDVI, this is also the case for wheat_maize and wheat_cotton. It was observed that the SAVI index did not change in relation to the NDVI index. As a result of the EVI index, the time series curves for four crops show some separation compared to the SAVI and NDVI indices. When analyzing the time series curves of the NDRE index, it can be seen that the curves for the two crops wheat_maize-wheat_cotton and lentil_maize-lentil_cotton are more separated compared to the other indices Fig. 8. In summary, the NDRE index values performed better than other indices in separating the time series curves of crops.

In addition to observing the changes in the time series curves of crops with different vegetation indices, the study also analysed the time series reflectance values of each spectral band for all crop types. Comparing the time series reflectance values of each spectral band for all crop types, it is seen that the B6 (Red Edge-2) and B11 (SWIR-1) bands are separated from the other bands Fig 9.

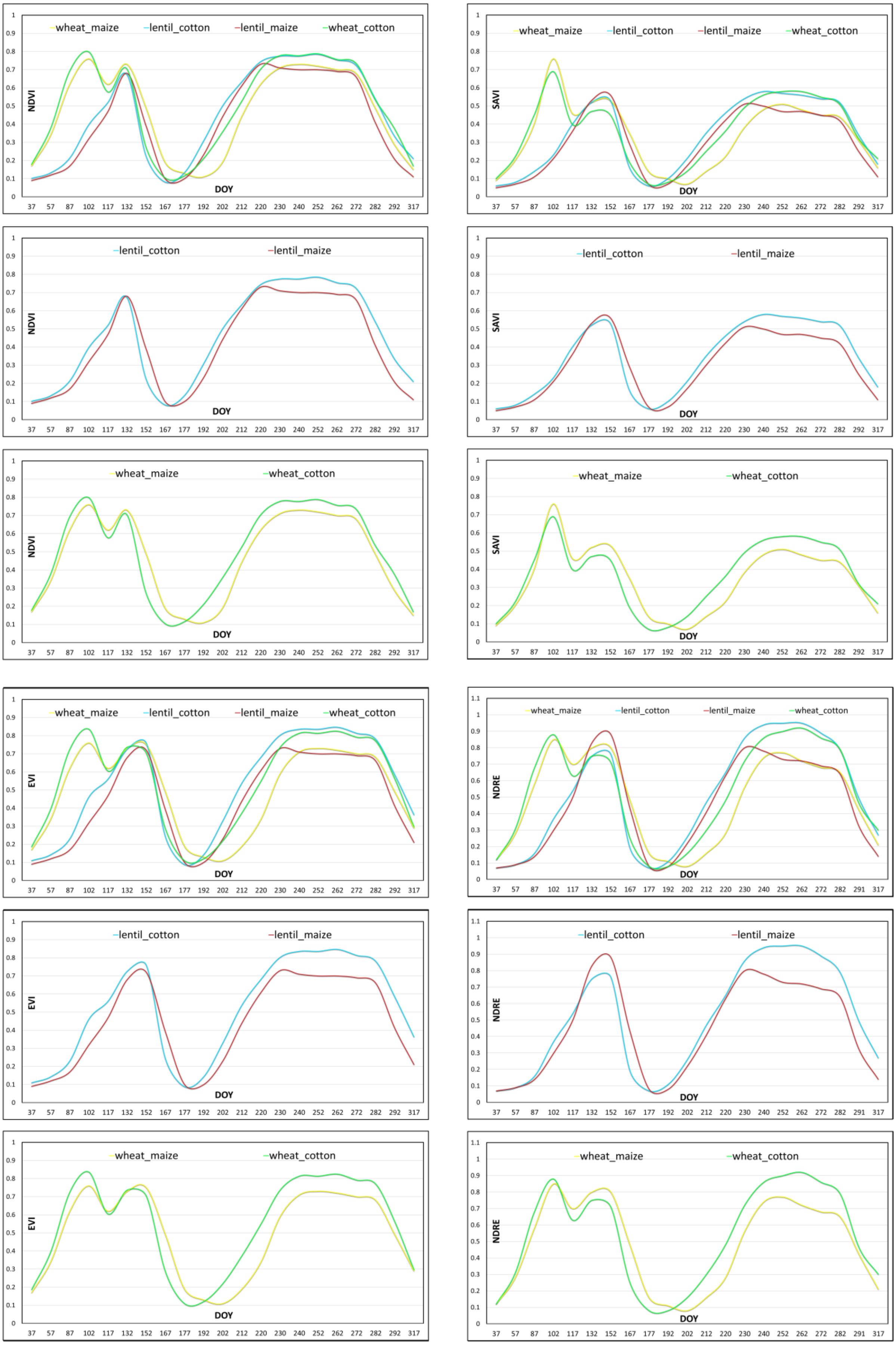

Fig.8. NDVI-EVI-SAVI-NDRE time series also were analyzed for double crops

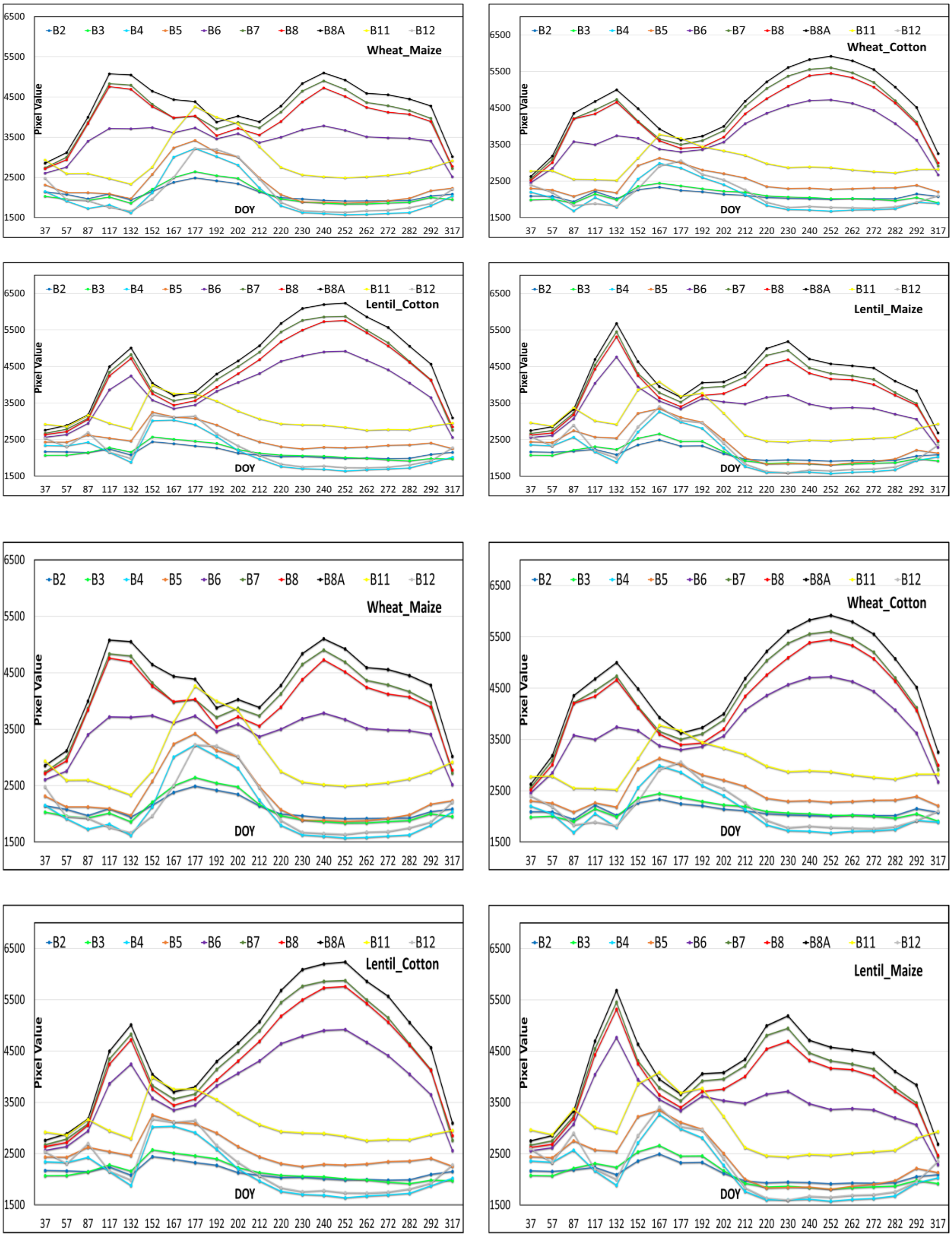

Fig.9. Reflectance values of different spectral bands for double crop type as time series.

Different datasets were generated using 4 different vegetation indices and 10 spectral bands Table 5. Classification studies were performed on these datasets and the results were compared. It was also investigated if the indices and bands that create time series curve differences in the generated datasets affect the classification result.

Table 5. Data sets and number of bands

Data Set	Features	Number of bands	Data Set	Features	Number of bands
Data Set (DS-1)	NDVI	21	**Data Set (DS-9)**	(4BAND)-EVI	105
Data Set (DS-2)	NDRE	21	**Data Set (DS-10)**	(4 BAND)-B6-B11	126
Data Set (DS-3)	SAVI	21	**Data Set (DS-11)**	(4 BAND)-B6-B11-NDRE	147
Data Set (DS-4)	EVI	21	**Data Set (DS-12)**	B2-B3-B4-B5-B6-B7-B8-B8A-B11-B12 (10 BAND)	210
Data Set (DS-5)	B2-B3-B4-B8 (4BAND)	84	**Data Set (DS-13)**	(10 BAND)-NDVI	231
Data Set (DS-6)	(4BAND)-NDVI	105	**Data Set (DS-14)**	(10 BAND)-NDRE	231
Data Set (DS-7)	(4BAND)-SAVI	105	**Data Set (DS-15)**	(10 BAND)-SAVI	231
Data Set (DS-8)	(4BAND)-NDRE	105	**Data Set (DS-16)**	(10 BAND)-EVI	231

Classification Using Random Forest

Random Forest (RF) is a combinatorial ensemble learning classification technique. RF is an improved algorithm based on an ensemble learning technique that builds multiple CARTs. (Breiman 2001) In fact, RF has been very successful as a general purpose classification and regression method (Biau and Scornet 2016). RF fits many classification trees to training data sets and then combines the predictions of all the trees to make a final decision. RF is an ensemble classifier that is currently widely used in remote sensing studies due to its classification accuracy (Belgiu and Dragut 2016). Higher accuracies have been achieved with RF compared to other machine learning algorithms in many crop mapping studies (Tatsumi et al. 2015). RF is known to work efficiently on large datasets with a large number of input variables to estimate which variables are significant in the classification process, and is relatively robust to noise and outliers. 44 many examples of the use of this algorithm can be found in the literature (Feng et al. 2019).

Hyperparameter optimization is the process of finding the optimal combination of parameters for a machine-learning algorithm according to specified success criteria. Hyperparameter optimization aims to achieve a balance between overlearning and under learning by balancing high model success and model complexity. The original RF has two hyperparameters including the number of trees (ntree) and the number of variables used to partition the nodes (mtry). Several studies have shown that satisfactory results can be achieved with the default parameters (Zhang and Roy 2017). In this study, to find the optimal RF model for classification, a range of values for both parameters were tested and evaluated using the grid search method for each dataset: ntree = 100, 200, 400, 600,800,1000; mtry = 1:20 Table 6.

After determining the optimal parameters of the algorithm to be used in the classification process, the k-fold cross-validation method is used. K-fold cross-validation allows to see whether the high performance of the model is random or not. In this method, the data set is divided into k parts and k-1 subset is used to train the model and the remaining subset is used to calculate the accuracy of the model. The process is repeated k times, each time using different pieces of training and test data. The average of the accuracy values obtained represents the accuracy of the model, and in this study the k value is taken as 5 (Kohavi 1995).

Table 6. Hyper parameter values for different data sets

Data Set	Number of bands	Ntree	Mtry
Data Set (DS: 1-4)	21	100	4
Data Set (DS-5)	84	200	9
Data Set (DS: 6-9)	105	200	10
Data Set (DS-10)	126	400	11
Data Set (DS-11)	147	400	12
Data Set (DS-12)	210	800	14
Data Set (DS: 13-16)	231	800	15

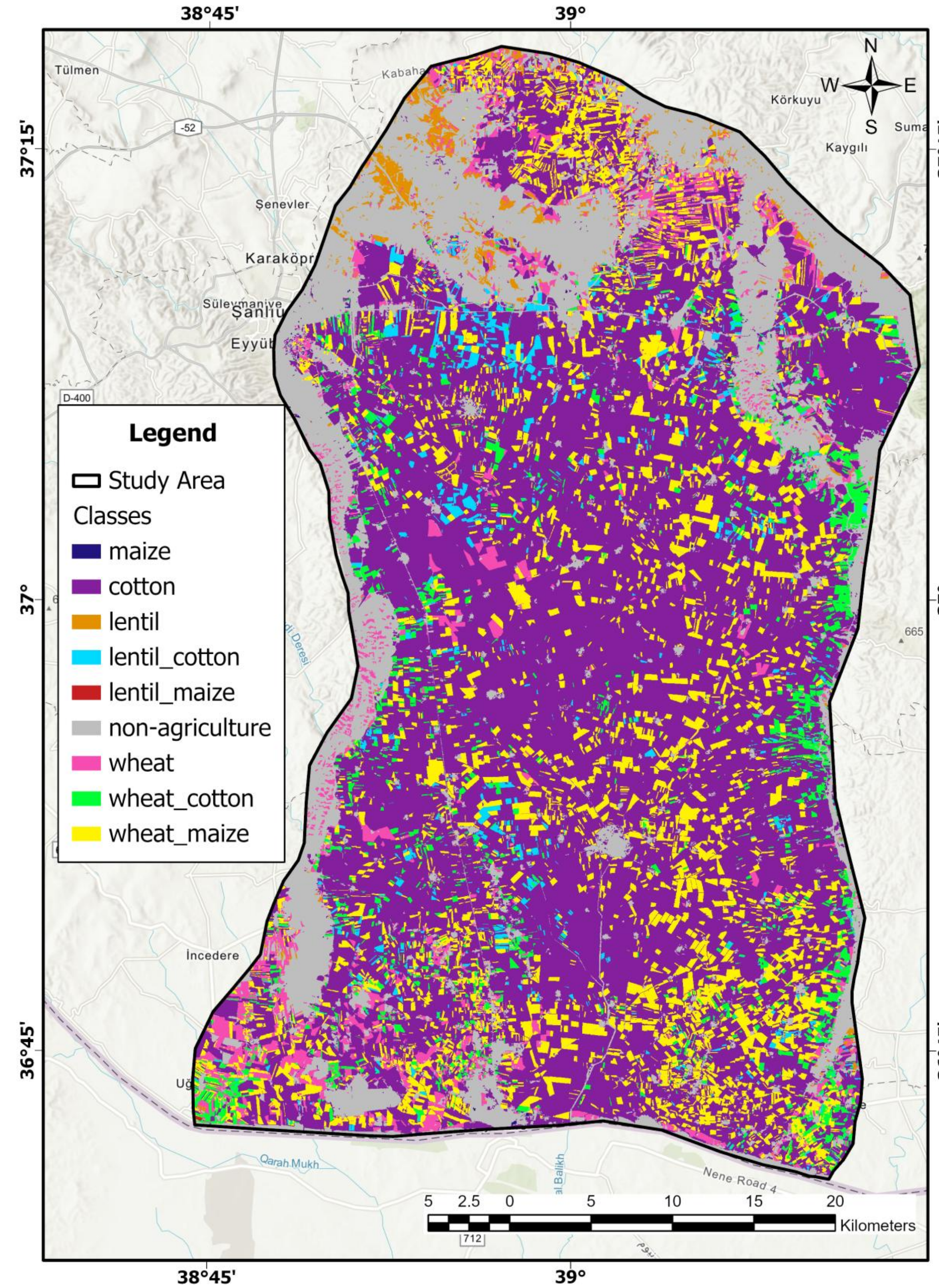

Fig.10. Classification result produced with DS-16 dataset

RESULTS AND DISCUSSION

In order to assess the accuracy of classification performance, a number of metrics are available in the literature. In this study, the following metrics were employed for the assessment of classification accuracy: precision (PA), recall (UA), accuracy (OA), and the F1 score. These results are presented in Table 7.

PA (Producer Accuracy): The ratio of correctly predicted positive observations to the total predicted positives. It measures the model's ability to correctly identify positive instances among the instances it predicted as positive.

$$PA:\ \mathrm{TP}/(\mathrm{TP}+\mathrm{FN})$$

UA (User Accuracy): The ratio of correctly predicted positive observations to the total actual positives. It measures the model's ability to correctly identify positive instances.

$$UA:\ \mathrm{TP}/(\mathrm{TP}+\mathrm{FP})$$

OA (Overall Accuracy): The ratio of correctly predicted instances (both positive and negative) to the total instances. It provides a general measure of the model's correctness.

$$OA:\ (\mathrm{TP}+\mathrm{TN})/\mathrm{N}$$

F1 Score: The harmonic mean of precision and recall. It provides a balance between precision and recall, especially useful when dealing with imbalanced datasets.

$$F1 : 2\times UA\times PA\,/\,(UA+PA)$$

These classification accuracy indicators can be used to reflect the overall classification accuracy and specific type identification accuracy of remote sensing images from different perspectives. (Congatol, 1991).

Table 7. Accuracy assessment for all data sets

Crop Type PA UA **F1**	**DS-1**	**DS-2**	**DS-3**	**DS-4**	**DS-5**	**DS-6**	**DS-7**	**DS-8**	**DS-9**	**DS-10**	**DS-11**	**DS-12**	**DS-13**	**DS-14**	**DS-15**	**DS-16**
	93.3	93.6	92.8	94.8	93.2	92.5	93.1	95.9	93.8	91.2	93.1	92.8	94.2	94.6	92.5	93.8
Cotton	90.9	93.4	91.8	92.7	94.2	93.8	93.9	90.6	93.2	95.0	93.0	93.4	93.4	93.7	93.9	93.9
	92.1	93.5	93.8	93.7	92.2	93.1	93.5	93.5	93.5	93.1	93.0	93.1	93.8	94.1	93.2	93.9
	93.3	93.4	91.4	95.1	93.1	93.5	95.0	93.0	94.4	92.2	95.7	93.3	94.0	94.6	94.4	94.5
Maize	93.4	93.0	91.8	92.9	91.2	93.0	93.1	93.4	94.0	93.7	92.4	93.1	94.1	94.0	95.1	94.9
	93.3	93.2	91.6	94.0	92.1	93.4	94.1	93.2	94.2	92.9	94.0	93.2	94.1	94.3	94.7	94.7
	89.9	91.8	88.6	90.7	87.6	92.5	92.4	94.8	92.8	89.9	91.3	90.6	93.5	92.4	92.9	92.6
Wheat	95.2	93.6	93.8	93.9	91.0	92.9	93.7	90.1	92.9	88.6	93.5	89.7	93.4	93.4	92.0	93.4
	92.4	92.7	91.1	92.3	89.3	92.7	93.1	92.4	92.8	89.2	92.4	90.2	92.9	92.9	92.4	92.8
	90.3	92.6	90.5	91.9	88.1	92.3	92.3	94.3	92.8	89.0	93.5	90.9	92.5	93.8	92.9	93.0
Lentil	95.2	93.2	93.2	91.8	92.2	92.9	93.9	90.9	92.7	89.4	92.4	90.5	93.3	93.0	92.5	93.6
	92.7	92.9	91.8	91.9	90.1	92.6	93.1	92.5	92.8	89.2	92.9	90.7	92.9	93.4	92.7	93.3
	88.1	89.2	82.4	86.6	77.2	86.2	91.0	84.6	87.9	83.7	92.0	83.5	87.4	93.7	89.3	90.2
Wheat_	81.0	90.1	86.1	86.0	85.7	84.0	90.2	85.9	87.5	84.4	93.2	84.7	87.0	93.3	88.2	90.0
Cotton	84.3	89.6	84.2	86.3	81.2	85.1	90.6	85.2	87.7	84.0	92.6	84.1	87.2	93.5	88.7	90.1
	82.2	89.3	82.0	85.9	78.7	85.0	92.1	88.1	88.3	83.8	92.7	85.1	89.5	92.7	87.5	91.0
Wheat_	88.1	90.5	87.1	87.6	82.9	87.0	89.3	83.7	88.1	85.5	91.3	85.6	86.7	93.3	90.0	89.0
Maize	85.0	89.9	84.5	86.7	80.7	86.0	90.7	85.8	88.2	84.6	92.0	85.3	88.1	93.0	88.7	90.0
	87.1	91.1	86.5	85.1	85.9	86.5	90.9	88.1	87.1	84.1	89.9	85.1	88.5	92.9	88.1	88.7
Lentil_	82.4	89.0	85.9	87.4	78.4	86.1	89.8	84.4	87.7	85.6	91.3	85.7	87.9	92.8	87.7	90.8
Cotton	84.7	90.1	86.2	86.2	82.0	86.3	92.1	86.2	87.4	84.8	90.6	85.4	88.2	92.9	87.9	89.6
	86.1	89.2	81.3	85.1	85.9	85.4	90.5	87.8	87.2	84.3	91.3	86.1	89.1	93.1	86.5	89.4
Lentil_	82.0	89.6	86.1	85.0	77.9	85.0	91.3	82.3	87.3	85.3	91.8	83.9	87.2	92.8	87.3	89.8
Maize	84.0	89.4	83.6	85.0	81.7	85.2	90.9	85.0	87.2	84.8	91.5	85.0	88.1	92.9	86.9	89.6
Non-	96.3	95.8	96.4	96.4	95.8	95.2	97.2	96.8	96.4	95.9	97.2	94.9	95.0	97.1	98.2	95.0
Agriculture	96.5	95.0	95.9	95.6	95.9	98.4	95.8	96.2	96.0	94.5	97.0	95.3	95.4	97.0	94.8	97.8
	96.4	95.4	96.1	96.0	95.9	96.8	96.5	96.5	96.2	95.1	97.1	95.1	95.2	97.1	96.5	96.5
Overall Accuracy	**88.7**	**90.0**	**87.0**	**89.0**	**86.4**	**89.2**	**91.2**	**88.2**	**90.0**	**90.5**	**93.4**	**90.8**	**92.1**	**94.8**	**91.2**	**92.9**

PA (%): Procuder Accuracy UA (%): User Accuracy F1 Score

In the analysis of wheat and lentil crops, an accuracy of 90% or higher was observed across 16 datasets. The DS-3 dataset yielded the lowest accuracy, while the highest accuracies were obtained with the DS-7 and DS-14 datasets. Notably, the classification results for DS-5 and DS-10 were indistinguishable. The distinct spectral separation curves of wheat and lentil facilitated high classification accuracy across all datasets. Similarly, for maize and cotton crops, an accuracy of 90% or higher was achieved in 16 datasets. The DS-5 dataset produced the lowest accuracy for cotton, whereas the DS-14 dataset had the highest accuracy for both cotton and maize.

The unique time series curves of maize and cotton, akin to those of wheat and lentil, resulted in high accuracy across all datasets. However, it was observed that increasing the number of spectral bands did not significantly enhance accuracy for these crop classes

The DS-5 dataset, with an accuracy range of 81-82%, provides the lowest accuracy for all double crops, while the DS-14 dataset achieves the highest accuracy at 94.8%. It is notable that the DS-2 dataset, which incorporates NDRE values, offers higher accuracy compared to datasets utilizing other indices (DS-1, DS-3, DS-4). This increased accuracy is attributed to the superior performance of the NDRE index in distinguishing the time series curves of the crops. Despite this, double crops remained with low accuracy in the DS-5 dataset (81-82%), and in the DS-12 dataset (84-85%), where accuracy improved by approximately 3%, but still remained inadequate, as depicted in Fig. 11.

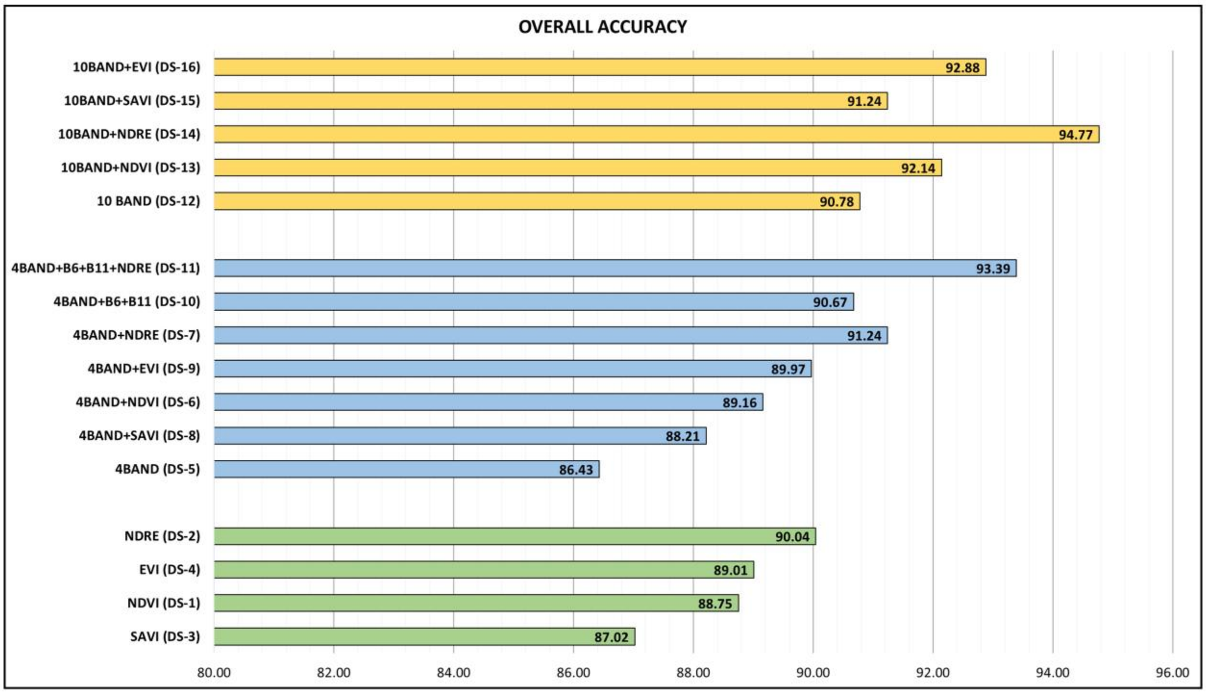

Fig.11. Overall accuracy for all data sets

Figure 11 reveals that the lowest overall accuracy values are observed in the DS-5 (86.4%) and DS-3 (87.02%) datasets, while the highest accuracy is recorded in the DS-14 dataset (94.77%). A comparison between the DS-7 (91.24%) and DS-14 (94.77%) datasets shows an approximate 3% increase in accuracy. Similarly, comparing DS-7 (91.24%) with DS-11 (93.39%) indicates that bands 6 and 11, which are distinct from other bands across all products, contribute to a 2% increase in accuracy. The results of DS-11 (93.39%) and DS-14 (94.77%) are also closely aligned. Datasets containing the NDRE index (DS-2, DS-7, DS-11, DS-14) and those with 10 bands (DS-12, DS-13, DS-14, DS-15, DS-16) consistently achieve accuracy values above 90%. Comparing the DS-5 (81-82%) dataset with the DS-2 (89-90%) dataset reveals an 8% improvement in accuracy for double crops, highlighting the NDRE index's ability to enhance classification results for crops with similar phenological stages. When DS-2 is compared with DS-7, it is evident that the addition of the +4 band in the NDRE dataset does not significantly impact classification accuracy for either double crops or overall accuracy. Further, a comparison of DS-7 (91%) with DS-11 (92%) demonstrates that bands 6 and 11 marginally improve the classification accuracy of double crops. For crops with similar time series, datasets with only 4 bands (DS-5) and those with only 10 bands (DS-12) did not achieve high classification accuracy for crops with close phenological stages.It is observed that datasets containing the NDRE index, which outperforms other indices in distinguishing the time series curves of crops, improve overall accuracy by 2-3% compared to other datasets. Additionally, the inclusion of the 6th and 11th bands in these datasets further increases accuracy by 2%. The most significant contributor to this accuracy improvement is Band 6 (Red Edge-2), which is also integral to the NDRE index.

When analyzing the classification results, the impact of appropriate spectral band selection—a key parameter influencing classification accuracy—is clearly evident, with accuracy varying depending on the dataset used. Datasets incorporating the B6 band and NDRE indices notably enhance classification outcomes. Üstüner et al. (2014) utilized RapidEye imagery to classify maize and cotton crops with NDVI, GNDVI, and NDRE indices, finding that the highest accuracy was achieved with the dataset containing the NDRE index, which uses the Red Edge and NIR bands. These findings align closely with the results of this study. Similarly, Kobayashi et al. (2020) conducted a classification study using Sentinel-2 imagery for potato, wheat, maize, grass, beans, and beetroot crops. They generated spectral curves for the reflectance values of each crop across 10 bands (excluding the 60m bands) in the B2-B12 range. Analysis of these curves revealed that crops were distinctly separated in B6, B7, B8, and B8a, with Band 11 particularly effective in differentiating wheat from other crops. This study further underscores that including the B11 (SWIR-1) band, despite its 60m resolution, improves classification accuracy. These findings collectively emphasize the critical importance of selecting appropriate spectral bands and indices in the classification process.

CONCLUSION

This study investigated the effect of vegetation indices and spectral bands on the classification of agricultural crops. Time series curves of classes with different vegetation indices were generated and compared, and time series reflectance values of each spectral band were also observed for all crops. The study shows the importance of time series curves (phenological period) generated from multi-temporal images of crops. In the time series curves generated with different vegetation indices, it was found that the crops that differ (with a unique curve) have a high accuracy value with optimal data sets, while increasing the number of features and bands in the input data set has almost no effect on the accuracy value of these crops. For crops with very close phenological periods, indices that reveal the difference between the time series curves (NDRE-EVI) were found to increase the classification result. When comparing the time series reflectance values of each spectral band for all crop types, except the crop indices, it was observed that the B6 (Red Edge-2) and B11 (SWIR-1) bands were separated from the other bands and increased the classification result by 2% when included in the dataset. This result showed that B6 (Red Edge-2) and B11 (SWIR-1) bands should be used in agricultural crop type classification studies, especially for crops covering close phenological stages. In particular, for classification studies carried out in large working areas such as this one, by determining the bands with indices that separate the time series curves of the crops, the bands and indices that will give the highest accuracy as a result of the classification can be determined and time can be saved by obtaining maximum accuracy with minimum data in classification studies. Future studies will extend the scope of the study by using different algorithms for different crop indices, different crop types and different study areas.

Conflict of Interest Statement: The authors declare that they have no conflict of interest.

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