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Armağan ALOE KARABULUT, Nihal CEYLAN, Erdem BAHAR, İlker KURŞUN

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Research Article

Crop Phenology-Based Object-Oriented Classification Approach Using SENTINEL-2A and NDVI Time Series: Sunflower Crops in Kırklareli TURKEY

Armağan Aloe Karabulut^{1,*} , Nihal Ceylan¹ , Erdem Bahar² , İlker Kurşun² 

¹Central Research Institute for Field Crops, Ankara, TURKEY

²Atatürk Soil, Water, and Agricultural Meteorology Research Institute, Kırklareli, TURKEY

* Corresponding author: A. A. Karabulut
E-mail: armagankarabulut@tarimorman.gov.tr

Received 11 Jan. 2021

Accepted 26 Feb. 2021

How to cite: Karabulut, et al., (2021). Crop phenology-based object-oriented classification approach using SENTINEL-2A and NDVI time series: Sunflower crops in Kırklareli. *International Journal of Environment and Geoinformatics (IJEGEO)*, 8(3): 316-327. doi. 10.30897/ijegeo.858456

Abstract

Achieving food security on a global scale depends on regular spatio-temporal monitoring and management of national and local agricultural production. The aim of this study is to develop a methodology for determining sunflower cultivated areas using high resolution time series of the SENTINEL-2A satellite images that represent phenological stages of crop growth cycle. A time series of spectral signatures of crop phenological periods and normalized difference vegetation index (NDVI) was produced from satellite images for year 2018. A stepwise object-oriented classification approach was developed. In this approach, object-oriented segmentation and classification decision tree algorithms were produced by using time series of spectral signatures and NDVI values as well as object shape criteria and other auxiliary thematic maps. The multiresolution method of "Canny edge" algorithm was used in order to determine boundary of agricultural parcels. The best performance in segmentation to determine the agricultural parcels was achieved by increasing weight coefficient of the "Canny edge" layer. Object-oriented classification was carried out based on these segmented parcels. First, summer crops, winter crops, fallow and permanent vegetated areas were determined through classification decision tree algorithms. Later, the summer and winter crops were classified using the parcel spectral signatures of samples collected with field work. The crops whose class definition could not be determined were passed through a second elimination in "unclassified" group and later assigned to their classes. Finally, the parcels whose class definition could not be determined were grouped as "other" class. According to results of confusion matrix and accuracy analysis, sunflower, which was determined in two classes as early and late sowing, was classified at 98% and 92% accuracy, respectively.

Keywords: Object-oriented Classification, NDVI Time Series, Sunflower, Crop Phenology, SENTINEL-2A, Decision Tree

Introduction

Within the framework of sustainable development goals, global food security requires meeting food needs of ever-increasing population, increasing food diversity and ensuring people access to food (GA, 2015). Food security of nations requires an increment in agricultural production capacity by optimizing the soil-water resources with appropriate land use and crop pattern planning. In this context, determining the cultivation areas of crops and spatio-temporal monitoring in crop production planning is very important to ensure decision makers have more precise crop yield estimates in their hands on time (Alganci et al.2014).

Updated data of annual crop pattern and rotation is essential for spatio-temporal management of crop production. In Turkey, such spatial data are provided by the "Farmer Registration System" (TOB-ÇKS) (2020) and the "Agricultural Parcels Information System" (APIS, 2020). However, as the information of crop type and yield of parcels is based on farmer declaration that is registered in the system, accuracy of data cannot be controlled for each parcel. Furthermore, there is a high probability that there are farmers who are not registered

in the system yet. Therefore, annual crop pattern and rotation data need to be provided and updated by a dynamic monitoring and control methods. Spatio-temporal analysis of satellite images at different wavelengths is an operational technological opportunity that enables examining dynamic structure of crop pattern and rotation.

Determination of agricultural areas and classification of crop patterns using remote sensing and GIS techniques, further development of crop monitoring techniques started with pixel-based approaches (Sabins, 1987; Drury, 1990; Evsahibioglu, 1994; Esetlili and Kurucu, 2003; Balcik and Kuzucu, 2016; Esetlili, et al., 2018), and later with the improvement of radiometric, spatial and temporal high-resolution images and high speed processing techniques, pixel-based classification techniques gave way to object-oriented classification methods where artificial intelligence, machine and deep learning methods are frequently used (Rahman and Saha, 2008; Irfanoglu and Balcik, 2018; Bargiel, 2017; Cicek and Founder, 2018; Colkesen and Kavzanoglu, 2017; Ghamisi et al.2017; Maxwell et al.2018). Even though studies on these issues at national scale are carried out within the body of different institutions affiliated to the

Ministry of Agriculture and Forestry in Turkey, they remain insufficient without mutual communication. Depending on feasibility of current situation, interoperability between institutions should also be ensured.

Sunflower, one of the most important oil-seed crops in the world, has a high production potential in Turkey as well. In Turkey, half of the oil-seed production is met from sunflower (ESKGM, 2019). Trakya region meets an important part of oil-seed sunflower and paddy production for the country as well as wheat is produced in the region with a yield above the country's average. As a result, 60-65% of sunflower and 10-15% of cereal production in dry conditions are produced in the Trakya region. While annual sunflower oil consumption in Turkey is 900 thousand tons/year, oil-seed sunflower production can only meet half of this need, and the remaining half is provided by imports (ESKGM, 2019). Despite its production potential of oil-seed sunflower, Turkey takes the second place after the European Union in importing oil-seed sunflower (TOBB, 2018). Therefore, more effective crop production plans need to be developed with support of highly accurate annual yield estimates in order to meet the sunflower needs in Turkey with domestic production as well as appropriately subsidizing farmers/producers. Highly accurate annual yield estimation primarily depends on the determination of accurate annual crop pattern.

In this context Kırklareli, which has an important role in agricultural economy in Turkey, was selected as the study area for determining sunflower cultivated areas. We aimed to develop a methodology for determining the sunflower cultivated areas using high resolution time

series of the SENTINEL-2A satellite images that represent phenological stages of the crop growth cycle. First, we generated a spectral signature database for growth cycle periods of main crops using time series of SENTINEL-2A satellite images and NDVI values. Then we developed a stepwise object-oriented classification method based on this spectral signature database as well as auxiliary GIS data and narrative-based knowledge. Finally, we determined the sunflower cultivated areas with a high accuracy and main crop pattern as well.

Study area

Kırklareli has an area of 6550 km² between the Istranca Mountains and Ergene plain in Thrace, and its average altitude above sea level is 203 m. The highest region is 1018 m in Mahya Mountain (Kuru and Terzi, 2018). Its north and east parts are covered by forests while other parts are surrounded by fertile agricultural plain land (Figure 1). The winters in the region are dominated by harsh and rainy continental climate conditions as well as cold weather coming from the Balkans while summers are hot with semi-arid climatic characteristics. Although inner regions of Kırklareli receive rainfall almost in every season, annual precipitation is low compared to coastal regions (Erginal and Uludağ, 2018). In these regions, the average temperature is 13°C and the mean annual precipitation is 772.8 mm (MGM, 2018). According to the Köppen Climate classification, Kırklareli Province is in the "Mediterranean / humid semi-tropical climate characteristics (border region)" class. The main rivers are Ergene River and Mutlu Creek where irrigated agriculture is practiced surround (Figure 1).

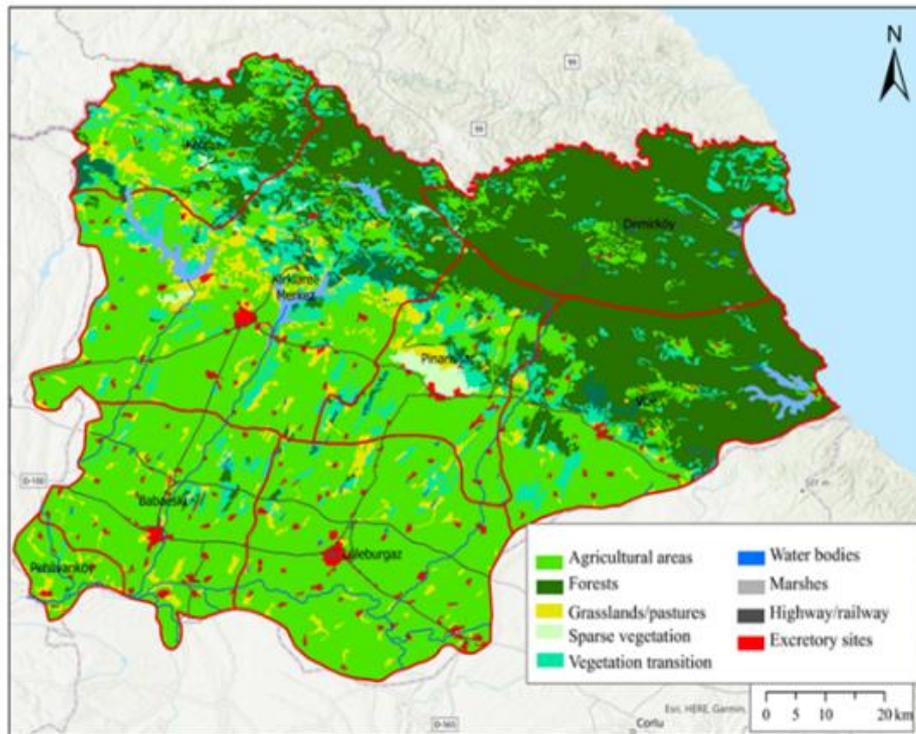


Figure 1. Study area and land use (CORINE CLC 2018).

According to the land use distribution of Kırklareli (CORINE-18 CLC) (Figure 1), total agricultural land is 264.532 hectares (ha) and size of the agricultural parcels varies between 5-20 ha. Cereals are among the most cultivated crops in Kırklareli, and sunflower production meets 10% of the country in general (TOB, 2018). While TOB-ÇKS data reports a sunflower cultivated area of 66.909 ha, Turkey’s Statistical Institution (TÜİK)’s data reports instead a total area of 75.000 ha for year 2018.

General crop production status

Kırklareli has a population of 351.684, and 70% of the active population is engaged in agriculture, animal husbandry, forestry and hunting (TOBB, 2018). Major agricultural products are cereals, sunflower, maize, grain legumes, sugar beet, canola, alfalfa and vetch (Çaldağ, 2009). Main winter crops cultivated in the region are grains, canola and vetch on the non-irrigated dry lands, while summer crops are sunflower, sugar beet, maize, alfalfa and vetch on the irrigated lands. Sunflower is grown at different sowing times depending on the rainfall regime on the non-irrigated areas.

Second crop cultivation on the irrigated lands has also increased in the last decade in the region. Silage maize, dry beans and second crop sunflower are planted as second crop after the harvest of cereals and winter canola. Different crop alternation models can be applied in the region as given below (TOBB, 2018):

Model 1: sunflower + canola + wheat + maize

Model 2: wheat + canola + legumes + sunflower

Model 3: wheat + canola + sugar beet + melon-watermelon

Materials and Methods

SENTINEL-2A satellite imagery time series

The SENTINEL-2A satellite images of year 2018 were scanned in the Copernicus database (EU-Copernicus, achieved at:20/05/2019), and the most suitable cloudless images were downloaded.

Kırklareli is located at a intersection of four image frames. For this reason, in a window of a certain time, an image existing in one frame may not exist in other frame. Those windows with cloudless complete frames that represent the phenological periods (see Figure 3) were pre-examined and prepared ready as a time series of multispectral satellite images for image processing and classification processes. ArcGIS, e-Cognition and Erdas programs were used interactively for all processes.

Crop phenology calendar matrix

While main purpose of this study is to determine the sunflower cultivation areas, in order to distinguish sunflower from other main crops, additional information about other crops should also be determined and used as an auxiliary criteria in classification algorithms. For instance, since phenological periods for main crops could not be monitored in the field, auxiliary algorithm criteria were determined based on the available data (Figure 2).

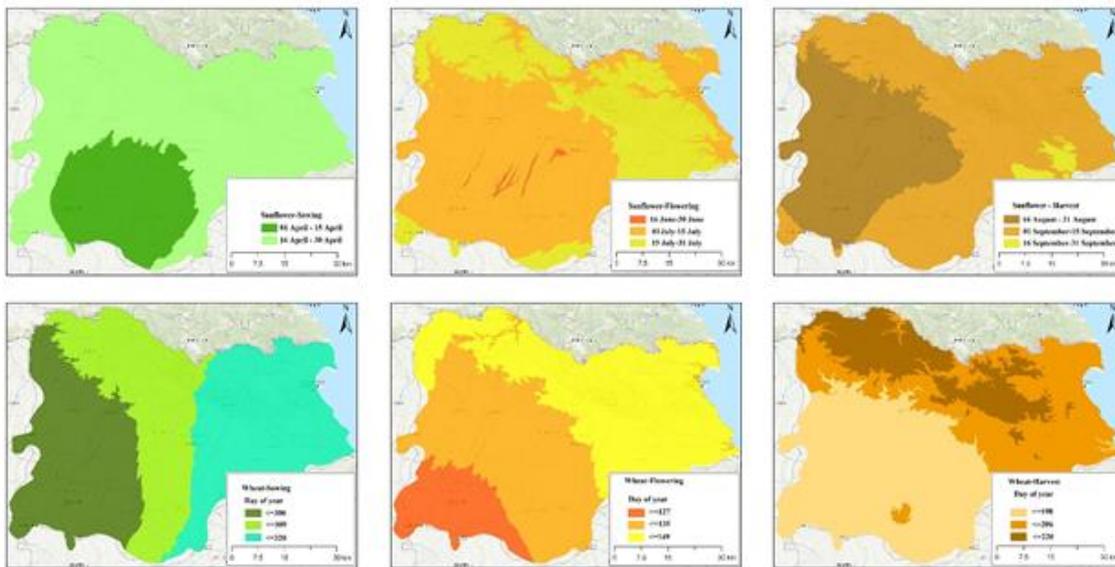


Figure 2. Atlas of sunflower and wheat phenological periods in Kırklareli (a-f) (MGM, 2014).

In this study, crop phenology atlases (MGM, 2014), expert and literature based knowledge were used to determine the phenological periods for the main crops. A phenology calendar matrix (see Figure 3) was created for the strategic main crops using the crop phenology atlases (see Figure 2) which were produced based on long-term phenological observation data (MGM, 2014). Ideally, phenological observations should be performed in

sample parcels for each crop, and the crop growth periods should be determined with the real time data.

The main agricultural crops are wheat, sunflower, paddy, barley, maize and sugar beet in the study area. Canola (rapeseed), which is an important source in bio-energy fuel production in recent years, is also produced as an alternative to sunflower. There are early, mid-early and

Table 1. Multispectral image windows timeframe and crop classification strategy by crop phenology for Kırklareli.

Window	Approximate time period	Main classification goals
1	1 March- 30 April	Bare land, winter cereals, winter rape (canola), summer crops
2	15 May-30 June	Rapeseed, sunflower, sugar beet, maize
3	15 July-15 August	Wheat,sunflower, maize, rapeseed, sugar beet
4	14 August-15 September	Paddy, sugar beet, maize sunflower
5	15 September-15 October	Sugar beet

Table 2. Auxiliary GIS layers.

Auxiliary layers	GIS	Resolution	Source
Pasture areas and quality classes map	Polygon		(Avağ et al., 2012), National Pasture Use and Management Project
Topography (elevation, slope, aspect)		30 m	SRTM
Administrative city and district borders	Polygon		TARM-GIS database
Corine Land Use (CLC) 2018,		100 m	(EEA, 2018)
Roads map	Polygon		KGM
River network map	Polygon		TARM-GIS database
Irrigated Areas	Polygon		DSI
Satellite images		10 m	ESA-The Copernicus Sentinel-2A
Forest areas (MESCERE)	Polygon		TOB

Stepwise segmentation algorithms were developed based on the literature to produce an “agricultural parcel layer” that would be used in classification algorithms. Segmentation (object-parcel) results were compared with the control parcels that were downloaded from the General Directorate of Land Registry and Cadastre Parcel Inquiry Portal (APIS, 2020).

Sampling dataset and NDVI time series for main crops

Two different sampling data sets were created for learning and validation (test) processes with the sampling parcels that are collected with GPS in the field work (At least 50% of sampling parcels were used in validation for each class) (Figure 4). Better classification results can be expected with the higher number of learning samples that are distributed homogeneously in the area, and if they are taken from at least 10 different parcels for each crop. (Waldhoff et al., 2017; Zhong et al., 2016; Islam et al., 2016; Panchal et al., 2021; Mehda et al., 2021).

Monthly NDVI Time Series (2018)

Normalized vegetation difference index (NDVI) is widely used in classification of land use, vegetation cover and crops (Ünal et al., 2004; Tucker et al., 2005; Wardlow and Egbert, 2008; Yıldız et al., 2012; Zheng et al., 2015; Skakun et al., 2017; Li et al, 2019). Within the scope of the study, NDVI time series of available clear images that represent the plant phenological periods were produced (Figure 5). The NDVI time series can effectively reveal the growth periods of the crops (Tucker et al., 2005; Zheng et al., 2015; Zhong et al., 2016; Skakun et al., 2017). The NDVI values and differences in the growth periods of main crops were determined and used as criteria in both segmentation and classification algorithms (Figure 5). NDVI time series for georeferenced learning and test (validation) sample parcels were produced for each crop depending on the average and median NDVI values of each parcel. Finally, the phenological growth cycle graphs of the main crops were produced as shown in Figure 5. VI (NDVI) values representing beginning of vegetation (D1), highest (D3) and ending (D4) periods of crop growth were determined by use of a limited number (7) of appropriate images for the stepwise separation of winter and summer crops (Figure 5) (Zhong et al. , 2016).

Development of decision tree rules & algorithms for segmentation and classification

Tree-based learning algorithms are the most commonly used supervised learning algorithms in classification techniques, and can generally be adapted to solution of problems (classification and regression) that were addressed in almost every discipline (Friedl and Brodley, 1997; Yang et al., 2003; Çalış et al., 2014). The decision tree rule series of the study consists of two stages: The first stage includes creation of the objects (approximate-parcels), namely stepwise segmentation algorithm processes, and the second stage includes stepwise classification algorithm processes (Figure 6).

The agricultural parcels are essential data layer in the studies of crop pattern determination and crop yield monitoring. If this layer does not exist, the most basic step is to create a layer of approximate-parcels using the most appropriate segmentation processes by determining crop field boundaries. In our study, The "Canny edge detection" algorithm, one of the methods proposed by Watkins and van Niekerk (2019) for automatic determination of agricultural parcel, was applied using time series of different bands and NDVI layers. Later, a series of different segmentation algorithms (Multispectral-Spectral difference-Region grow) were performed to achieve the best result. Since there was no digital parcel layer, the results were compared visually with the satellite images of different periods, and appropriate parcellation was produced (Alganci et al., 2013).

A classification decision tree consisting of rule series was created based on the method of “covering-bottom up-separate-conquer” depending on the crop phenological stages (Zhong, et al., 2016; Waldhoff et al.,

2017; Zhong and Zhou, 2019). In this method, all samples in the rules are parsed, and remaining ones are transferred to a class. Stepwise process continues until all classes are assigned (Zhong et al., 2019). The differences of NDVI values in the crop growth cycle like growing (high vegetation index), maturity and harvest (low vegetation index) periods effectively worked in the crop separation processes. The NDVI, RGB and NIR reflectance values in the phenological periods and physical parameters (length / width ratio etc.) were used as separation criteria in the classification algorithms.

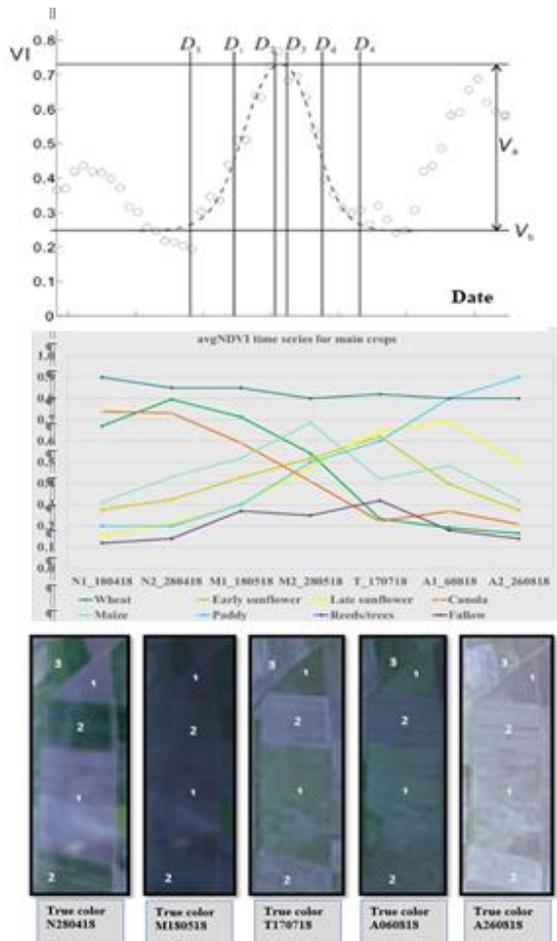


Figure 5. NDVI Time series (D_i) and decision threshold (V_j) values of crops (after Zhong, et al., 2016).

The growth cycle of some crops could not be fully captured due to absence of clear images in March, June and September. However, more precise classification results can be obtained by knowing exact sowing date of the crops, and using a day of the year criterion for the crop growth cycle effectively in the algorithms (Zhong et al., 2016).

Classes were determined only for the main crops in the study area. Sugar beet, alfalfa, legumes and other crops were grouped under the "other" class since the study focused on the determination of sunflower fields.

Confusion matrix and accuracy assessments

The sampling parcels, which were qualified to represent the main crops and determined in homogeneous distribution as far as field conditions allow, were used in

identifying the criteria in the classification processes. Half of the samples (50%) was used as test (validation) data set in confusion matrix and accuracy analysis. The confusion matrix was created using the test data set to compare estimated classified parcels with actual classes that were determined in the field.

Classification performance was validated by confusion matrices, accuracy parameters (User's Accuracy (UA) and Producer's Accuracy (PA), the Overall Accuracy (OA) and Kappa Coefficient (K)), and confusion error (Congalton and Green, 2009; Zhong et al., 2016; Waldhoff et al., 2017).

The Kappa coefficient, which shows accordance between actual crop parcels and overall classification results of the model, varies between 0-1, and shows that the accuracy rate of the classification increases as it approaches 1.

Results

Segmentation and parceling

As a first stage, "edge detection" algorithm (automatic determination of parcel boundaries) was applied for each band layer (e.g. April NIR, July R band etc.) and NDVI time series. We selected layers that provide the best contrast in the cultivated areas using the time series of the year 2018 which consists of seven different time periods. The images of May did not provide high contrast in the parcel boundaries, since nearly each crop was in a period of high vegetation growth. On the other hand, as each image band and NDVI layer had different levels of contrast in different parcels, we overlaid all these layers to obtain the final explicit parcel boundaries layer (Figure 7).

As a second stage, segmentation was performed by iterating different combinations of weight coefficients for each band layer as well as the final parcel boundaries layer. The best segmentation result was obtained when the highest weight coefficient is given to the 'Canny Edge' layer (Figure 7).

The "Multispectral segmentation" method was applied as the first step in the segmentation process (8a,b,c and d). In this method, different weight coefficients were given to each image band layer and combinations of different segmentation parameters were tried. As "scale" value, which is one of the determining parameters of this method, increases, size of the object also increases. High values of "shape" parameter disrupted the homogeneous structure of RGB-NIR and NDVI values in the object. It was observed that high "compactness" values also enable to obtain a more detailed parcel structure that increases the number of the objects. Considering these effects, many different parametric combinations were iterated to achieve the best final parcels layer.

The results of the segmentations were compared on the images and the most appropriate segmentation result was accepted as a final parcels layer for use in the

classification processes. (Figure 8c and d). However, more effective segmentation result can be obtained by developing additional auxiliary algorithms by using

available digital agricultural parcel data, and the segmentation results can be compared more precisely by calculating error rates.

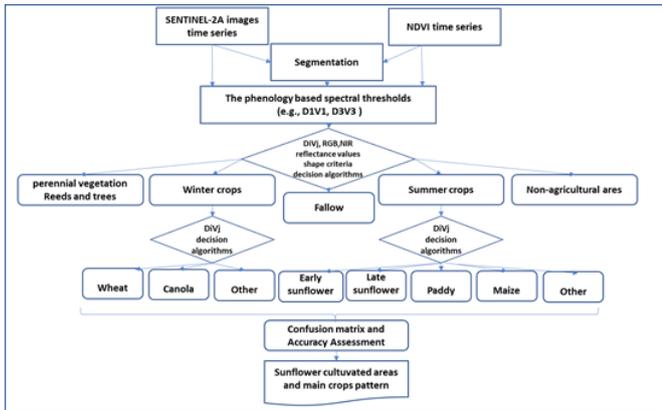


Figure 6. Flowchart of segmentation and classification decision tree rules

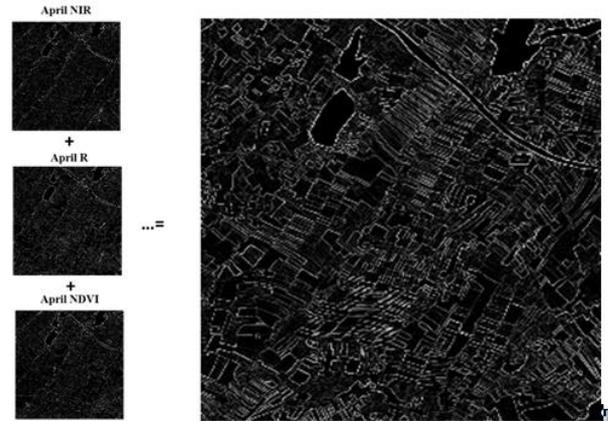


Figure 7. Agricultural parcel boundaries layer (Canny edge layer). In the image bands and NDVI time series, the "Canny edge" boundary layers with high contrast were determined and combined as final raster. Non-agricultural areas are masked using auxiliary GIS layers.

As a result of "Multispectral segmentation" 66.075.107 objects were determined. Some neighbouring objects with similar features was combined to reduce the vast number of objects that were straining the processing capacity of the hardware and software. For this purpose, "Spectral difference segmentation" and "region grow" methods were applied as the second step. At this stage, similar segments were combined using the mean differences of NDVI and band layers, and giving different weight coefficients to each layer. As a result, the number of objects has been reduced to 201.221. Actual cultivated areas and segmentation parceling results were visually compared on the satellite images for different periods, and made ready for classification process (Figure 8d). The parceling differences in the stepwise segmentation processes and their compatibility with the images can be clearly observed from the parcels in the red circle. (Figures 8a-d).

Desired comparison result could not be achieved since the land registry cadastral parcels and actual cultivated parcels were not very compatible (Figure 9). For this reason, the final parcels layer was decided by comparing the segmentation parcels with the actual cultivated areas on the satellite images at different phenological periods. (Figure 8d). In Turkey, agricultural parcels can be very small in size, and parcel size is varying between 5-20 ha in Kırklareli. Small-sized agricultural parcels can cause a vast number of objects depending on the algorithm criteria; therefore, automatically identifying parcels through segmentation processes can strain the processing capacity of the computer. Another bottleneck during the segmentation processes is in-field differences that is observed in a same parcel which can be resulted from the spatial variability of land and crop vegetation or differences in

Segmentation properties	Images	Object numbers
(a) true-color image combination (28.04.18)		66.075.107 parcels
"Canny-edge" parcel borders		66.075.107 parcels
(c) "Multispectral-segmentation" parcels Segmentation-criteria Scale: 50 Shape: 0.6 Compactness: 0.85		201.221 parcels
(d) "Spectral-difference-segmentation" parcels		201.221 parcels

Figure 8. Parcel identification and segmentation processes.

simultaneous-time image frames. The “region grow” and “spectral difference segmentation” methods were effectively performed overcoming these problems by merging in-field parts (Figure 8d).

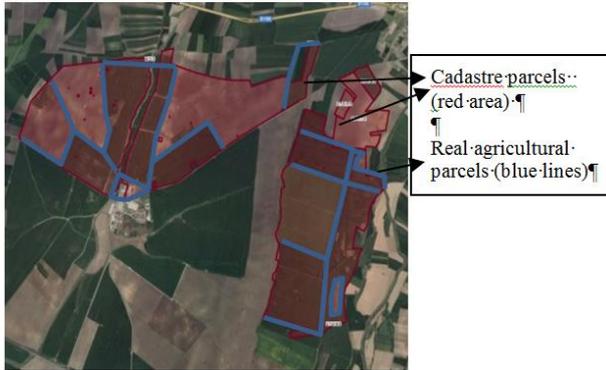


Figure 9. Cadastre (red polygons) parcels and segmentation parcels (blue polygons).

Sunflower cultivated areas and main crops pattern

The final parcels layer was used as a basement object layer for the classification processes. The classification decision tree and rule set were created using the NDVI and RGB time series of each crop. In addition to that, the shape criteria were also used in the classification algorithms where it is necessary. Firstly, permanent green (woodland between the fields and reeds) and bare lands (fallow, crossroad, etc.); then winter and summer crops were determined. In the second stage, summer and winter crops were again separated by crop-based classification algorithms using periodic differences in the NDVI and reflectance values of the layers. Finally, the crops that could not be distinguished and the rest of the “unclassified” segments were grouped under the “other” class (Figure 10). The maximum, minimum, average and median values of the NDVI were iterated at different threshold levels for each crop in the classification algorithms. The crops pattern map was produced using the iteration result with the lowest standard error and highest classification goodness coefficient (Kappa) of confusion matrix (Figure 10).

As a result, sunflower cultivated areas were precisely determined by developing site-specific object-oriented classification algorithms (Figure 10). According to our classification result, the estimated sunflower cultivated areas were 89,487 ha in total for the year 2018, and the result was compared with TÜİK (TÜİK, 2018) and ÇKS (ÇKS-TOBB, 2018) data sources. Sunflower cultivated areas that we estimated are 14 400 and 19 500 ha higher than those of TÜİK and ÇKS data, respectively. Furthermore, approximately 8000 ha of differences was observed between both data sources. In conclusion, in our study, early and late sunflowers were classified with 98% and 92% accuracy, respectively, with the sampling parcels. These differences in data sources of different institutions once again reveals a need of establishing a

centralised systematic control mechanism that is supported by remote sensing technologies, keeping up with the ever-evolving technology in the field.

Confusion matrix and accuracy assessments

The appropriate number of samples that are homogeneously distributed over the whole study area (at least 10 samples per crop parcel) is an important factor to increase the accuracy of the classification (Foody, 2005; Zhong et al., 2016; Walldhoff et al., 2017; Khaliq et al. al., 2018). However, the actual terrain and weather conditions often do not let researchers perform the same grid sampling pattern that is prepared at the desk, and require us to adapt to the real-time conditions in the field (see Figure 4).

Confusion matrix and accuracy coefficients (P_accuracy, U-accuracy, Kappa) are indicators that indicate performance of classification (Congalton and Green, 2009; Zhong and Zhou, 2019). These indicators provide us to control how accurately classification criteria values obtained with actual ground data.

The learning sampling dataset was used when creating the criteria at the classification processes while the test sampling dataset was used in setting the Confusion matrix to determine accuracy of the classification (Figure 11).

While 4 out of 70 test samples of early sunflower were confused with late sunflower, 3 of samples was confused with the “other” class (Figure 11). Likewise, confusion occurred between the late sunflower and paddy classes. The lowest accuracy percentage (0.22) was obtained in the "other" class due to the insufficient learning and test samples. Likewise, insufficient accuracy rate was obtained in the maize (0.67) and paddy (0.76) classification due to the small number of sampling as well. This confusion between paddy and second or late sunflower is thought to be the result of a coincidence of their growth periods when they reach the highest vegetation levels. For this reason, it would be appropriate to develop intermediate algorithms by using different properties (distinctive reflectance differences in different periods and bands) to eliminate this confusions.

The differences in the reflectance and NDVI values of sunflower during the sowing, ripening and harvesting periods allowed to create very good class assignment algorithms despite the confusions that encountered in the classification. Finally, early and late sunflowers were classified with 98% and 92% accuracy, respectively. Although sunflower itself provided high accuracy, the lack of sufficient representative samples for other crops reduced the overall accuracy of the classification (Kappa: 0.82). Increasing the number of samples for all crops makes it possible to obtain more precise results as it can improve the crop separation algorithms.

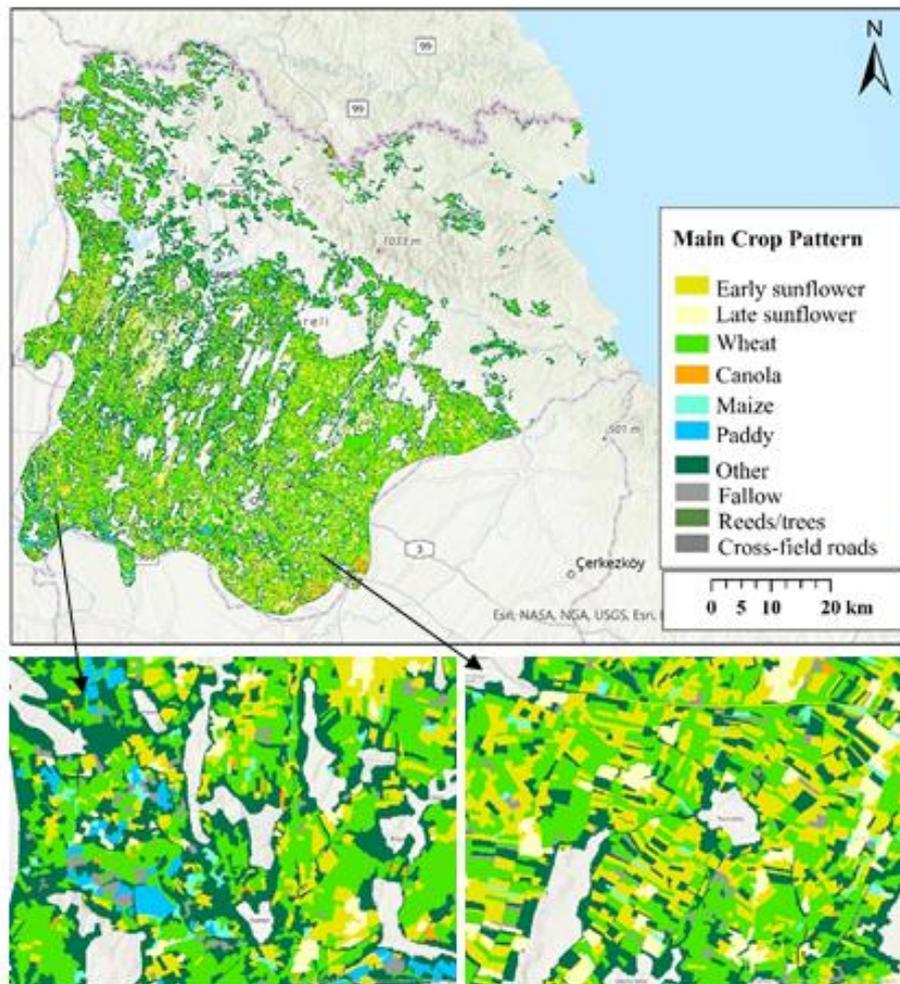


Figure 10. Sunflower cultivated areas and main crop pattern in Kırklareli (2018).

Class	Early sunflower	Late sunflower	Wheat	Maize	Canola	Paddy	Fallow	Other	Total	U Accuracy	Kappa
Early sunflower	61	1	0	0	0	0	0	0	62	0.98	0
Late sunflower	4	44	0	0	0	0	0	0	48	0.92	0
Wheat	0	0	36	0	6	0	0	1	43	0.84	0
Maize	1	0	1	6	0	0	0	1	9	0.67	0
Canola	0	0	2	0	11	0	0	0	13	0.85	0
Paddy	0	4	0	0	0	13	0	0	17	0.76	0
Fallow	1	0	0	0	0	0	5	0	6	0.83	0
Other	3	1	1	1	0	1	0	2	9	0.22	0
Total	70	50	40	7	17	14	5	4	207	0	0
P_Accuracy	0.87	0.88	0.9	0.86	0.65	0.93	1	0.5	0	0.86	0
Kappa	0	0	0	0	0	0	0	0	0	0	0.82

Figure 11. Confusion matrix and accuracy coefficients.

Discussion

Our primary aim in this study was to develop a methodology for determining sunflower cultivated areas using crop growth cycle time series of satellite images and vegetation index (NDVI). For this purpose, a pilot study was conducted to determine one-year (2018) crops pattern for the province of Kırklareli. Sampling study was carried out to set crop-based learning and test datasets in July. However, in order to make long-term crop production planning, a spatio-temporal database of crop rotation pattern is essential (Waldhoff et al., 2017).

In this study, classification decision algorithms were developed by overlapping the sampling parcels with

spectral signature and NDVI time series. The algorithms were developed by creating sub-regions in different land structures in the East-West-North-South directions of the study area, and tested in the whole area in order to achieve the final decision.

A parceling structure that could represent the actual cultivated areas was produced in order to make object-oriented crop classification with image processing techniques. A series of segmentation algorithms was developed in the creation of this parceling structure (Watkins and Van Niekerk, 2019). The biggest problem encountered in segmentation was the identification of non-agricultural areas. Especially, determining the roads between the fields and scattered settlements required a

different sorting process. In order to reduce the impact of non-agricultural areas on the classification quality, the agricultural areas were masked using CORINE 2018 CLC and other auxiliary GIS layers. Better results were obtained when segmentation and subsequent classifications were performed on this masked layer. However, despite the masking, scattered settlements, woodlands, reeds, transitions between the fields in the agricultural areas caused irregularities in segmentation. Some auxiliary thematic layers such as roads, river network etc. were used to create a proximity and shape algorithms to reduce the confusion and over-segmentation that was resulted from these irregular structures (Waldhoff et al. (2017; Zhong, et al., 2016; Zhong and Zhou, 2019). However, some of these thematic layers (e.g. river network) did not fit the actual terrain when overlapped with satellite images due to the errors in coordinate transformations and/or digitization. For this reason, highly incompatible layers were not included in the classification decision algorithms.

The test sample parcels were downloaded from the cadastral parcels data portal of the General Directorate of Land Registry and Cadastre, and the segmentation parcels were compared with the cadastral parcels. However, the existence of different crop areas and different agricultural practices in a single cadastral parcel made this comparison meaningless. (Figure 9). As a matter of fact, since the algorithms were created over the actual status of the cultivated areas using the satellite images, the segmentation parcels were directly compared with the satellite images, and the iteration process continued until the most visually optimal result was obtained.

Crop-based classification decision algorithms were developed using the crop growth threshold values of spectral signature and NDVI time series. These algorithms were tested with different periodic threshold values and classification hierarchies, and then improved with the confusion matrix and error coefficients (Congalton and Green, 2009; Zhong and Zhou, 2019).

As a result, a high accuracy level of 98% has been obtained in determining the early sunflower cultivated areas while improvement is still required in determining the late sunflower (92%) areas as well as the other main crops.

Conclusion

Crop growth periods may differ in terms of both crop growth cycle and remotely sensed features depending on many factors such as climate, topography, altitude, soil characteristics, variety and irrigation. For this reason, the crop pattern should be evaluated depending on these change factors, and the classification algorithms should be developed on a local basis by creating sub-homogeneous areas. In Turkey, crop monitoring is performed according to the farmer's statements that are registered in the farmer registration system (ÇKS). Although the accuracy of these statements is discussed on every platform, still no technological monitoring

system has been established across the country or regionally. Within the scope of the Agricultural Information System (TARBİL), an agricultural observation network was established with considerable investments. A vast amount of data was accumulated through this monitoring network, but unfortunately, it could not be transformed into a valuable information for decision-makers due to its underlying complexity.

Turkey has very variable topographical, morphological, soil and climate characteristics. This complex structure makes it almost impossible to manage crop monitoring in a national scale with a holistic approach. Even though the agricultural basins were produced to serve regional action plans, they are still insufficient since spatio-temporal changes of cultivated areas are not being monitored by real-time remote sensing data. This study shows that a local algorithm approach is needed even in an area of 6550 km² (Kırklareli) where the difference in altitude is about 200 m. Therefore, better economic solutions for crop monitoring actions in Turkey can be planned in local and regional scale using time series of high resolution low-cost or free images like SENTINEL 2A.

Mapping of crop rotation and yield estimates are an increasing requirement to determine effective governmental subsidies for crop production, and to develop policies that can be measured more accurately in production planning. Considering the size of Turkey's agricultural lands and the current agricultural potential, we are still increasingly dependent on imports for many agricultural products. However, we can overcome this struggle with domestic agricultural production by developing innovative and applicable low-cost local crop production monitoring systems, and with effective farmer/producer support policies based on controllable spatio-temporal data. Therefore, it is an inevitable fact that central and local governments should cooperate in order to develop local crop monitoring and management systems and to provide more effective support to farmers/producers. The crop pattern variety can be detailed by increasing the learning and test samples of all cultivated crops especially the crops in the 'other' class in future works of this area. All grains were grouped in the 'wheat' class due to the high amount of wheat cultivation than other cereals. However, in the future studies, methods can be developed for separation of similar crops such as cereals by increasing the radiometric and spatial resolutions besides more detailed crop-based field observations.

In this study, with its methodological approach, has revealed that crop pattern can be accurately determined by using time series of high spatial-radiometric resolution satellite images and including field observation into the classification algorithms that is performed by crop experts.

Acknowledgements

This study was performed within the scope of the "National Product Monitoring and Yield Estimation

Project" that was supported by TOB-TAGEM Research Program.

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