DETERMINATION OF MAIZE PLANTATIONS ON A LARGE-SCALE AGRICULTURAL BASIN WITH SENTINEL 2 SATELLITE IMAGES

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KEY WORDS: Sentinel 2; maize plantation, object-based classification, Cukurova Basin

ABSTRACT: This study focused on the determination of maize cultivated lands in Cukurova Basin, Turkey with the object-based classification of Sentinel 2 satellite images assisted with near real-time field campaigns. Cukurova Basin includes one of the biggest agricultural plains of Turkey and ranks first in the production of maize, soybean and pistachio. In addition, a considerable amount of cotton plantations are applied on the plain in addition to citrus farming, which makes the agricultural pattern of the plain too complex. This study uses a single-date image mosaic as input data for classification. Field campaigns provided several ground-truth parcel data with planted crop type, which is used to extract the spectral responses of crops through image bands. This information is used for defining a threshold-based classification schema. Results of the study indicate that, by designing a threshold-based hierarchical classification schema concerning spectral responses of the crops, over 90% accuracy can be achieved in the detection of maize planted parcels.

1. INTRODUCTION

Increment in the human population brings out extensive food requirements all around the world, which increases the need for efficient monitoring and management of the agricultural fields. Especially, basic food products such as wheat, barley, maize are becoming more vital for the world's food policies (Löw and Duveiller, 2014). Mapping and monitoring the agricultural lands is useful for managing crop risks, implementing plantation policies and controlling the water use (Gallego et al., 2014, Araya et al., 2016). However, monitoring the agricultural lands that spread over large areas is a challenging task.

Remote sensing satellites provided valuable support in agricultural monitoring at local and regional scales for decades, by providing multispectral images, thus providing repeatable and continuous measurements over large areas (Gitelson et al., 2002, Begue et al., 2018). The use of remote sensing data in agricultural monitoring has increased especially with the launch of free of charge Landsat satellite series (Biradar et al., 2009). In the last decade, Sentinel 2 twin satellites improved this opportunity with high spectral and temporal resolution capabilities. Specifically, the availability of red edge bands and five-day revisit time, makes the Sentinel 2 satellite images an efficient data source for agricultural studies (Vanino et al., 2018, Feng et al., 2019).

From the satellite image perspective, there are mainly two categorical camps for agricultural monitoring and cultivated area detection. One group of methods mainly focuses on crop mapping by use of spectral features of the satellite images combined with textural or spatial features such as homogeneity entropy, dissimilarity etc. (Bannari et al., 2006). The second group of methods use high temporal image dataset and to analyze the crop phenology with help of spectral vegetation indices and spectral features to determine the crop type (Shao et al., 2016). On the analysis side, one of the main requirements is to determine the cultivated area detection of crops. While machine learning classifiers are popular among pixel-based approaches (Cai et al., 2018), object-based classification becomes an important option especially if a parcel-level determination is required (Pena-Barragan et al., 2011).

This study proposes an object –based classification approach to determine the maize planted parcels in a large basin with use of single date Sentinel 2 satellite image mosaic and threshold based rule set extracted from spectral and textural properties of the image with the aid of near real time field campaign. The rest of the paper is organized as, description of the study area and used dataset, methodology that includes pre-processing of the data, object-based classification and accuracy assessment, experimental results and accuracy metrics and lastly the concluding remarks.

2. STUDY AREA AND DATA

Cukurova Basin is located in the southern part of Turkey and hosts a large alluvial plain named Cukurova Plain that is surrounded by mountains on its North and East (Figure 1). The plain is fed by important rivers that are Ceyhan, Seyhan and Goksu, which makes the basin as one of the most agriculturally productive areas in Turkey. Main agricultural products of the region are cotton, soy, peanuts, corn, wheat, maize and various fruits and vegetables. Mid and east parts of the basin receive an annual precipitation of 1000 - 1500 mm while west part receives 600 - 700 mm (Papila et al., 2020).

As the main data of this study, Sentinel 2A satellite images of basin were downloaded as MSI L1C processing level. The region is covered by six image frames all of which were acquired on 16.05.2018. The ground truth data used in this study are collected through field work, an initial 100 coordinated samples with different agricultural crops, to be used for spectral information extraction - classification (Figure 2), and an independent 635 coordinated samples for accuracy assessment.

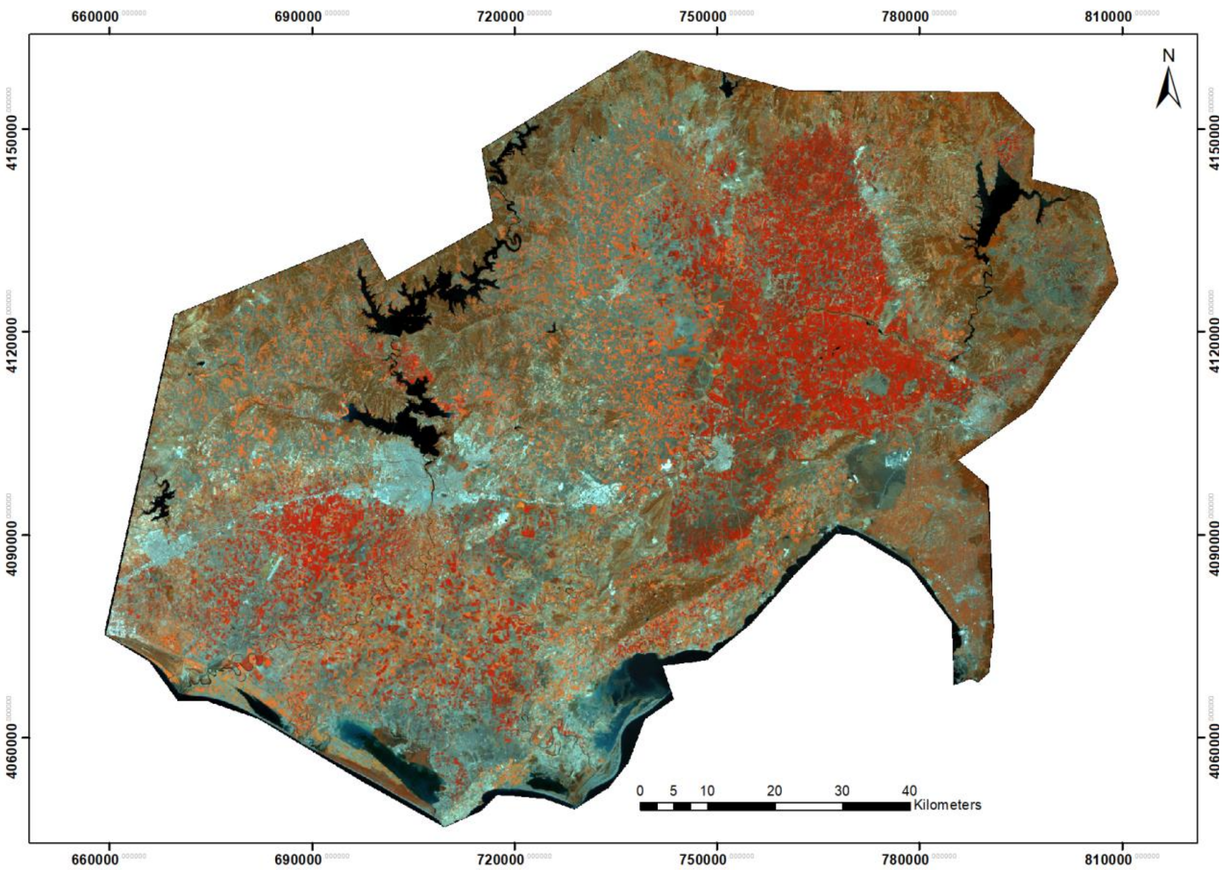
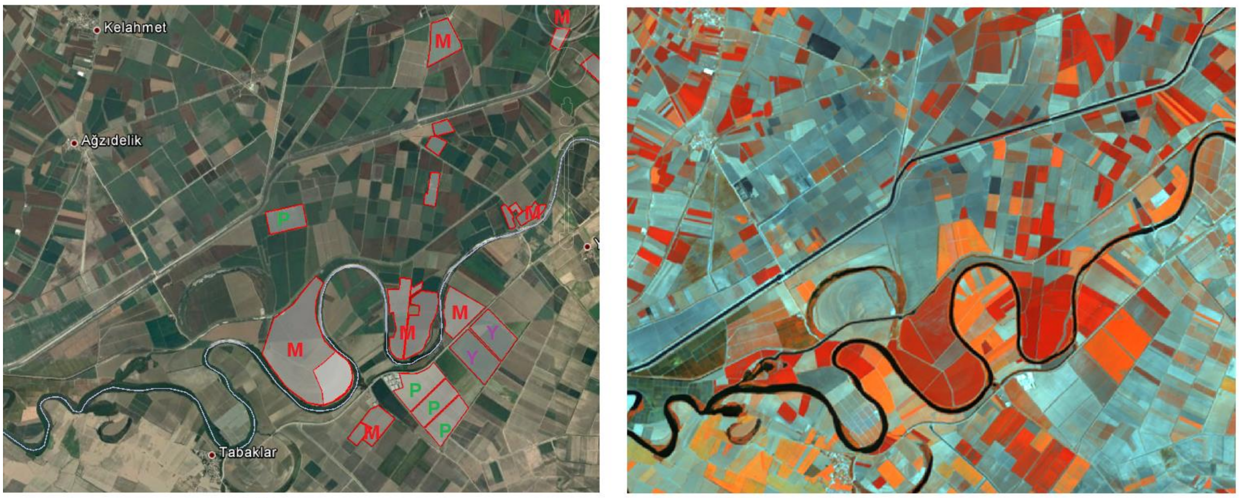


Figure 1. Sentinel 2 satellite image composite of Cukurova Basin dated 16.05.2018 (R: Red edge 3, G: Red edge 1, B: Red)



(a) (b)

Figure 2. a) Set of ground samples overlaid on Google Earth © (M: Maize, P: Cotton, Y: Clover), and b) corresponding Sentinel 2 mosaic dated 16.05.2018 (R: Red edge 3, G: Red edge 1, B: Red)

3. METHODOLOGY

3.1 Pre-processing

The first step of the preprocessing is the atmospheric correction of the Sentinel 2 MSI L1C processed satellite images to obtain the ground reflectance values from the quantized digital numbers. This process was performed using the ATCOR module of PCI Geomatica© software. The process requires image acquisition date, solar zenith and azimuth angles, and band order information as the basic input parameters to perform correction, that were extracted from the metadata file of the image. In the first step, a cloud mask was produced from the blue band of the image with "26%" seed ToA, "20%" lowest ToA, and "4 pixels" dilation parameters. For the next step, Aerosol type, seasonal condition, and constant visibility parameters were set to "rural", "mid-latitude winter" and "30 km" respectively. Further correction steps require the use of a digital elevation model (DEM) to derive the topographic variation, illumination variation, and spectral scattering information. In this research, slope, aspect, illumination and shadow maps were produced from ALOS –W3D DEM data due to its reported accuracy performance (Alganci et al., 2018). In the last step of atmospheric correction, adjacency effects and bidirectional reflectance effects were minimized. The adjacency correction is performed with a 9 pixels size kernel filter through 2 iterations. A linear BRDF function with incidence and exitance angles based on correction factor was applied in this research. The atmospherically corrected Sentinel 2 images were recorded as 16-bit surface reflectance data.

In the second step, six 20m spatial resolution bands of the images were up sampled to fit the initial four 10m resolution image bands. This process was performed by cubic convolution resampling method. In the third step, the process of creating image mosaics that will cover the whole area from the pre-processed image frames was employed. At this stage, the mosaic process was completed by determining the image overlap areas, determining the junction lines on these areas, histogram equalization and color balancing processes. In the last step, mosaic image was clipped by mask vector in order to maximize the coverage of the agricultural areas in mosaic.

3.2 Object-Based Classification

Within the scope of parcel level image classification, an object-based approach was deemed appropriate. For the segmentation process, which is the first stage of the analysis, a multiresolution segmentation algorithm is used. The algorithm aims to determine the most appropriate scale parameter for the whole area, based on the necessity of expressing different objects in different scales in line with their size and texture characteristics, especially in study areas with heterogeneous cover types. The scale parameter controls the amount of spectral variation of the pixel group that will make up the object and the resulting segment size. The first of the two complementary parameter sets in the segmentation process is the Shape – Color components. Shape and color are defined to complement each other with a value of 1, and which parameter will be prioritized in determining the object boundaries is determined according to this weighting. Shape properties are also determined by the sub-parameters of compactness and smoothness (Bhaskaran et al., 2010, Blaschke, 2010).

Different parameter set experiments were carried out on the data set created within the scope of the study, and the parameters that produce the objects in which the surface cover types are represented in a meaningful way were determined. In this context, the most appropriate segmentation was achieved with the parameter set defined with scale factor: 40, shape: 0.3, and compactness: 0.5. After the segmentation process, the class definition was made with the help of the threshold values determined for different image bands according to the spectral and texture statistics of the segment, taking into account the ground-based verification data of the maize plant and the spectral characteristics given in Figure 3. In the next step, the class definition was tested on the image and the visual interpretation of the formed class elements, the threshold values were revised and the optimum threshold value set was determined. Accordingly, the threshold values determined for the maize class are given in Table 1.

Table 1. Optimized thresholds for the parameters for maize determination

Feature	Threshold
Band 3 (Mean Val.)	$0 \leq B3 \leq 600$
Band 5 (Mean Val.)	$B5 \leq 1100$
Band 7 (Mean Val.)	$2900 \leq B7 \leq 5200$
Band 9 (Mean Val.)	$1000 \leq B7 \leq 2200$
GLCM Homogeneity	GLCM $\geq$ 0,20

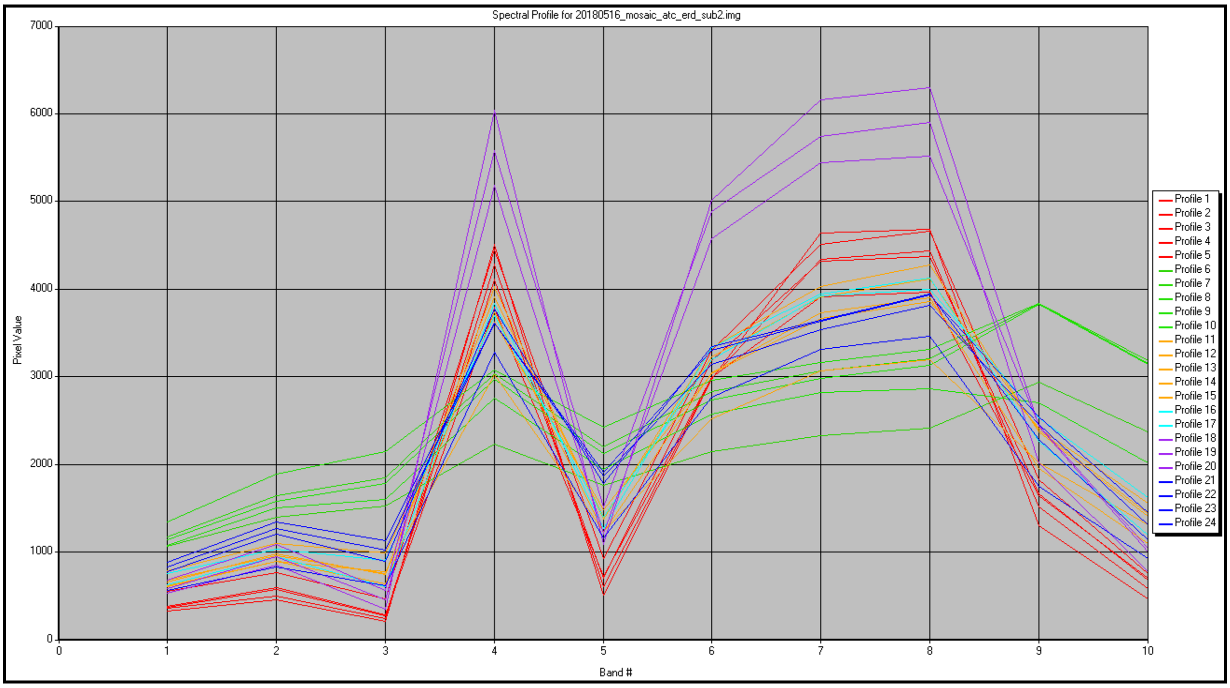


Figure 3. Sentinel 2 spectral characteristic curves of different product types (Profile 1-5: Corn, Profile 6-10: Cotton; Profile 11-15: Mandarin – Orange, Profile 16-17: Lemon, Profile 18-20: Clover, Profile 21- 24: Other perennial) according to band order (Blue, Green, Red, NIR, Red Edge 1, Red Edge 2, Red Edge 3, NIR 2, SWIR 1 and SWIR 2)

3.3 Accuracy Assessment

The accuracy assessment procedure was applied on the classification result throughout a single class strategy. In this approach a class overall accuracy is found by dividing the validated ground samples to sum of validated and invalidated samples and multiply by 100 as given in Formulae 1:

$$\text{ACCURACY} = (\text{OK} / (\text{OK} + \text{NOK})) \times 100 \qquad (1)$$

4. RESULTS AND DISCUSSION

Classification results were converted to vector data and bend simplification was applied. Areal calculations were performed based on four sub regions; Region 1: Ceyhan, Region 2: Tarsus and Seyhan, Region 3: Imamoglu and Kadirli, and Region 4: Yuregir. These sub regions were defined according to field campaigns in which ground truth information was collected. The classification result visual is presented in Figure 4, and areal statistics were provided in Table 2.

Table 2. Areal maize plantation statistics for the sub regions of Cukurova Basin.

Sub Region	Area (Ha)
Region 1	37,531.71
Region 2	15,518.06
Region 3	29,762.66
Region 4	20,211.56
TOTAL	103,023.99

When the results are both visually and statistically evaluated, it can be asserted that, overall performance of the object-based classification in maize detection is acceptable. The analysis approach performed better in vast and homogenous maize planted areas and errors are raised from low cultivated and fragmented agricultural lands especially nearby the urban lands.

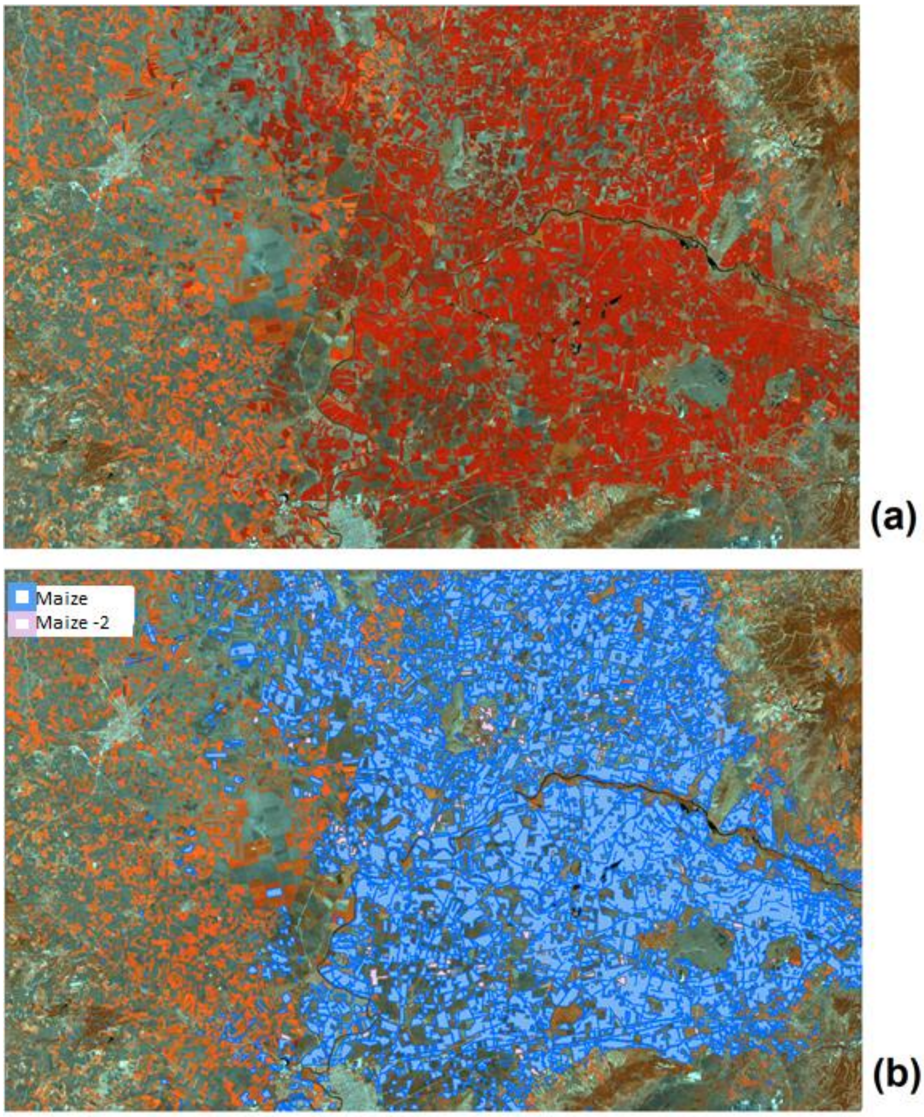


Figure 4. a) Original Sentinel 2 image and b) maize and maize candidate classes as vector overlaid on image.

When the maize planted plot areas determined by this parametric set were evaluated using the validation data, it was determined that most of the ground truth parcels defined as maize were classified correctly and few of the ground truth parcels belonging to other species were classified as maize. On the other hand, some parcel groups, which have a lower spectral average than the value ranges determined in the 7th band, and which are not similar to other cultivated product types, were encountered. It is highly probable that maize is cultivated in these plots (2nd level maize candidate), and the spectral difference in question may arise due to the shift in the planting calendar or the problems that occur in plant development. Considering this situation an additional field check with 35 points was performed for the maize candidate class and it is observed that 72.73% of them are maize and 27.27% is corresponding to orange and lemon gardens. However, these mixed parcels were not removed from the final map to avoid biased accuracy assessment. The independent accuracy assessment results are provided in Table 3.

Table 3. Accuracy assessment results of maize planted and other agricultural lands from classification.

REGION /CLASS	MAIZE				OTHER				OVERALL
	TOT	OK	NOK	ACC (%)	TOT	OK	NOK	ACC (%)	ACC (%)
Region 1	63	59	4	93.65	43	40	3	93.02	93.40
Region 2	78	70	8	89.74	49	48	1	97.96	92.91
Region 3	139	129	10	92.81	16	16	0	100.00	93.55
Region 4	121	107	14	88.43	126	122	4	96.83	92.71
TOTAL	401	365	36	91.02	234	226	8	96.58	93.07

5. CONCLUSION

The purpose of this study is to provide an object-based approach to determine the maize cultivated lands in parcel level. The results of the study provided that object-based classification of Sentinel 2 satellite images provided reliable results for maize plantation detection and suggests an area estimation that can be used by agricultural stake holders. The findings of the experimental setup inform that a hierarchical threshold based ruleset can be effectively constructed if ground truth parcel information is available for different crop types. Experiments also suggest that high crop mapping accuracies can be achieved with even single-dated satellite image data set if the crop phenology of the region is known. Further studies are planned to compare these results with multi-temporal dataset and machine learning classifiers to achieve a comparative evaluation.

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