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Object-Based Crop Mapping Using Multi-Temporal Landsat 8 Imagery

Ahmet Cilek*, Suha Berberoglu*
**(Department of Landscape Architecture, Cukurova University, 01330, Adana, Turkey*
Corresponding Author : Ahmet Cilek

ABSTRACT
This study aimed to map crop pattern using object-based classification technique within a Mediterranean agricultural land in Turkey. Many Mediterranean land covers show similar spectral characteristics that make it difficult to identify in feature space by simple per-pixel classifiers. Therefore, an object-based classification is a potential solution for the classification of land cover in such environments., Appropriate segmentation parameters play a vital role for accurate mapping in object-based image classification. The optimum segmentation parameters were determined by testing on complex agricultural parcels. Each agricultural parcel was assigned a crop type using object-based classification techniques. Two different periods, classified as winter and summer, were classified with high accuracy in the study area. For the crop mapping, March and April are the best imaging times for winter, and between May and August are the best imaging times for summer crop season. Overall accuracy of the classification results, were derived through kappa statistics of 0.85 for winter and summer crop mapping.

Keywords - agricultural land cover, object-based classification, Remote Sensing.

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I. INTRODUCTION

Optical remote sensing (RS) plays a vital role in defining land use/cover and monitoring interactions between nature and human activities. Additionally, RS provides time, energy and cost saving. Nowadays, optical RS data such as satellite sensor images and aerial photos are used widely to detect land cover dynamics [1].

Remote sensing images from space have always been an obvious and promising source of information for deriving crop mapping. Monitoring crop yield near-real-time and covering many crops are essential. This is particularly true for Cukurova plain, which is one of the most fertile plain in Turkey and a primary producer and exporter of agricultural commodities.

Supervised classification methods are the traditional methods used to determine the agricultural crop pattern using multi-temporal satellite (Landsat MSS, TM, ETM, OLI, Spot-XS, Rapideye, Sentinel-2 etc.) [2].

The irrigated agricultural areas in Turkey increased from 1.6 million ha in 1965 to 5.0 million ha in 2006 [3]. Now, Turkey is 11th country in the global ranking regarding the coverage of irrigated area, and yet irrigated area is still intended to increase with new projects, especially at the southeastern part of Turkey. So, the use of RS data through object-based crop mapping has been largely explored within this study.

II. MATERIALS AND METHOD

2.1. Study area

In South Central Turkey, three main rivers, namely the Ceyhan, the Seyhan and the Berdan, rise in the Taurus mountains and flow into the Mediterranean Sea. They form a broad, alluvial plain called Çukurova Plain. The climate which is relatively mild and humid in the winter months, and the alluvial soil make the area highly suitable for agriculture [4]. Cukurova, as a study area is one of the major agricultural production areas of Turkey including crops such as, citrus, maize, cotton, wheat and soya. Cukurova covers an area of 217.000 ha, and almost 174.088 ha was arable lands, and the 80% of the area is irrigated through Seyhan Dam Lake [5] (Fig. 1).

Fig. 1. The location of the study area.

The delta is very flat, with most of the area is under the 20 m altitude. The altitude reduces towards the South, approaching to the Mediterranean Sea. The slope of the delta ranges between 0.1 to 1 %. The soil in the delta is alluvial developed from deposits of the three main rivers. These are the deepest and most fertile soils, with significant soil being calcic fluvisol (young river terrace soil) and chromic vertisol (old river terrace soil) [4,6].

2.2. Dataset

Ground surveys were conducted in April 2015, July 2015 and September 2015 to collect data on crop types and other land cover classes. Dominant agricultural crops were used in this study as a basis for land cover/use types. In total, 255 parcels are collected as a ground truth using mobile devices with built-in GPS.

Remote sensing images acquired by Operational Land Imager (OLI) sensor aboard Landsat-8 satellite was used for crop mapping over the study area. Landsat-8/OLI acquires images in eight spectral bands (bands 1-7, 9) at 30 m spatial resolution and in panchromatic band eight at 15 m resolution [7]. Two scenes with path/row coordinates, 175/34 and 175/35 cover the region. Dates of acquisition were February 07, April 28; May 06 used for winter crop mapping, June 17, August 02-08, September 03-11 for summer crops.

2.3. Methods

The study consisted of crop identification by object-based classification using multi-temporal satellite images. This method is based on image objects combining the pixels with the similar spectral characteristics. It is a thriving approach to address pixel-based problems, particularly in the classification areas of specific shape and reflection (such as agriculture, settlements, roads, etc.). There are three stages in object-based classification as segmentation, classification and accuracy assessment (Fig. 2). In the segmentation phase, the scale factor, complexity and shape factors determine the quality of each image object. The scale factor indicates the minimum number of pixels in an object while the shape factor determines whether its formal integrity (square, rectangular, arc, etc.) is the norm. The complexity factor is concerned with how sensitive the reflection differences could be.

The error matrix approach is generally used in accuracy assessment [8]. Reference data collection, classification scheme, sampling scheme, spatial autocorrelation, and sample size & unit must be considered to produce an error matrix [9]. Kappa is the difference between the observed accuracy and the chance agreement divided by one minus that chance agreement [1, 10].

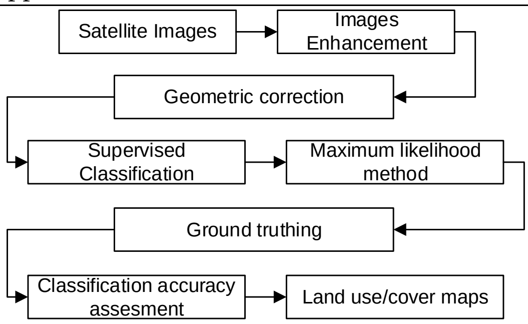

Fig. 2. Flow chart of the methodology.

III. RESULTS

Agricultural crop pattern was determined in two periods as summer and winter. These crops are predominantly wheat in the winter season, while corn, cotton and soybean are predominant in the summer season. Citrus production in the area also has an economic importance.

Segmentation variables were defined experimentally considering pixel spectral similarities, the structure of the image and surface texture characteristics. In this context, the overall object size was estimated as 15 pixels equal to 1.35 ha.

Ground truth data were also derived from interpreting high-resolution imagery, existing classified imagery, or GIS data layers. The most common way to assess the accuracy of a classified map is to create a set of random points from the ground truth data and compare with classified data in a confusion matrix.

Each land use/cover class shows different reflection values at different wavelengths. However, some class reflections are similar in some growing periods. In order to distinguish such crops, satellite images in March and April were selected for the winter crop pattern, and satellite images in May–June and July–August were chosen for summer crop patterns to improve the classification results.

As a result of winter classification, 33033 ha wheat, 30457 ha citrus were determined in the study area for 2015 winter cropping season (Fig. 3).

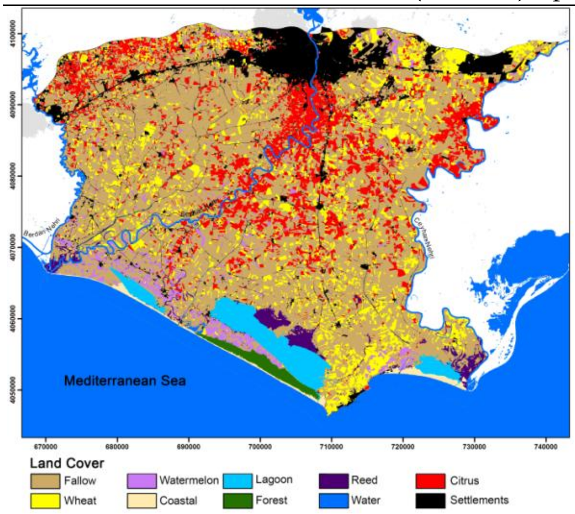

Fig. 3. 2015 Winter land cover map of the study area.

Summer crop classification for 2015 resulted 76778.5 ha of 1st maize, 20499.6 ha of cotton, 17796.7 of 2nd soya and 6343.6 ha of watermelon in the study area (Fig. 4). Kappa statistics of 2015 classification was derived using ground truth dataset collected during each crop rotation period.

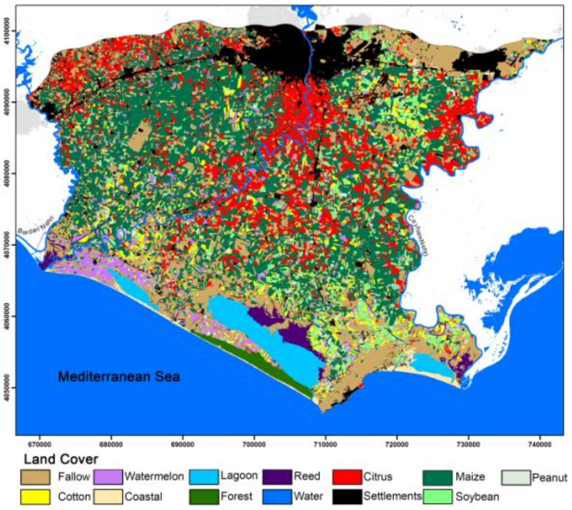

Fig. 4. 2015 Summer land cover map of the study area.

Classification accuracy was derived using 120 ground truth points using kappa statistics. Kappa co-efficiencies of 2015 crop pattern classifications were derived using ground truth dataset where is collected from field works in each crop rotation period. Winter crop classification of wheat and citrus was 0.84, 0.80, respectively (Fig. 5).

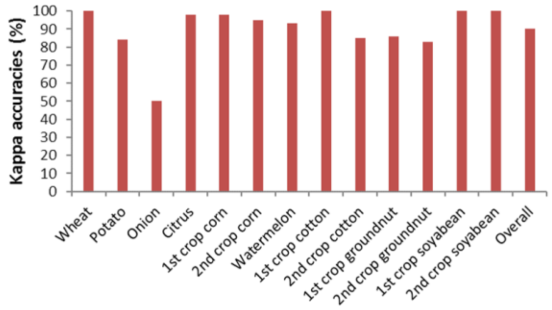

Fig. 5. Kappa statistics of winter and summer crops

IV. CONCLUSION

This research was conducted to predict the spatial distribution of crops using object based remote sensing techniques in the Cukurova plain, Turkey. Winter and summer agricultural crops were classified from multi-temporal Landsat 8 images. In conclusion, Landsat dataset was efficient to predict wheat, citrus, maize and cotton crops. Object-based classification technique has strong potential for monitoring crops. Especially for annual crops, the use of single time image is insufficient to classify agricultural land cover due to the presence of high variation in spectral signatures of different crop types during the growing periods.

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