PARCEL-BASED CROP MAPPING THROUGH MULTI-TEMPORAL MASKING CLASSIFICATION OF LANDSAT 7 IMAGES IN KARACABEY, TURKEY.

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ABSTRACT:

This study describes the parcel-based classification of agricultural crops using multi-date Landsat 7 ETM+ images acquired in May, July, and August 2000. The study area is located in North-West of Turkey with an area of about 170 km^2 and grows a variety of crops. The objective was to map the summer (August) crops within the agricultural land parcels. The classification methodology is based on a multi-temporal masking of Landsat 7 ETM+ images. First, a supervised per-pixel classification of the three images (May, July, and August 2000) was performed using a maximum likelihood classifier algorithm. The accuracy of classified outputs was computed by comparing them with the ground truth information. Those classes that meet the threshold values were masked out and the August image was re-classified using the unmasked classes only, excluding the masked fields from the classification. The masking technique was applied to overcome the problems caused by the spectral overlaps between the information classes. After completing the classification process, the multi-temporal classified output of the August image was analyzed in a field specific manner in the integration of remote sensing and geographic information system (GIS). In each parcel, the percentages of classified pixels were computed and the modal class label was assigned to the parcel. The analysis results were fed back to a GIS database for immediate update. The resulting classification accuracy of the multi-temporal masking technique was 81%, which was 10% more accurate than the classification of the August image only.

INTRODUCTION

Automated image classification is one of the most widely used techniques to extract thematic information from remotely sensed data of the earth. The thematic information is increasingly being used in varies fields, such as in agriculture to monitor and estimate crop development and its spatial distribution. Thus, up-to-date and accurate classification results are required for analyses which provide basis for deciding and implementing policies and plans for management of agricultural crops in local, regional and global scale.

Classification can be subdivided into two methodologies pixel-based and parcel-based classification. Unfortunately, the land cover classes do not have uniform spectral response due to atmospheric effects, noise, heterogeneity within the land cover types, and mixed pixels present at the boundaries (Ioka and Koda, 1986; Janssen et al., 1990; Lunetta et al., 1991). Thus, resulting classification often includes misclassified land cover types. In order to overcome this problem and increase the reliability of classification accuracy for land cover identification in agricultural lands, the classification can be performed using a parcel-based approach.

In parcel-based classification, the remotely sensed imagery is integrated with vector parcel boundaries that explicitly provide the spatial context of agricultural parcels. By including the spatial context in the classification, individual parcels are classified instead of single pixels. Thus, the uncertainty caused by per-pixel classification is eliminated and the classification accuracy can be increased up to a certain extent (Janssen et. al., 1990; Johnson, 1994; Aplin et. al., 1999). Parcel-based classification techniques are applicable through integration of remote sensing and geographic information systems which provide integrated analysis for raster imagery, vector graphics and attributes. An improvement in the classification accuracy can be achieved by extending the classification method by means of incorporating expert knowledge and ancillary data (Mason et al., 1988; Middelkoop and Janssen, 1991). In the absence of spatial context information, multi-temporal classification together with decision rules yields acceptable accuracies. Such the studies were performed by Beltran and Belmote (2001), and Lanjeri et al (2001).

This study introduces a methodology for integrating remote sensing and geographic information systems to accurately classify agricultural crops. Parcel-based image classification with expert knowledge is carried out to better discriminate agricultural land cover classes. The selected study area is an agricultural land located in Karacabey, Bursa.

STUDY AREA AND DATA

Study Area

The selected study area is situated in Marmara region, near Karacabey, Bursa (Figure 1). The region is a level plain (within 10 m) agricultural land, which is one of the most important agricultural areas in Turkey. The area covers an agricultural land of approximately 170 km^2 of nine villages namely: Hotanli, Kucukkaraagac, Yolagazi, Sultaniye, Eskisaribey, Ortasaribey, Yenisaribey, Akhisar, and Ismetpasa fall within the study site.

The area is characterized by rich, loamy soils which, in addition to the excellent weather conditions, make agriculture the main land use in the region. The agricultural land is predominantly used for the cultivation of arable crops that are wheat, corn, tomato, sugar beet, rice, pepper, and watermelon as well as other crops of secondary importance that are pea, onion and cauliflower. In addition, several pasture and clover fields and small townships are scattered throughout the area.

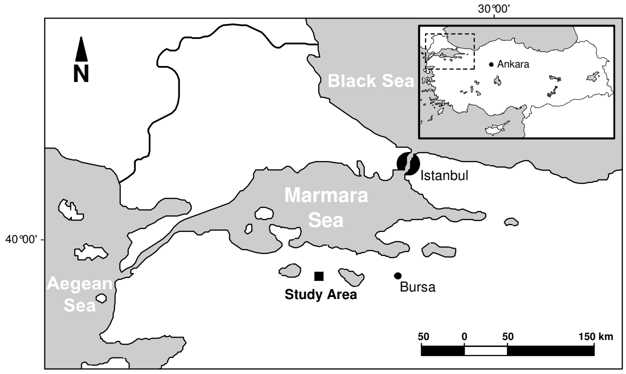

Figure 1. Location of the study area, Karacabey, Turkey.

Figure 2. A color composite of Landsat 7 ETM+ Bands 4, 5, and 3 (RGB) overlaid with the agricultural parcel boundaries.

Data Description

As remotely sensed imagery, Landsat 7 ETM+ data was selected due its wider spectral coverage and availability of a high resolution band (ETM Band 8) for enhancing spatial resolution and features. Landsat 7 ETM+ data having Path: 180 and Row: 32 scenes were acquired on three dates: May 15, July 02, and August 19 2000. These scenes were found to be the suitable dates for monitoring vegetation development in the study area. From each scene, six visible infrared bands (Band 1-5 & 7) having 30 m resolution and one panchromatic band (Band 8) having 15 m resolution were used for the analyses. All three scenes were cloud free and of good quality. Since full scenes were not required for the achievement of this study, the subsets of the images were extracted to match approximately the same coverage with the vector parcel data (Figure 2).

The ground reference data for the study area were collected through communicating with the farmers and making an accurate land cover survey in mid August 2000. Particular attention was paid to the selection of samples representative of the extent and distribution of the land cover categories in the study area. For each agricultural parcel, the current crop situation together with the previous crop grown (where valid) was recorded on the reference land cover map. Final ground reference data of the study was generated through combining information collected from farmers and the land cover survey in the field. The reference data were subsequently used for training and validating the classified outputs. In addition, the knowledge obtained about the relationships between the agricultural land cover classes and the agricultural parcel boundaries were utilized (i.e. sugar beet restricted zones) to improve classification accuracy.

The cadastral maps of the study area were obtained as hard copy form from the cadastral office of Mustafa Kemal Pasa. The area covered by eleven 1:5,000-scale and one 1:7,500-scale cadastral maps.

ANALYSIS

Preliminary Data Processing

The preliminary data processing steps consist of digitizing agricultural parcel boundaries from 1:5,000 to 1:7,500-scale map sheets and relating the attribute data to existing database; and geometric correction following data fusion of the satellite images.

Preparation of Vector Parcel Data: The cadastral maps were subsequently scanned and registered using available control points on the maps. The control points collected in a national datum were georefenced to UTM (Zone 35) projection using nearest neighbor resampling method. The maximum produced RMSE value of 3.60 m was found to be quite satisfactory, since it was less than a half pixel size of Landsat 7 ETM+ imagery. Next, each raster map was digitized using a polygonal topology. When digitizing of raster maps were completed, edge matching was performed to obtain a continuous data layer of agricultural parcels (Figure 2). Together with agricultural parcel boundaries, the supplementary data that came from the cadastral map and the site visit were stored in a geographical information system. The database held parcel information in conjunction with the available land cover information in each parcel for further analyses.

Data fusion: For each subscene, 30-m resolution Landsat 7 ETM+ multispectral bands 1 to 5 and 7 were fused with the 15-m resolution panchromatic band. The resulting fused bands were spatially enhanced while keeping the spectral characteristics close to the original multispectral bands. The algorithm used has been developed by Atlantic Aerospace. It is based on local correlation of edges to improve edges in lower resolution bands wherever a corresponding edge is found in the panchromatic band (Cheng et al., 2000). This is unlike the popular technique of IHS type enhancement, in which the spectral characteristic of each bands are not preserved (Liu, 1999). The Atlantic technique has been integrated to PCI Geomatica and available through the function IMGFUSE (PCI, 2003). The resulting output images were then used as input to subsequent geometric correction process. It is important to note that the geometric correction is not required prior to data fusion in case of Landsat 7 ETM+ since both data are co-registered at the satellite.

Geometric correction: To integrate Landsat 7 ETM+ images with the vector polygon parcel boundaries, it was necessary to register both data sets to a common map coordinate system. For this purpose, vector to image registration is performed using Landsat 7 (L1G) images and vector parcel data as reference layer. Georeferencing was carried out using just about 35 ground control points (GCPs) for each subscene through a polynomial transformation and nearest neighbor resampling method. For all images, RMSE values were calculated less than 0.5 pixels (7.5 m) in both X and Y directions.

Parcel based Analysis

The principal objective of this study was to develop a parcel-based classification methodology in the integration of remote sensing and GIS in order to map the summer (August) crops within the agricultural land parcels. For this purpose, a number of agricultural land cover classes were determined for each of the Landsat 7 ETM+ images with the help of reference data kept in a GIS database. Prior to collecting the training areas, boundary pixels of adjacent agricultural parcels were excluded using a binary raster mask. Since, boundary pixels manifest the spectral mixture of two or more land cover classes, thus cause misclassification. Therefore, only those pixels that fall within the agricultural parcel were kept for further analyses.

For each scene, Bands 3, 2, 1 and 4, 5, 3 were utilized as RGB components on separate video display windows. Displaying bands 4, 5 and 3 as infrared colour composite is useful for monitoring the vegetation development during training process. The images were overlaid with vector polygon layer and then through querying GIS database, boundary of each land cover type were separately displayed over the images to locate the known land cover classes and define training areas. Block training was carried out to select blocks of pixels from the centre parts of the referenced land parcels. During training procedure, heterogeneous land cover classes were avoided since they would increase the spectral overlap between the classes. A number of samples were collected for each class with respect to amount and the size of the parcels as well as their dispersion throughout the study area.

The August training set comprises the following eleven information classes: corn (Cor), residue (Res), tomato (Tom), sugar beet (Sbe), clover (Clo), pasture (Pas), pepper (Pep), watermelon (Wme), uncultivated land/bare soil (Unc/Bso), rice (Ric) and cauliflower (Cfl). The training samples were refined through examining their histograms and scatter plots. Those classes that include two or more different spectral characteristics were subdivided into separate spectral classes. Such as the corn subclasses: cor-01, cor-02, cor-03 and cor-04. The classification accuracy is generally improved when each subclass represented as separate spectral class (Lillesand & Kiefer, 1994).

After completing the training selection for August image, the same agricultural parcels were utilized to collect the training samples for July and May images, respectively. However, training areas were re-edited to reflect any variation in spectral characteristic of a particular class or altering land cover type for a particular scene. A final set of statistics were generated for seven classes in May and twelve classes in July.

Optimum band selection: Once the training statistics were assembled from each band for each land cover, a decision must be made to determine the most suitable bands for discriminating the land cover classes in the imagery. For this purpose, the Principal Component Analysis (PCA) was performed to obtain new channels in the classification process. The first four PCA channels of each date having total variance higher than 99% were used within the analysis. In addition to PCA channels, most effective bands were identified through examining class separability based on the divergence of the class signatures. As a result, a subset of best four bands was extracted for each scene. These were ETM+ Bands 3, 4, 5, 7 for May and July scenes, and Bands 2, 3, 4 and 7 for August scene.

Classification: For each date, maximum likelihood classifier was utilized with equal probability assumption for all classes. The classification was essentially performed using the bands 1 to 5 and 7. In addition, the first four PCA channels and the best four band combinations were also classified. Each classified image was subsequently processed to aggregate the spectral sub-classes into associated information classes using a scripting language. The resulting classified images were then integrated with the vector polygon layer to perform parcel-based analysis.

Parcel-based analysis was performed by computing the class frequencies within each parcel and assigning the parcel the class labels based on the highest frequency computed from pixel-based classified image. The results of parcel-based analysis were stored as attribute within the database.

Regional masking: Prior to the multi-temporal analysis, we have performed a masking based on the knowledge obtained from the relations between land cover classes and the agricultural parcel boundaries. In our case, the knowledge represents the cultivation practice in the study area. That is, the cultivation of sugar beet was restricted by the government agencies into a group of agricultural parcels. And similarly, cauliflower was merely grown within the boundaries of Hotanli village. Knowing these facts, the database was populated to reflect the relations regarding to restriction zones for cultivation. Using the database, regions of cultivation were defined as regional masks to include and/or to exclude training areas of sugar beet and cauliflower. Then using the regional masks, parcel-based classification was performed on both July and August images, where both sugar beet and cauliflower were cultivated.

Multitemprol Analysis

The methodology presented in this part of the paper is based on enhancing the discrimination potential of supervised image classification through combining maximum likelihood classifier, parcel-based analyses, and multi-temporal masking technique (Figure 3). The method was implemented using Landsat 7 ETM+ images. In addition, Principal Component Analysis (PCA) channels and the best four bands were used in the analyses. Through analyses of multi-temporal images set, it is possible to achieve better discrimination of land cover classes that simply could not be achieved, otherwise, through analysis conducted on single date imagery.

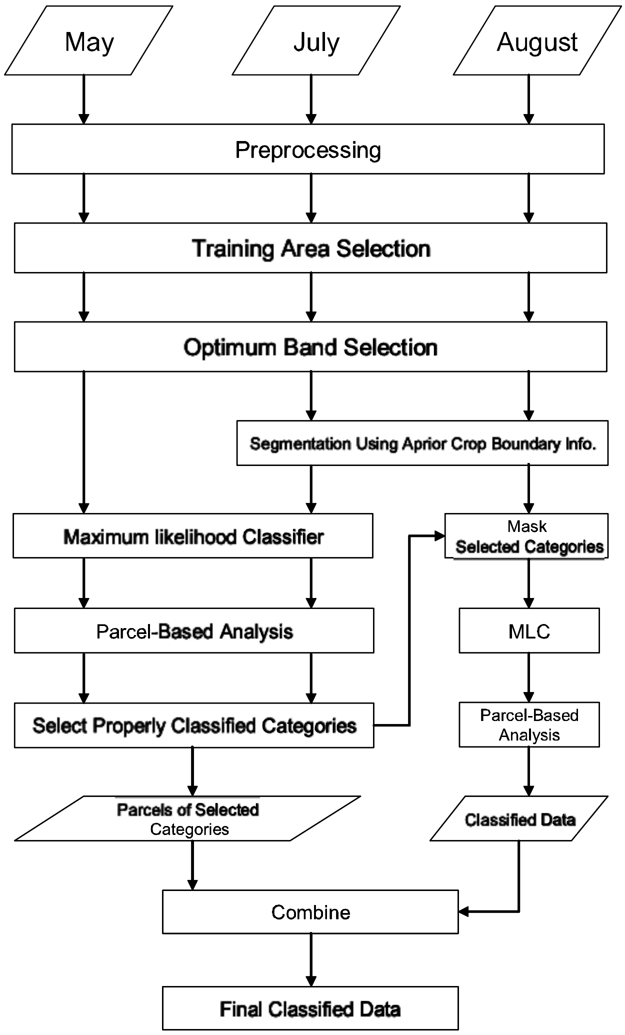

Figure 3. The flow chart of the multi-temporal masking classification technique.

In this study, to overcome the spectral confusion between the agricultural land cover classes using multi-temporal satellite images, a sequential multi-temporal crop masking procedure was utilized through the classification. After each classification step, those categories accurately classified were taken out from the classification process.

The procedure was carried out as follows: The classified images of the original bands, the PCA channels and the optimum bands from each date were evaluated to determine the accurately classified land cover classes. Those common classes with high accuracy in May and July classified images were identified and their training set were taken out from the classification of August imagery. For a particular class to be masked out from further classification process the accuracy threshold was selected as 80% and 90% for the producer's and user's accuracies respectively. The following crops, which fulfilled above accuracy requirement, were determined not to be included in the classification of August imagery: clover from classified May PCA image, residue and rice from classified July original image with regional masking applied, and sugar beet from classified July PCA image with regional masking applied (Table 1). Therefore, these classes were masked out and were not included within further classification process.

Image Classified	Class	Producer's Accuracy (%)	User's Accuracy (%)
May PCA Channels	Clover	100.0	100.0
July Originals Bands (with regional masking)	Residue	93.1	92.0
July Original Bands (with regional masking)	Rice	80.0	100.0
July PCA Channels (with regional masking)	Sugar beet	80.2	95.5

Table 1. The accuracy of the classes to be used in multi-temporal masking.

The original bands of the August image were re-classified using only the training areas of unmasked classes. At each step of pixel-based classification, successively, the crops not cultivated within the crop cultivation zones were excluded together with the crops classified on previous dates. The classification output of the August image was then combined with the classification outputs of the masked classes in order to obtain final summer crop inventory of the study area (Figure 4).

RESULTS

The accuracy assessment of a classified image is an important step as it indicates a measure to show how reliable is the information extracted from the remotely sensed data. To assess the classified images, the ground reference data were compared, parcel by parcel, with each of the three classified images for May, July and August, respectively.

On May image, overall the classification accuracy of the original bands (ETM+ bands 1 to 5 and 7) was 88.9%. That was 0.5% more accurate than PCA bands and 1.4% more accurate than the optimum bands. On July image, the number of classes was increased to twelve since the crops seeded in May were grown and therefore represented heterogeneity within the study area. As well, owing to phenological evolution of the vegetation, the spectral variation increased within the parcels. Thus, the number of spectral class as belonging to each information class increased per information class to be extracted. In this sense it was logical to expect drop in overall accuracy. The overall accuracy of 66.8% was achieved from the classified original bands of July. The overall accuracies for classified optimum bands and the PCA bands was 62.5% and 61.2%, respectively. After applying regional masking, no change was observed in the overall accuracy of the classified original bands of July, however, improvements were observed in the user's accuracy of some classes such as cauliflower by %15.

Most of the land cover types that were present in the July image were also observed in the August image. A total of eleven classes were classified from the August image. Most of the crops were in their late stages of the development. Therefore, their spectral responses were better representative of their inherent spectral characteristic compared to July image. This introduced a reduction in the number of subclasses for each class and therefore, an improvement was observed in the accuracies of several classes and in the overall accuracy. The overall accuracies of the classified original bands and the optimum four bands were quite close. The accuracy of the classified PCA bands was found to be 69.2%. In August, the overall accuracy of the parcel-based classified original bands was 70.8%. After applying the regional masking in the classification, the overall accuracy was computed as 73.8%. Applying the multi-temporal masking technique together with the regional masking to original bands (1 to 5 and 7) of the August image provided an overall accuracy of 81% (Table 2). The improvement in the classification accuracy was gained through the masking of the classes which were accurately classified on previous dates (May and July 2000). The resulting classification accuracy of the multi-temporal masking technique was 10% more accurate than the parcel-based classification of the original bands of the August image only. The misclassifications might have been caused largely by spectral confusion which was not overcome through parcel-based analyses, multi-temporal analyses, available ancillary data and remotely sensed data in hand.

August	Parcel-based		Multitemporal	
Class	Producer's Acc. %	User's Acc. %	Producer's Acc. %	User's Acc. %
Corn	76.0	87.4	77.4	86.2
Residue	70.2	98.9	93.1	100.0
Tomato	85.4	72.3	86.6	77.3
Sugar beet	60.4	95.3	80.0	100.0
Clover	50.0	100.0	100.0	100.0
Pasture	100.0	40.0	100.0	66.7
Pepper	50.9	32.9	52.8	38.4
Watermelon	57.1	80.0	64.3	75.0
Unc/Bso	22.4	42.9	57.1	23.5
Rise	90.0	75.0	80.0	100.0
Cauliflower	57.1	27.0	53.1	81.0
Overall	70.8		81.3	

Table 2. Producer's and User's accuracies for each class, for parcel-based and multitemporal analysis of August original bands.

As a summary, the accuracies of the parcel-based classified August images were found to be higher than the July images. It is not logical to make a comparison with the May image since the May image contains significantly less number of classes than the August image. The classified original all bands provided higher overall accuracies than the other classified band sets. However, several classes that provided low accuracy in the classified original all bands yielded higher accuracy in the other band sets. For example, the classified PCA channels of the May image yielded an accuracy of 100 percent for clover, while the accuracy of sugar beet was 2 percent higher in the classified PCA bands than the classified original all bands for July.

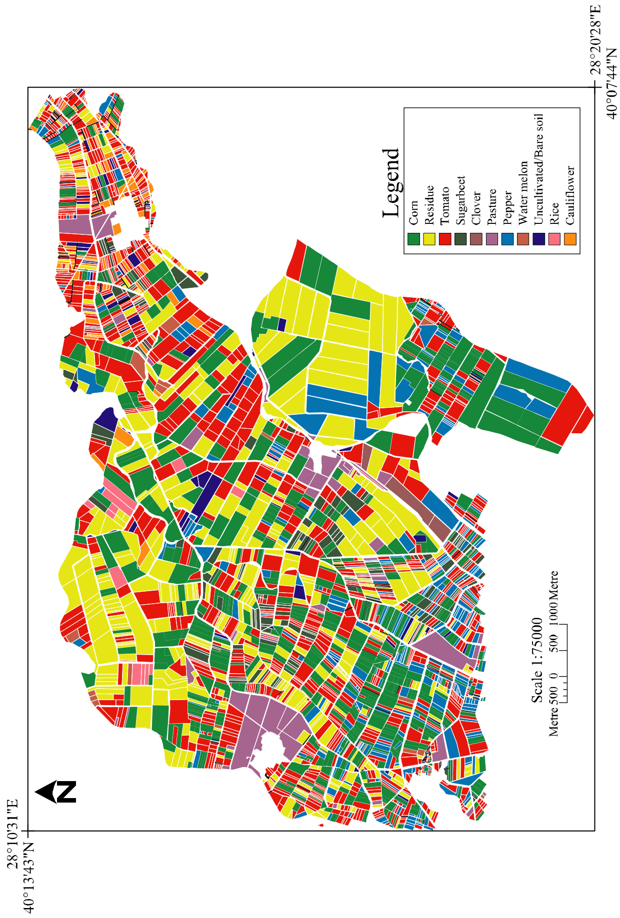

Figure 4. The multi-temporal classification output of the August image.

CONCLUSION

Nowadays, crop estimation and monitoring become one of the major applications in remote sensing. In this study, mapping of the summer (August) crops was performed using a multi-temporal masking technique together with the parcel-based analyses of the classified images. The discrimination of the agricultural land cover classes in the study area, Karacabey, was carried out using variations in spectral responses throughout the growing season. The proposed methodology includes a synergistic combination of maximum likelihood classifier, parcel-based analyses, and the multi-temporal masking technique.

The limitation of the spatial resolution of Landsat 7 ETM+ was overcome through fusing the multispectral bands with the panchromatic band. The spectral variations introduced within agricultural parcels were resolved through incorporating the spatial context kept in a GIS vector polygon layer. The classification accuracy attained from the parcel-based classification was improved after introducing the PC channels and the best four bands as well as masking the selected crops for which the phenological evolution were taken into consideration. The class labels were assigned to each agricultural parcel in a field specific manner in the integration of remote sensing and GIS. The accuracy of the final classified data was increased from 70.8% (for parcel-based classification only) to 81.3% for the 2000 summer crops (August) classification.

The parcel-based classification together with the multi-temporal masking technique was found to be quite effective for establishing the inventory of the summer crops in the selected study area. However, multi-temporal analyses become less effective to resolve spectral confusion between classes if one of the scenes has fewer amounts of classes. Using the multi-temporal crop masking technique, misclassifications, which were caused by spectral overlaps was overcome up to a certain extent.

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