

FIELD-BASED CROP MAPPING THROUGH SEQUENTIAL MASKING CLASSIFICATION OF MULTI-TEMPORAL LANDSAT-7 ETM+ IMAGES IN KARACABEY, TURKEY

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ABSTRACT:

This study presents a field-based crop mapping through sequential masking classification of multi-temporal Landsat-7 ETM+ images acquired in May, July, and August 2000 in Karacabey, Turkey. First, the classification of each image date was carried out on a standard per pixel basis. The results of the per pixel classification were integrated with digital agricultural field boundaries and for each field, a crop type was determined based on the modal crop class calculated within the field. The classification accuracy was computed by comparing the reference data, field-by-field, to each classified image. The individual crop accuracies were examined on each classified data to determine those crops whose accuracy exceeds a preset threshold level. Then, the multi-temporal masking classification of the crops was carried out in sequential steps using the three image dates, excluding after each classification the crop properly classified. The masking technique was applied to overcome the problems caused by the spectral overlaps between some classes. The final classified data was analyzed in a field specific manner to assign each field a crop label. An immediate update of the database was provided by directly entering the results of the analysis into the database. The use of sequential masking procedure for field-based crop mapping improved the overall accuracies of the classifications of the July and August images alone by more than 10%.

1. INTRODUCTION

The availability of remotely sensed images and the advances in digital processing and analysis techniques have enabled research scientists to have information about the type, condition, area, and the growth of agricultural crops. Image classification is one of the crucial techniques in detecting the crops from remotely sensed data. Most current automatic classification techniques to obtain land cover maps from digital imagery operate on a per-pixel basis in isolation from other pertinent information. Therefore, per-pixel techniques often yield results with limited reliability. The reliability of image classification can be improved by including a priori knowledge about the contextual relationships of the pixels in the classification process. Agricultural field boundaries integrated with remotely sensed data divide the image into homogeneous units each of which can be analyzed separately. In each field, the geometry of field boundaries defines the spatial relationships between the pixels contained within, and enables those pixels to be processed in coherence. The decision by the analysis is taken, for each field, based on the coherent processing of the pixels falling within the field. Therefore, the standard per-pixel image classification can be replaced by a classification which operates in a field specific manner.

Field-based approaches to the classification have been adopted by several researchers (Catlow *et al.* 1984; Mason *et al.* 1988; Janssen *et al.* 1990; Janssen *et al.* 1992; Aplin *et al.* 1999; Turker and Derenyi 2000; Aplin and Atkinson 2001). To perform field-based classification, the vector field boundaries must be integrated with the imagery. The integration between the two data sets can be achieved at three

stages: (i) before classification, (ii) during classification, and (iii) after classification. Usually, field-based classification employs the integration between raster imagery and vector data after classification (Brisco *et al.* 1989; Janssen *et al.* 1990; Janssen *et al.* 1992; Aplin *et al.* 1999; Turker and Derenyi 2000; Aplin and Atkinson 2001). The imagery is classified on a per-pixel basis before integrating the classified output with digital vector data. A per-field analysis is then carried out to assign each field a class label based on the analysis of the classified pixels contained within the field. The success of a field-based approach that incorporates vector data after a per-pixel classification depends mainly on the success of the classification. Several studies have shown that multi-temporal images improve the classification accuracy by utilizing different spectral responses of the land cover classes over a period of time according to phenological evolution (Maracci and Aifadopoulou 1990; Conesa and Maselli 1991; Kurosu *et al.* 1997; Panigrahy and Sharma 1997; Beltran *et al.* 2001; Lanjeri *et al.* 2001; Murakami *et al.* 2001).

The objective of this study was field-based mapping of summer (August) crops in Karacabey, Turkey through sequential masking classification of Landsat7 ETM+ satellite data. The sequential masking classification technique was applied to improve discrimination between the crop classes. We made an assumption that each field grows one type of crop. Field-based classification was performed by computing the percentages of classified pixels within each field and assigning a class label to the field based on the majority class. The fields were selected through a database query and the results were directly inserted into the database.

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2. THE STUDY AREA AND DATA DESCRIPTION

The study area is a 18 km by 13.5 km site situated near the town of Karacabey, Bursa in northwest of Turkey (Figure 1). The geographic boundaries of the area are N40°07'44" - N40°13'43" and E28°10'31" - E28°20'28". The main crops grown in the region are tomato, corn, pepper, wheat, onion, and sugar beet. The villages that fall within the study area include Akhisar, Eskisaribey, Hotanlı, Ismetpasa, Kucukaraagac, Sultaniye, Yenisaribey, and Yolagzi. In the region, a land consolidation project was performed between 1988 and 1992. Therefore, majority of the fields have regular shapes that affect the classification accuracy. However, a significant number of small fields exist in the area. The size of the fields range from 0.0074 to 48 ha. The elevation difference across the study area is very small (within 10 m). The Landsat7 ETM+ images (Path:180, Row:32) used in the classification were acquired on May 15, 2000, July 2, 2000, and August 19, 2000. All images were cloud free and of good quality. A 600 pixels x 450 lines (multispectral) subscene covering the study area was extracted to perform the proposed sequential masking classification procedure.

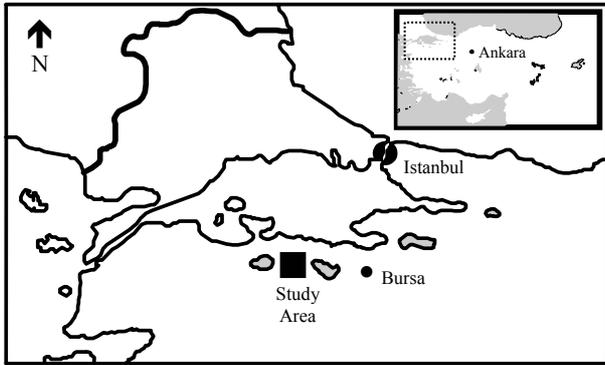


Figure 1. The study area.

3. DATA PRE-PROCESSING

The field boundaries were digitized from the cadastral map sheets. The maps were converted into a raster form by scanning them. Each raster map was registered to Gauss-Kruger (Zone-5) projection and datum ED50 using six grid intersections. The registration was based on first-degree polynomial and nearest neighbor resampling techniques. The registration accuracies were between ± 1.14 m and ± 3.59 m. Next, the field boundaries were manually delineated through on screen digitization and stored as vector polygons in the database. Each polygon was assigned an identification number and the crop types were recorded as attributes for those fields from which reference information was collected during site visit. There were a total of 2977 fields.

The multispectral bands (1-to-5 and 7) and the panchromatic band were merged for each image date. The fused image retains the spatial resolution of the panchromatic band, yet provides the spectral properties of multispectral bands. Furthermore, the field-based classification of a higher spatial resolution image would be advantageous for small fields since the number of pixels falling within the fields will increase. The fused images were geometrically corrected to Universal Transverse Mercator (UTM)-zone 35 projection and the European Datum 1950 (ED50). The geometric

correction was based on second-degree polynomial and nearest neighbor resampling techniques. The root mean square error (RMSE) values were computed as ± 0.52 pixels for the May image, ± 0.67 pixels for the July image, and ± 0.59 pixels for the August image.

We displayed the merged August image on the screen with the digitized field boundaries overlaid, and those fields (275 in total) that contain multiple crops were identified through visual inspection. The sub-boundaries within the fixed geometry of these fields were then delineated through on screen digitization and each sub-field was assigned an identification number. There were 424 new sub-fields. With these new sub-fields the total number of fields increased to 3401.

4. THE METHODOLOGY

A total of 1083 fields were visited on the ground. For each field, crop type was collected as essential information and the database was populated with the new data. For each image date, the training samples were selected from all crops found in the study area. The field boundaries were displayed on the screen in superimposition with the raster imagery. For each class, those fields from which reference information was collected during site visit were selected through a database query. Thereby, the boundary pixels were avoided. The following classes were defined for the May image: bare soil, wheat, clover, pasture, rice, pea, and onion. The July classes include corn, residue, tomato, sugar beet, clover, pasture, pepper, watermelon, bare soil, rice, cauliflower, and onion. The classes defined for the August image are the same as the July classes except for onion, which does not exist in August. For each class, a group of representative pixels were delineated within designated fields. Approximately 10% of the ground-visited fields were used in training, while the other fields were set aside to be used as check fields to perform accuracy assessment.

A per-pixel supervised classification of the images was performed using the maximum likelihood method. For each image date, the classification was carried out on bands 1, 2, 3, 4, 5, and 7. In addition, Principal Component Analysis (PCA) was carried out to obtain new channels. In the present case the first 4 components of the May, July, and August images provided 99.77%, 99.60%, and 99.76% respectively of the total variance of the original data sets. Therefore, the first 4 PCs were used in the classification.

Upon completing the per-pixel classification, the integrated analysis of the classified images and the vector field data was carried out. To eliminate the effect of the boundary pixels on the classification, a narrow corridor was generated along the boundary inside each field. Field-based analysis was performed by computing the class percentages within inside corridor boundaries of each field and applying the entire field the label of the modal class. For each field, the class percentages and the final class label were automatically inserted into the database. To compute classification accuracy, the reference data were compared, field-by-field, to each of the six classified images. The error matrix was used to measure the accuracy of each classified output. The accuracies of individual classes and the overall accuracy of all bands and the first 4 PCs classifications are given in tables 1 and 2.

May			July			August		
	PA (%)	UA (%)		PA (%)	UA (%)		PA (%)	UA (%)
Bs	94.2	97.9	Cr	56.1	76.1	Cr	76.0	87.4
Wt	86.8	99.4	Rs	93.1	92.6	Rs	70.2	98.9
Cl	50.0	100	Tm	71.9	65.8	Tm	85.4	72.3
Pa	100	64.7	Sb	78.3	95.4	Sb	60.4	95.3
Rc	50.0	62.5	Cl	50.0	100	Cl	50.0	100
Pe	60.0	81.8	Pa	66.7	83.3	Pa	100	40.0
On	60.0	10.0	Pp	16.4	18.0	Pp	50.9	32.9
Overall: 88.9	Wm	7.7	25.0	Wm	57.1	80.0		
	Bs	80.0	9.8	Bs	22.4	42.9		
	Rc	80.0	100	Rc	90.0	75.0		
	Cw	34.3	48.0	Cw	57.1	27.0		
	On	50.0	7.0					
				Overall: 66.8			Overall: 70.8	

Table1. Producer’s and user’s accuracies of individual classes for the classification of all bands.

Bs: Bare Soil; Wt: Wheat; Cl: Clover; Pa: Pasture; Rc: Rice; Pe: Pea; On: Onion; Cr: Corn; Rs: Residue; Tm: Tomato; Sb: Sugar Beet; Pp: Pepper; Wm: Watermelon; Cw: Cauliflower; PA: Producer’s Accuracy; UA: User’s Accuracy

May			July			August		
	PA (%)	UA (%)		PA (%)	UA (%)		PA (%)	UA (%)
Bs	92.8	98.3	Cr	43.9	67.7	Cr	76.4	87.4
Wt	85.8	100	Rs	92.0	93.0	Rs	67.2	98.9
Cl	100	100	Tm	66.1	61.3	Tm	83.7	70.7
Pa	100	61.1	Sb	80.2	95.5	Sb	54.5	96.5
Rc	60.0	54.5	Cl	50.0	100	Cl	50.0	50.0
Pe	62.2	84.8	Pa	60.0	69.2	Pa	100	37.8
On	70.0	10.6	Pp	14.5	13.6	Pp	49.1	31.3
Overall: 88.4	Wm	7.7	10.0	Wm	64.3	69.2		
	Bs	40.0	3.8	Bs	23.9	37.2		
	Rc	70.0	50.0	Rc	80.0	80.0		
	Cw	28.6	34.5	Cw	51.4	25.7		
	On	50.0	8.5					
				Overall: 61.2			Overall: 69.2	

Table 2. Producer’s and user’s accuracies of individual classes for the classification of the first 4 PCs.

Next, the sequential masking classification was performed. To design the classification procedure, we analyzed the producer’s and user’s accuracies of individual crops and determined those classes with high accuracy. The thresholds of 80% and 90% were defined for producer’s and user’s accuracies respectively. The threshold for the user’s accuracy was kept higher for avoiding wrong masking of the fields belonging to other classes due to commission error. The accuracies of residue and rice were higher than the thresholds on the all bands classification of the July image. The producer’s and user’s accuracies of residue were 93.1% and 92.6% respectively. Rice had a user’s accuracy of 100% and a producer’s accuracy of 80%. The other classes that meet the preset accuracy criteria are clover and sugar beet. While the producer’s and user’s accuracies of sugar beet were 80.2% and 95.5% respectively on the classification of the first 4 PCs of the July image, clover had the highest producer’s and user’s accuracies of 100% on the classification of the first 4

PCs of the May image. The considerably high classification accuracies of residue, rice, clover, and sugar beet can be attributed to their phenological evolution. Therefore, a sequential-masking classification seems to be more suitable. It allows us to perform step-by-step classification of the classes using the multi-date images, excluding after each classification the class properly classified.

The main steps of the proposed sequential classification procedure is illustrated in figure 2. We should indicate that the areas other than agricultural fields, such as roads, channels, and villages were not included in the classification and were eliminated by masking them out. The classification procedure was carried out as follows: First, clover was masked out on the classification of the first 4 PCs of the May image. Those fields classified as clover were excluded prior to further classification and the class training corresponding to clover was taken out. After this operation, the reduced class trainings were used to perform further classification. Next, those fields labeled as residue on the classification of the all bands of the July image were masked out. The reduced class training-set will now contain all crops except clover and residue. Further classification will now be performed over unmasked fields only. After that, those fields corresponding to rice on the classification of the July image were masked before proceeding the classification procedure. The last class to be masked was sugar beet. Finally, the remaining crops (corn, tomato, pasture, pepper, watermelon, bare soil, and cauliflower) were classified using all the bands of the August image through their training statistics only.

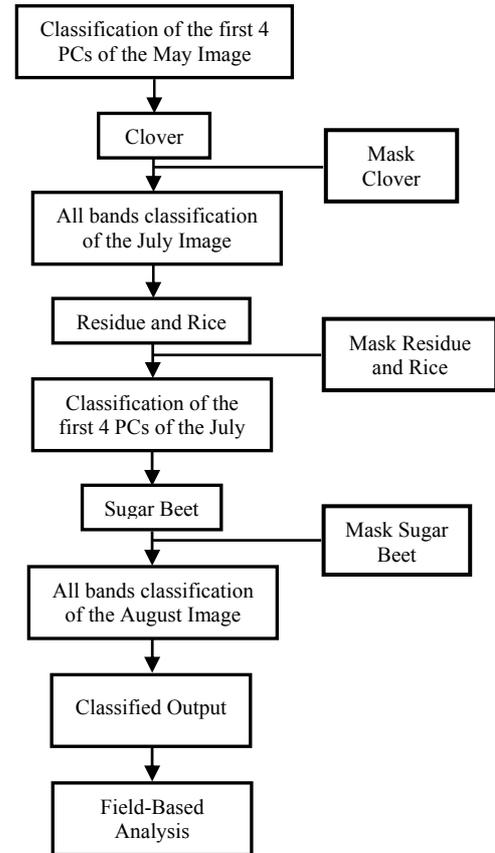


Figure 2. The sequential masking classification procedure.

After completing the masking classification procedure, the classified outputs were combined to make a single classified image. A field-based analysis was then performed on the final classified output by computing the class percentages within each field and applying the entire field the label of the modal class. The result of the multi-temporal masking classification is illustrated in figure 3. The validation of the masking classification was carried out by comparing the reference data, field-by-field, to the classified image. The individual class accuracies and the overall accuracy are illustrated in an error matrix in table 3.

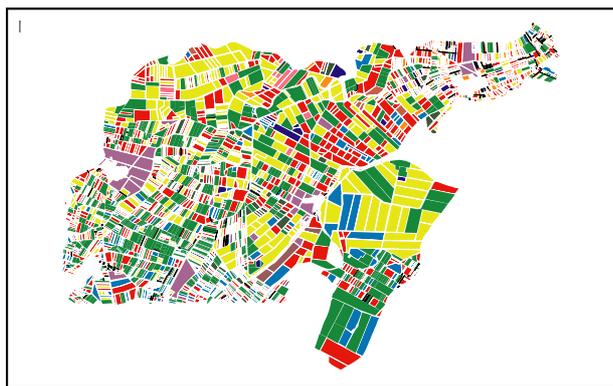


Figure 3. The result of sequential masking classification.

	Reference											
	Cr	Rs	Tm	Sb	Cl	Pa	Pp	Wm	Bs	Rc	Cw	
Cr	181	0	10	1	0	0	14	2	0	1	1	210
Rs	0	162	0	0	0	0	0	0	0	0	0	162
Tm	33	5	252	15	0	0	11	2	3	0	5	326
Sb	0	0	0	84	0	0	0	0	0	0	0	84
Cl	0	0	0	0	2	0	0	0	0	0	0	2
Pa	0	4	1	0	0	14	0	0	0	0	2	21
Pp	18	0	21	4	0	0	28	1	0	0	1	73
Wm	0	0	1	1	0	0	0	9	0	1	0	12
Bs	2	2	3	0	0	0	0	0	4	0	6	17
Rc	0	0	0	0	0	0	0	0	0	8	0	8
Cw	0	1	3	0	0	0	0	0	0	0	17	21
	234	174	291	105	2	14	53	14	7	10	32	936
PA	77.4	93.1	86.6	80.0	100	100	52.8	64.3	57.1	80.0	53.1	
UA	86.2	100	77.3	100	100	66.7	38.4	75.0	23.5	100	81.0	
	Overall: 81.3 %											

Table 3. Error matrix for the sequential masking classification.

5. RESULTS AND DISCUSSION

The producer's and user's accuracies and the overall accuracy for the classification of all bands of the May, July, and August images are summarized in table 1. The overall accuracy of the May image (88.9%) was the highest. The overall accuracies for the July and August images were 68.8% and 70.8% respectively. On May image, bare soil had a producer's accuracy of 94.2% and a user's accuracy of 97.9%. The producer's and user's accuracies of wheat were found to be 86.8% and 99.4% respectively. Among the remaining classes, onion had the lowest user's accuracy. Of the two clover fields, one was omitted. All pasture fields were correctly classified. However, some confusion is evident between pea and pasture. Both the producer's accuracy (50%) and the user's accuracy (62.5%) of rice were below the overall accuracy. The user's and producer's accuracies of pea were 81.8% and 60% respectively. Some

confusion is evident between the pea class and the onion and pasture classes.

The overall accuracies of the July image (66.8%) and the August image (70.8%) were lower than the May image. A large number of fields (446) that were classified as bare soil on May image contain crops at their active growth phase on July and August images. Tomato, pepper, sugar beet, and corn present an important vegetative development in the June-August period. On July image, residue had the highest producer's accuracy of 93.1% and a very high user's accuracy of 92.6%. Both rice and sugar beet also exhibit significantly high accuracies. Pepper, uncultivated land, onion, and watermelon exhibit a significant amount of errors of commission. The producer's and user's accuracies of tomato and pasture were above the overall accuracy. The user's accuracy of clover was computed to be 100% but the producer's accuracy (50%) was significantly low. Similarly, corn exhibits a relatively high user's accuracy (76.1%) and a rather low producer's accuracy (56.1%). The classification of the August image indicates that the producer's and user's accuracies of corn, tomato, pepper and watermelon increased. The user's accuracy of residue and uncultivated land improved but their producer's accuracies decreased. The reverse trend is observed for pasture, rice, and cauliflower which exhibit higher producer's accuracy and lower user's accuracy in the August image classification than the July image classification. The August image classification revealed no difference in the accuracies of clover.

The results of the first 4 PCs classification (Table 2) reveal that the overall accuracy of the May image (88.4%) is the highest. Similar to all bands classification (Table 1) the overall accuracies of both the July and August images are remarkably lower than that of May image. When we compare the overall accuracies of the PCs classification to that of all bands classification it is evident that the PCs classification accuracies are slightly lower. The July image shows the maximum decrease of 5.4%.

The multi-temporal masking classification yields better results (Table 3) than both the all bands classification and the first 4 PCs classification of the July and August images alone. The overall accuracy of the masking classification was computed as 81.3%. When compared to the classification of the July and August images alone the improvement in overall accuracy of more than 10% is evident. This improvement in accuracy with the masking procedure is due to the use of different spectral responses of the crops over a period of time according to phenological evolution. The accuracy of the clover, residue, sugar beet, rice, tomato, and corn classes were quite high. The producer's and user's accuracies of clover were 100%. Residue had a user's accuracy of 100% and a producer's accuracy of 93.1%. It was found that of the 174 reference fields, only 12 were omitted from the residue category. The user's and producer's accuracies of sugar beet were 100% and 80% respectively. It is evident that sugar beet does not exhibit commission error. However, the exclusion of 21 fields out of 105 from this class resulted in 20% omission error. The user's and producer's accuracies of rice were also computed as 100% and 80% respectively. Of the total ten fields, eight were correctly classified through masking classification procedure and two were omitted from rice. Tomato had a producer's accuracy of 86.6% and a user's accuracy of 77.3%. Of the 291 reference tomato fields, 252 were correctly classified. Tomato is most often confused with corn and pepper, and additional imagery can improve

classification accuracy. For corn, the masking procedure resulted in a producer's accuracy of 77.4% and a user's accuracy of 86.2%. Pasture had a very high producer's accuracy (100%) and a rather low user's accuracy (66.7%). It was observed that four residue fields, one tomato field, and two cauliflower fields were improperly included in the pasture class. Watermelon exhibits a relatively low producer's accuracy of 64.3% and a user's accuracy of 75%. Of the 14 reference fields, 5 were omitted from this class resulting an omission error of 35.7%. The user's accuracy of cauliflower (81%) is relatively high when compared to other classes. However, this class illustrates a considerably high error of omission (46.9%) which is caused by the exclusion of 15 fields from this category. Both pepper and bare soil exhibit low classification accuracy. While the producer's and user's accuracies of pepper were 52.8% and 38.4% respectively, bare soil had the lowest user's accuracy of 23.5% and a considerably low producer's accuracy of 57.1%. It is evident that the spectral signatures of pepper and both tomato and corn greatly overlap in the images used in this study.

In comparison with the all bands classification of the August image, the multi-temporal masking classification shows 10.5% increase in overall accuracy. Clover exhibits the highest increase of 50% in the producer's accuracy. A significant increase in the producer's accuracy is also evident for bare soil, residue, and sugar beet. However, while residue and sugar beet exhibit 1.1% and 4.7% increase in the user's accuracy respectively, bare soil shows 19.4% decrease. It appears that the number of the fields that were improperly included in the bare soil class increased with the masking procedure. Among the classes which do not exhibit a significant improvement are corn, tomato, pepper, and watermelon. A significant increase (26.7%) in the user's accuracy of pasture indicates that some of the fields that were improperly included in pasture in all bands classification of the August image were correctly classified with the sequential masking procedure. Cauliflower presents the highest increase of 54% in the user's accuracy. A significant improvement in the user's accuracy (25%) is also evident for rice. However, both cauliflower and rice exhibit a decrease in the producer's accuracy. As an overall, the results show that the masking procedure improve the accuracies and the increase is significant for several classes.

6. CONCLUSIONS

The sequential masking classification of Landsat7 ETM+ images acquired in three different dates (May, July, and August 2000), coupled with field-based analysis, to identify summer crops proved to be better than the uni-temporal classifications. The overall accuracy for the all bands classification of the May image (88.9%) was the highest. This is attributed to the fact that the number of classes are less on May image than that of July and August images and the classes are spectrally distinct from each other. The overall accuracies for the all bands classification of the July and August images were found to be 66.8% and 70.8% respectively. The overall accuracies for the first 4 PCs classifications were found to be slightly lower than that of all bands classifications.

In comparison with the uni-temporal classification results, the sequential masking classification performs better, giving an overall accuracy of 81.3%. The use of sequential masking

procedure improved the overall accuracies of the classifications of the July and August images performed alone by more than 10%. It appears that the masking technique has overcome the problems caused by the spectral overlaps between the classes. The level of classification accuracy achieved in this study through masking procedure is possibly high enough for crop mapping from Landsat7 ETM+ images, and better results may be achieved if additional images are used.

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