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Comparison of Object and Pixel-Based Classifications for Mapping Crops Using Rapideye Imagery: A Case Study of Menemen Plain, Turkey

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Abstract

With the latest development and increasing availability of high spatial resolution sensors, earth observation technology offers a viable solution for crop identification and management. There is a strong need to produce accurate, reliable and up to date crop type maps for sustainable agriculture monitoring and management. In this study, RapidEye, the first high-resolution multi-spectral satellite system that operationally provides a Red-edge channel, was used to test the potential of the data for crop type mapping. This study was investigated at a selected region mostly covered with agricultural fields locates in the low lands of Menemen (İzmir) Plain, TURKEY. The potential of the three classification algorithms such as Maximum Likelihood Classification, Support Vector Machine and Object Based Image Analysis is tested. Accuracy assessment of land cover maps has been performed through error matrix and kappa indexes. The results highlighted that all selected classifiers as highly useful (over 90%) in mapping of crop types in the study region however the object-based approach slightly outperforming the Support Vector Machine classification by both overall accuracy and Kappa statistics. The success of selected methods also underlines the potential of RapidEye data for mapping crop types in Aegean region.

Keywords: Crop mapping, RapidEye, Support vector machine, Object based classification, Maximum Likelihood Classification

Introduction

Accurate, reliable and up-to-date crop type mapping has significant role for economic issues, food policy and environmental implementation and, is very important for sustainable agricultural production. Since climate chancing, agricultural crop pattern and natural vegetation changes need to be monitoring. Compared to conventional methods of surveying, there are many advantages in using remote sensing technology for crop acreage assessment. Remote sensing technology is considered as a powerful and useful tool that enables feasible and practical data acquisition to determine either the extent or the geographical distribution of major crops. It is an important tool for many aspects of agricultural applications due to its ability to acquire measurements of land surfaces cost effectively at various spatial and temporal scales. Typically, the classification is one of the widely used approaches for the extraction of land cover information from remotely sensed data. Since the early 1970s numerous classification algorithms have been developed and applied to digital image processing in different contexts (Townshend, 1992; Pal and Mather, 2004; Lu and Weng, 2007; Kaya et al., 2014; Kumar et al., 2016; Göksel et al., 2018). Among the most popular ones which are the maximum likelihood classifier (MLC), neural network classifiers (NNC) (Pao, 1989) and decision tree classifiers (DTC) (Quinlan, 1993)

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have been commonly used in the past two decades (Pal, 2012). As a parametric classifier MLC has been preferred and commonly used in remote sensing community (Hansen et al, 1996). due to the its simplicity and availability in most remote sensing software packages and, it generates acceptable results (Huang et al., 2002; Zhang et al., 2007).

Neural networks have been widely used in remote sensing as a favored alternative to the statistical classifiers (Benediktsson et al., 1990; Tso and Mather, 2001) since they overcome some problems of MLC by adopting a non-parametric approach. In the literature it is proved that ANNs give better results than MLC (Friedl and Brodley, 1997), due to the fact that ANNs have no assumption on the statistical distribution of the data, thus avoiding problems on estimation of statistical parameters that existed in MLC. As another non-parametric classifier decision trees are also not based on parametric model but use the training data directly for training. Decision tree classifiers first breaks classification problem into multiple stages of simpler decision-making processes (Brodley and Utgoff, 1995) then solves it using univariate and multivariate decision trees depending on the number of variables used at each stage (Tao et al, 2014; Hosseini et al., 2012).

In recent years, Support Vector Machines (SVM), which is based on statistical theory and one of the machine learning algorithms, have been preferred in land use/cover classification since their superior classification performance compared to aforementioned classification techniques (Pal, 2012; Tao et al., 2014). There are many different SVM research applications from coal reserve detection to urban growth monitoring by using different types of remotely sensed data includes spatial resolutions from sub-meter to several kilometers in pixels size and spectral resolutions from panchromatic to hyperspectral (Hosseini et al., 2012). There are several factors they may affect the selection of suitable classification algorithms, such as spatial resolution of preferred satellite imagery, the availability of the classification software and different type of data sources. The spatial resolution is key factor to select the suitable classification method (Liu and Mason, 2009). The latest development of the earth observation technology and increasing availability of high spatial resolution sensors such as the IKONOS, SPOT-5 and RapidEye offers new opportunities and advantages (easiness) for accurate mapping and observation of land surfaces, especially agricultural crops and vegetation (Yang et al., 2011). Though the high spatial resolution satellite images have some advantages to observe the earth surface in detailed, there are some challenges and limitations on data processing such as image classification. Traditional pixel-based analysis of remotely sensed data results in inaccurate identification of some crops due to pixel heterogeneity, mixed pixels, spectral similarity, and crop pattern variability. These problems can be overcome using object based image analysis (OBIA) techniques, which incorporate new spectral, textural and hierarchical features after segmentation of imagery (Barragan et al., 2011). Object-based classification is a technique, which is based on the classification of image objects after segmentation process of remote sensing imagery. This method depends on knowledge-based membership functions that clearly define rules to classify a feature, essentially a group of pixels, rather than applying a single decision rule on a pixel-by-pixel basis (Wuest and Zhang, 2009). Recently, all-inclusive overview of the use of object-based classification research, underlined its potential for thematic information extraction from remote sensing observations (Blaschke, 2010. Object based method (classification) is often related (preferred) to cases in high spatial resolution at many different purposes such as agricultural or economic issues since it outperforms pixel based classification on high spatial resolution (Blaschke, 2010).

Materials and Methods

Study Area

The study region (26 40 E-27 07 E Long; 38 26 N – 38 40 N Lat.) includes ~ 7200 ha area of Menemen (Izmir) plain located in the Gediz Basin in the West of Turkey (Figure 1). The Menemen Plain has a Mediterranean climate. It is uniform in terms of climate and has the typical features of the Aegean Region in general. An arid-humid mesothermal climate prevails with-in the plain. During summer the weather is hot and dry whereas during winter it is warm and rainy. Menemen plain is one of the most well-known agricultural areas of western Turkey. The area is famous for high agricultural production of some traditional crops such as cotton, corn, grapes, vegetables, wheat and other grains, etc. Viniculture is also common in the area. Menemen Plain, has been shaped depending on the activity of Gediz River generally during geological periods and undergone the effect of sea from time to time. Subsurface morphology of Menemen Plain is depression and aggradation styles. The plain is lowland through which the Gediz River is flowing. The river drains a huge region inwards in western Anatolia. The Gediz River floodings have created plain fields, levees and geomorphological depression formations in their surroundings. The land use types of the areas nearby the sea, which have become very salty due to improper drainage practices, are natural pastures. The soil texture and moisture distribution is compatible with the geomorphological units of the plain. The area has a micro relief however the slope in general is between 0%-2%.

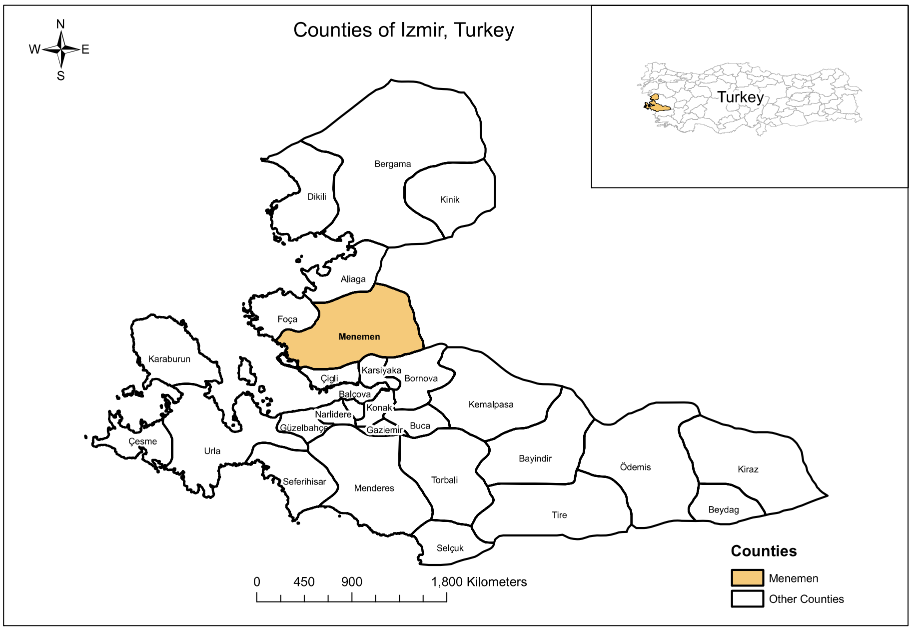

Fig1. Location map of the study area.

Data and field observations

RapidEye is a commercial optical Earth observation mission. It represents a constellation of five mini-satellites and provides high-resolution multi-spectral imagery in five optical bands in the 400–850 nm range. It has been delivering imagery since February 2009 and represents the first space-borne sensor to operationally provide the red edge spectrum (690–730 nm) in addition to providing the standard channels of multi-spectral satellite sensors. The satellites are equally spaced in a single sun-synchronous orbit at an altitude of 630 km. The swath width is 77 km, the revisit time is 5.5 days and the ground sampling distance is 6.5 m (Sandau et al., 2010). Level 3A images were acquired on 08 October 2010 were used in the study to analyze the performance of RapidEye high-resolution data. The delivered scene is free of cloud or haze. The images have 5 m spatial and 16-byte radiometric resolution. All field works synchronized with the remotely sensed data and 115 field data collected during field study using handhold GPS for classification process. Field works were done to determine location of different crop pattern and other land cover types. And also, spatial properties of objects that classified were observed during the fieldwork.

Methodology

In this study, support vector machine (SVM), maximum likelihood classification (MLC), and object based image analysis (OBIA) methods were conducted to high-resolution multi-spectral RapidEye imagery to extract information about crop types in selected region. A summary of the methodology adopted in the study is illustrated in Figure 2 and the image processing details are given in the following sections.

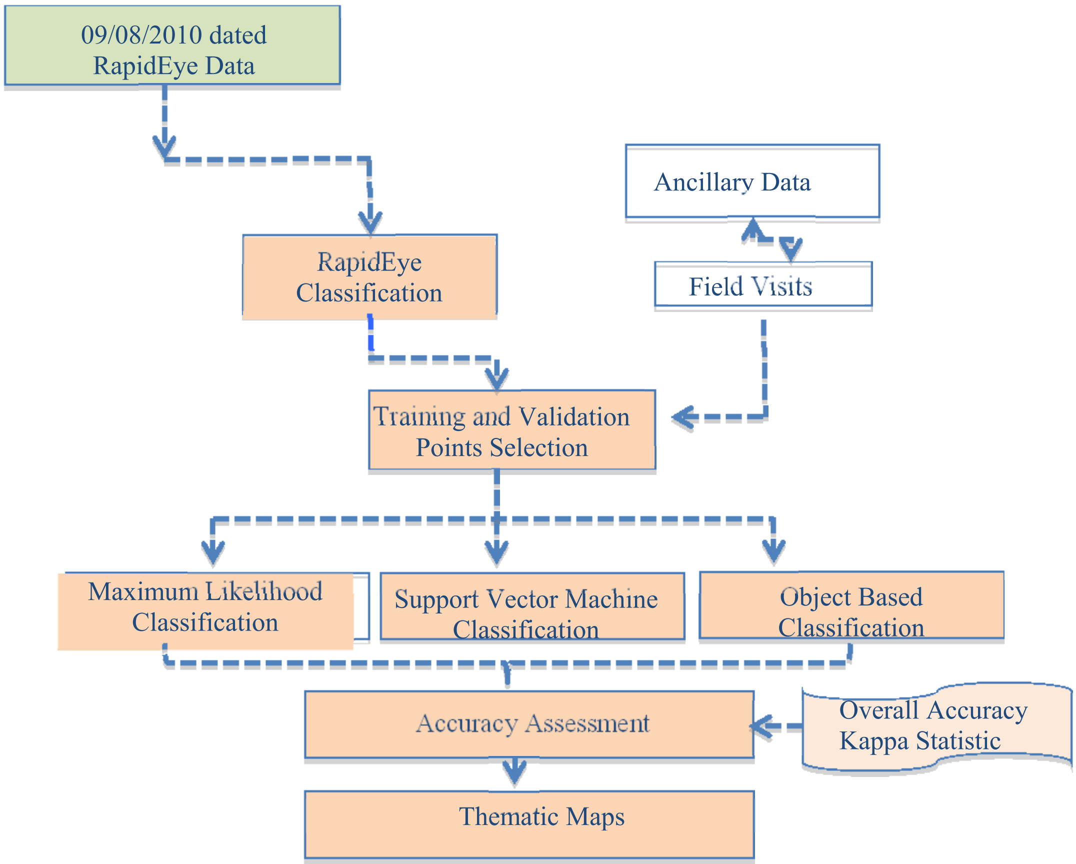

Fig2. Flowchart showing the processing scheme for the implementation of the methodology adopted in the present research study

Classification Methods

Maximum Likelihood Classification

Supervised classification is a technique that based on the statistics of training areas representing different ground objects selected subjectively by users on the basis of their own knowledge or experience (Liu and Mason, 2009). In this study, Maximum Likelihood classification (MLC), which is the most common classification method in remote sensing, was used to derive land use/cover categories. In this method, the pixel is assigned to the class for which the probability of pixel belonging is highest. MLC is based on Bayes' Theorem (Gong, 2002). In the classification stage of RapidEye data, 2393 training and 235 validation samples were determined.

Support Vector Machines Classification

The Support Vector Machine (SVM), which is one of the machine learning algorithms, is based on statistical learning theory and has been extensively used in remote sensing for pattern recognition and classification recently though emerged in the late 1970s by Vapnik

(1995). The brief review and basic information are provided here, readers can find further details for SVM in Vapnik (Mather and Koch, 2011; Huang et al., 2002). It was originally designed for binary classification and provides use of optimal algorithms to locate best boundary separating the binary classes in feature space (Huang et al., 2002). Here the boundary is called optimum separating hyperplane aimed maximize the margin width (Mather and Koch, 2011) (Figure 3).

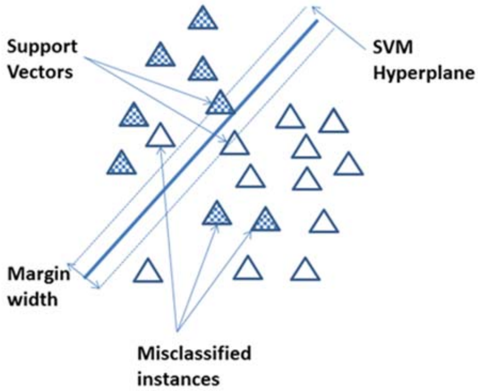

Fig3. Linear support vector machine (Burges, 1998)

The main advantage of SVM is the ability of good generalization of high dimensional data with few training sample (Shao and Lunetta 2012). SVM works with pixels in the boundary of classes which are called support vectors, thus it is possible to get accurate classification with small training set (Foody and Mathur, 2004). For the cases of complex data which cannot be separated by linear hyperplanes, it is possible to define optimal hyperplane separating the classes by non-linear mapping functions called kernel functions. There are many kernels which can be used in SVM however only four of them which are linear, polynomial, radial basis function (RBF) and sigmoid kernels have been commonly used in SVM classification of remotely-sensed images (Huang et al., 2002; Vapnik, 1995; Kavzaoglu and Colkesen, 2009). These four types of kernels, namely linear, polynomial, RBF and sigmoid have been used here for the classification and RBF kernel obtained higher classification accuracy than the others. Moreover, the RBF kernel is commonly preferred for SVM classification since it's superior performance (Kavzaoglu and Colkesen, 2009; Blaschke, 2010; Yang et al., 2011). The definition of two parameters C (cost) and γ (gamma), where γ is the kernel width and C is the regularization parameter, are needed for RBF kernel. C (cost) can be referred as penalty parameter associated with misclassified samples as well (Huang et al., 2007; Burges, 1998).

There are two main strategies as 'one against one' and 'one against others' can be used for multi class classification and most of the studies suggest the 'one against one' approach that is employed here (Pal, 2012; Kavzaoglu and Colkesen, 2009).

For this study, ENVI-plug-in Support Vector Machine was used. The method is based on LIBSVM library, adapted by ITT Visual Information Solutions for remote sensing image supervised classification purposes (Chang and Lin, 2014).

The training and validation samples which were selected by ground truth data first and ancillary data based upon spatial coverage of classes as well as analyst's experience for each class could be seen on the Table 1.

Table1. Training and validation sample

Class	Training Samples	Validation (Reference) Sample
First Crop Corn	241	30
Second Crop Corn	235	39
Cotton	582	73
Water	280	13
Bare land	395	44
Artificial Areas	392	24
Orchard	268	12
Total	2393	235

SVM classification method was implemented by using radial basis function (RBF) kernel. The most challenging and important factor of the SVM multiclass classifications are suitable choice of the kernel types and its parameters. Grid search method has been implemented for determination of the optimum parameters of RBF kernel. The parameters needed for RBF kernel were set to 0,2 and 100 for γ and C, respectively for the SVM classification. The pyramid parameter was set to a value of zero to process the satellite data at full resolution (5 m).

Object Based Classification

In the object-based classification, each classification task addresses a certain scale. The image information can be represented in different scales based on the average size of image objects and the same imagery can be segmented into smaller or larger objects (Walsh et al., 2008). Object-based classification relies on the assessment of spatially neighboring groups of pixels with a certain degree of spectral similarity, rather than individual pixels. The process of identifying such groups of pixels having similar characteristic is called segmentation and this process can produce variable numbers and sizes of objects depending on the thresholds of spectral similarity and compactness (Kok et al., 1999). In addition, the objects are described by shape, size, tone, texture, compactness, and other characteristics describing the spatial features of the object (Bock et al., 2005). All of those variables can be used in the classification process to assist in the discrimination of the objects and their correct assignment to the land-use/cover classes. Further, each object ‘‘inherits’’ the characteristics of the super object to which it belongs, and passes its own characteristics to the sub objects (Foody and Mathur, 2004; Wuest and Zhang, 2009).

In this study, the RapidEye image was segmented using scale factor of 50, shape parameter of 0.5, and compactness of 0.5. Homogeneity criteria values were chosen based on experimental tests by using different scale factors and parameters. Agricultural fields occur in the real world in linear shapes. These linear shapes can be obtained by increasing shape parameter. In order to use both shape linearity and spectral differences an optimum value of 0.5 was chosen for shape parameter of segmentation. Scale factor of 50 resulted in optimum size of agricultural fields in 5-meter resolution of RapidEye imagery.

Agricultural fields can be identified by their distinct geometrical characteristics. Besides the geometrical characteristics of agricultural types, using spectral properties of these fields can help to distinguish crop types. For this aim, five different remote sensing indices were used in this study to create class descriptions of different crop type classes (Table 2).

Table2. Remote sensing indices selected for OBIA

Acronym	Name	VI	Eq.	Reference
NDVI	Normalized Difference Vegetation Index	$NDVI = \frac{(NIR - \mathrm{Re}d)}{(NIR + \mathrm{Re}d)}$	(1)	Rouse et al., 1974
NDRE	Normalized Difference Red Edge Index	$NDRE = \frac{\mathrm{Re}\,dEdge - \mathrm{Re}\,d}{\mathrm{Re}\,dEdge + \mathrm{Re}\,d}$	(2)	Barnes et al., 2000
RE-NDVI	Red Edge Normalized Difference Vegetation Index	$REDEDGE - NDVI = \frac{NIR - \mathrm{Re}\,dEdge}{NIR + \mathrm{Re}\,dEdge}$	(3)	Wu et al., 2009
SR	Simple Ratio	$SR = \frac{NIR}{\mathrm{Re}d}$	(4)	Birth and McVey, (1968)
NDWI	Normalized Difference Water Index	$NDWI = \frac{NIR - Green}{NIR + Green}$	(5)	Gao, 1996

Threshold values and spectral ranges were used to detect class descriptions for object-based classification (Table 3). In this study, process-based rule-set was created to classify different object type classes by using class descriptions. Class description step is the most important step after segmentation process to define classes by using their both textural and spectral properties. Membership functions and threshold values were used to define classes in this study. Training data set from field works were chosen to find optimum ranges for class descriptions. By combination of different ranges from different indices, classes were classified by using object information of segments in the imagery (Table 3).

Table 3. Threshold values for class descriptions

Classes	*NDVI	*NDRE	*RE_NDVI	*SR	NDWI	Compactness
First Crop Corn	37-47	7-11	30-40	200-280		
Second Crop Corn	40-65	9-14	34-55	310-440		
Cotton		17,9-29				
Water					<-0,2	
Bare Land		<6			>-0,2	
Artificial Surfaces						<0,01
Orchards	30-52	7-16	20-50	180-320		

* values multiplied by 100

Results and Discussion

In this study, three different classification methods were conducted using RapidEye data to analyze the potential of mapping crop types.

As a result of classification methods seven land use categories were distinguished including, first crop corn, second crop corn, cotton, orchards and artificial surfaces, water bodies and bare lands in the selected region (Figure 4).

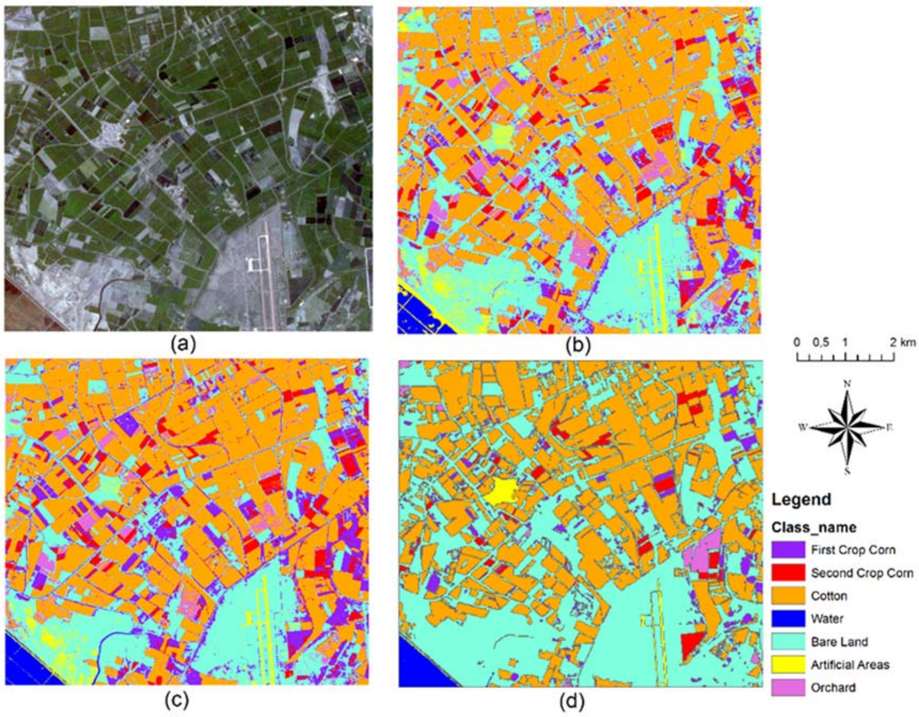

Figure 4. Classification results a) original image b) MLC c) SVM d) OBIA.

The output of the classified image without any error or bias is the accurate thematic map (Foody, 2002). There are a number of equations that can show the level of error statistically such as producer accuracy, user accuracy, overall accuracy and Kappa which can be calculated using the confusion matrix (Su et al., 2009). An accuracy assessment was performed using collected ground truth data for all three types of classification using standard confusion matrix. Kappa statistics and overall accuracy were used to evaluate accuracy of the classification methods. Table 4 presents the producer accuracy, user accuracy, and overall accuracy and Kappa statistics for three classification methods.

Table 4. Accuracy assessment results a) MLC b) SVM c) OBIA.

CLASS (A)	Reference	Classified	Number Correct	Producer Accuracy	User Accuracy
First Crop Corn	30	24	24	80,00%	100,00%
Second Crop Corn	39	43	37	94,87%	86,05%
Cotton	73	75	73	100,00%	97,33%
Water	13	12	12	92,31%	100,00%
Bare Land	44	40	36	81,82%	90,00%
Artificial Areas	24	24	18	83,33%	68,97%
Orchard	12	12	12	100,00%	100,00%
Total	235	235	214		
Overall Accuracy	91,06%				
Kappa	0,8839				

CLASS (B)	Reference	Classified	Number Correct	Producer Accuracy	User Accuracy
First Crop Corn	30	28	28	93,33%	100,00%
Second Crop Corn	39	39	37	94,87%	94,87%
Cotton	73	75	73	100,00%	97,33%
Water	13	13	13	100,00%	100,00%
Bare Land	44	44	38	86,36%	86,36%
Artificial Areas	24	24	18	75,00%	75,00%
Orchard	12	12	12	100,00%	100,00%
Total	235	235	219		
Overall Accuracy	93,19%				
Kappa	0,9156				

Class (C)	Reference	Classified	Number Correct	Producer Accuracy	User Accuracy
First Crop Corn	32	26	26	81,25%	100,00%
Second Crop Corn	39	37	37	94,87%	100,00%
Cotton	73	72	72	98,63%	100,00%
Water	13	13	13	100,00%	100,00%
Bare Land	44	56	44	100,00%	78,57%
Artificial Areas	25	21	21	84,00%	100,00%
Orchard	12	12	11	91,67%	91,67%
Total	238	237	224		
Overall Accuracy	94,12%				
Kappa	0,9272				

The overall accuracy of the object-based classification was slightly higher than for the pixel-based SVM classification, 94.12% versus 93.19 %, respectively. The approach that yielded the highest value of Kappa coefficient was the object based with 0.92, followed by SVM with 0.91. From Table 4, it can be observed that the pixel based MLC produced low overall accuracy (91.06%) and kappa coefficient (0.88).

The object-based image analysis method applied in this paper provided results with higher accuracies than the pixel-based SVM and ML classification. This is consistent with findings within the literature (Gao and Mas, 2008). This result suggests that object-based analysis has potential as an alternative method (over per-pixel approaches) for extracting crop type information from high resolution satellite imagery captured over agricultural lands in Menemen, Turkey.

Linear forms of agricultural lands make their determination easier by object-oriented classification method. Object-based classification classifies objects referring to the spectral properties of the pixel groups as well as shape and texture. Since the segments are created by grouping pixels, accuracy of the segmentation phase directly affects the classification results. The different class features falling in to the segmented groups of pixels, can lead to incorrect classification results. Therefore, segmentation parameters must be selected carefully based on different trials. High-resolution characteristics of images are emerging as another important parameter of the object-oriented classification. Since the objects are determined regarding the defined scale parameter, the homogeneity of the determined object will increase when the pixel size decreases. In addition, besides the spatial resolution the spectral resolution is important in object-based image classification. The majority of the object class definition is done by utilizing spectral properties, thus using high spectral resolution will facilitate class definitions as well. Besides all it was seen in the results of our study that, the use of object-oriented classification for agricultural applications with high spatial and spectral resolution images is very advantageous. One of the advantages of object-based classification is the ability to use ancillary data (such as derivative data sets: different remote sensing indices) as additional information layers to produce crop type mapping.

There are number of issues for the comparison of object based and pixel based classification such as salt and pepper or noise effect, types of training and validation points (pixels in a pixel-based classification and specific points within objects). In order to compare the potential of the selected methods, visual interpretation used to validate the salt and pepper effect based on field area for each crop type. According to visual interpretation crop types were classified homogenously using object based classification.

The tendency to produce spurious or misclassified pixels within classes (the so-called ‘salt and pepper’ effect) means that heterogeneous land covers will nearly invariably have slightly lower accuracies for pixel-based classifications than object-based using classes such as used here. Part of this may attributed to mis-registration between the imagery and field data. Methods to improve accuracies for pixel-based classifications include some post-classification editing such as filtering and manual removal (Gao et al., 2006). Potential under-evaluation will occur within certain classes that are heterogeneous in cover such as agricultural lands in which cover is co-dominated by cotton and discontinuous and variable woody cover. Trees will be assigned to a forest class and understory gaps between trees will be assigned to grass- land class. Thus it may be necessary to redefine classes away from the ‘traditional’ land cover or vegetation classes into more contextual classes, e.g. canopy versus non-canopy or using quantitative measures (e.g. % canopy cover). This is where the hierarchical structure of OB classification has potential in enabling the use of these types of classes at a particular level and then the proportions of these classes in super-objects at higher level to determine level of canopy cover in those objects. Due to these slightly different results, each metric was ranked for the class types. Use of ranking system demonstrated a better understanding and provided an efficient way of comparison between results. For this purpose, the averages of three classification methods were calculated taking in to account both user’s (U) and producer’s (P) accuracies of each classes, as assigning the higher weight to the better result. Classification algorithms were ranked using their quality scores as in Table 5. We conclude that the according to the user’s accuracy, OBIA is the best classification method as well as it has the same rank with SVM according to the producer’s accuracy. Considering the user accuracy, SVM is ranked second among the all methods. MLC is resulted as the worst with ranking among the all methods considering both user’s and producer’s accuracy. Nevertheless, considering the overall accuracies and Kappa statistics of classification results, the all of the three methods have acceptable higher values. Regarding the best classified land use types, corn is classified with the best accuracy among the all, since it was the dominant land use type in the test site and the largest number of training sample was used for it.

Table 5. Rank values of classification methods.

	Corn I		Corn II		Cotton		Water		B Land		Artificial		Orchard		AVR		Rank	
	U	P	U	P	U	P	U	P	U	P	U	P	U	P	U	P	U	P
SVM	1	3	2	1	2	2	1	2	2	2	2	1	2	2	1.71	1.86	2	2
OBIA	1	2	3	1	3	1	1	2	1	3	3	3	1	1	1.86	1.86	3	2
MLC	1	1	1	1	2	2	1	1	3	1	1	2	2	2	1.57	1.43	1	1
AVR	1	2	2	1	2.3	1.7	1	1.7	2	2	2	2	1.7	1.7				

U:User, P:Producer

Conclusion

The results of this study show differences in the accuracy between a pixel-based maximum likelihood classifier and Support vector machine classifier and object-based classifier for mapping crop types from agricultural land using RapidEye data. Resultant noise in the pixel-based classification suggests that thematic mapping using high spatial resolution satellite data requires a new methodology in land cover classification forgoing the traditional community level classifications for the initial stages of classification and perhaps focusing on the smaller spatial elements such as cotton, corn, and bare ground. These objects could then be the basis to develop the structural level classification grouping based on the proportional values of the various components. This is why OBIA has great advantage over per-pixel classification methods. Based upon to the results of the study, the point-based accuracy assessment proved that the object-oriented classification has slightly higher accuracy than the other methods performed. It is the fact that the accuracies of the classification methods are very close. If we compare MLC is seen as a more easily applied method due to the fact that defining the parameters for both object-based and support vector machine classification is more challenging and based on the user experience. Considering the results, MLC which is easier to apply also has an acceptable kappa and overall accuracy of 0.8899 and 91.06%, respectively. This study proves that it is possible to get high accuracy with MLC by using high resolution satellite images in the areas having flat topography and consisting linear objects with the less variety of crop types. However, obviously the success of OBIA and SVM is determined in the rank of first and second, respectively.

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