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COMPARISON OF CROP CLASSIFICATION METHODS FOR THE SUSTAINABLE AGRICULTURE MANAGEMENT

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Abstract. Accurate and reliable information regarding crop yields and soil conditions of agricultural fields are essential for the sustainable management of agricultural areas. The increasing necessity of the food due to the high population, global climate change and rapid urbanisation, the sustainable management of the agricultural resources is becoming more crucial for countries. Remote sensing technology offers a feasible solution for gathering the cost-effective, reliable and up-to-date information about crop monitoring by using high-resolution remote sensing data. Image classification is the one of most common method to obtain information from the remotely sensed images. Despite machine learning based classifiers such as Support Vector Machines (SVM) could provide high classification accuracy, the researchers have been still working to improve the classification accuracy. Recently, the utilisation of ensemble learning approaches in remote sensing classification is the research of interest for this purpose. In this study, we implemented six different supervised classification techniques and a classifier ensemble: Maximum Likelihood, Mahalanobis Distance, Minimum Distance, Spectral Angle Mapper, Parallelepiped, Support Vector Machines and Winner-takes-all (WTA) classification which is an ensemble based classifier. In this study, we investigated the comparative performance of the classifiers within overall and corn-class category for the study area located in Aydin, Turkey. Radial Basis Function (RBF) kernel was used here for the SVM classification. Results demonstrate that WTA classification outperformed other classification methods whilst the Parallelepiped obtained the lowest classification accuracy 13.24%. Moreover SVM gave the second highest overall classification accuracy of 89.90%.

Keywords: remote sensing, image classification, RapidEye, agriculture management.

AIMS AND BACKGROUND

Over the years, food demand in the world has been increasing and global food security have been crucial due to the global climate change, high population growth and extreme weather events. These changes reduce the agriculture productivity

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and hence push the countries whose economy is mostly based upon the agriculture to enhance the efficiency, productivity, and performance of their sustainable agriculture system. The extreme weather events damage the crops thus cause the agflation[1–3]. In FAO (Food and Agriculture Organisation of the United Nations) report in 2013, it is estimated that global population will be over nine billion by 2050 and the food production will have to increase by 60% to meet the expected demand for food of the world[4]. Therefore, sustainable agriculture management is pretty essential and crucial for global food security.

Recent advances in earth observation satellites have been making remote sensing very important and essential tool for the environmental monitoring and assessment as well as the agricultural applications since it could provide up-to-date and cost-effective information of land use/cover types at different spatial and temporal domain[5–8]. Remote sensing could provide many important information such as spatio-temporal distribution of crops or yield estimation for the agricultural decision support systems[3,6,9]. Classification of remotely sensed data is one of the most common method for obtaining the land use/cover information[10]. The accuracy and reliability of the information gathered by the imagery is much depending on the classification. Despite there are some advanced classification methods in remote sensing such as support vector machines, random forest, rotation forest etc., scientists and researchers have been still working to improve the classification accuracy because classified images provide many important base information for GIS application and analysis on decision making process. Several methods have been used to increase the image classification accuracy such as combination of spectral and texture features, multi-sensor image fusion or ensembles of classifiers[11–13]. Data fusion in remote sensing can be categorised into three different levels: pixel-level, feature-level and decision level[14,15]. In this study, we implemented six different supervised classification methods: Maximum Likelihood, Mahalanobis Distance, Minimum Distance, Spectral Angle Mapper, Parallelepiped, Support Vector Machines and an ensemble of classifiers or multiple classifiers, is based on decision level fusion strategy, that is called Winner Takes All (WTA) for the classification of RapidEye imagery of our study area.

This study examined the applicability and comparative performance of supervised classification techniques and classifier ensemble technique for crop mapping using RapidEye in Aydin Province. Moreover classification accuracy for corn-class category has been investigated as a specific task.

EXPERIMENTAL

Study area and data. The study area is located in Aydin Province, Aegean region of Turkey and comprised of approximately 17.3 km^2 of agricultural areas (Fig. 1). Besides favourable climate and soil conditions of Aegean region, most of the agricultural lands in Aydin province are fed by Great Meander River, which enables to intensive agriculture for the area. Study area covers nine land use classes which are corn (first crop, second crop), cotton (well developed, moderate developed, weak developed), soil (wet, moist, dry) and water surface (Fig. 2). The acquisition date of the RapidEye imagery was August 23rd 2012.

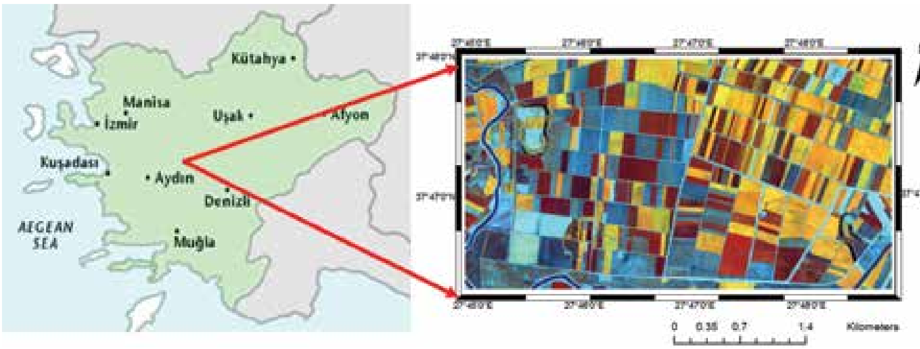

Fig. 1. Study area

Fig. 2. Crop types

RapidEye was launched in 2008 with a primary focus of agricultural, environmental and cartographic applications[16,17]. Blackbridge, the provider of RapidEye imagery, offers RapidEye data at three different processing levels. The imagery was obtained in Level 3A (RapidEye Ortho product) processing level in which radiometric, geometric and sensor corrections were applied. The RapidEye data provides five spectral bands which are blue (440–510 nm), green (520–590 nm), red (630–685 nm), rededge (690–730 nm) and near-infrared (760–850 nm) (Ref. 18).

Methods. Each method will be briefly described here however reader could reach the further details and theoretical background for each method at remote sensing textbooks such as Tso and Mather[19], Mather and Koch[20], and Richards[21].

Maximum likelihood classification is the most common method in remote sensing image classification. In this method, a pixel is assigned to the class of highest probability of belonging[19,22,23]. Minimum distance and Mahalanobis distance classification uses the euclidean distance and mahalanobis distance, respectively. Both methods assign the pixel to the corresponding class in which distance between class centre[19,21,22]. Spectral Angle Mapper classification compares the image spectra and a known spectrum (or endmember) and calculates the spectral angle between them to determine the spectral similarity[24,25]. Paralelpiped classification uses maximum and minimum pixel values for each class, which is the boundaries of paralelpiped. If a given pixel in features space is within class limits, the pixel is assigned to the corresponding class[19,20]. SVM is a supervised machine learning algorithm. It was initially developed for the binary classification by defining the optimum hyperplane separating the two classes. SVM uses the kernels to contruct the optimum hyperplane for the complex data that can not be linearly separated[26–28]. Kernel based SVMs are commonly used in remote sensing for classification and need parameters for kernel functions. The optimum parameters of cost (C) and kernel width (σ) which are required for the Radial Basis Function (RBF) kernel have been determined by using grid search method as 100 and 0.125, respectively. Further details of SVM algorithms were given by Huang et al.[27] and Melgani and Bruzzone[28] in the context of remote sensing.

The ensemble based approaches or multiple classifiers have been utilised in order to improve the classification accuracy by combining the outputs of several classifiers[11,29,30]. Some strategies have been developed for the ensemble learning approaches such as majority voting, fuzzy integral, Dempster-Shafer evidence theory[11,31]. Majority voting is the most common method that collects label outputs of each classifiers for a given pixel then assign the pixel to the majority label[19,31]. We performed the classifier ensemble based upon WTA method in which majority voting was used. WTA classification assign each pixel to the corresponding class that has the majority for all classification methods implemented[32]. Readers requiring more and comprehensive detail for classifier ensembles should refer to Briem et al.[33], Foody et al.[29] and Du et al.[11]

RESULTS AND DISCUSSION

In this section, comparative performance of the classifiers will be analysed by means of overall accuracy and kappa coefficients (Table 1). Moreover the individual class accuracies for most accurate three methods will be assessed by producer accuracy for in-depth analysis of comparison (Table 2).

Minimum distance, SVM and WTA are the most accurate three classification methods as their overall accuracy were obtained as 89.20, 89.90 and 90.94%, respectively. Since the accuracies of these three methods close to each other especially minimum distance and SVM, we will compare the individual class-based accuracy for comprehensive analysis by using producer accuracy. Among all methods performed here, Parallelepiped had the lowest classification performance as 13.25% of overall accuracy while WTA had the highest one as 90.94% for this study. In general, SVM performs better than single classifiers if the optimum parameters have been used for kernel.

Table 1. Classification accuracy

Method	Overall kappa	Overall accuracy (%)
Parallelepiped	0.1202	13.25
Mahalanobis distance	0.7276	76.31
Maximum likelihood	0.8010	82.58
Spectral angle mapper	0.8179	83.97
Minimum distance	**0.8762**	**89.20**
Support vector machines	**0.8845**	**89.90**
Winner-takes-all	**0.8964**	**90.94**

Table 2. Producer and user accuracy

Classes	Classification methods (most accurate three ones)					
	minimum distance		support vector machines		winner takes all	
	prod. acc.	user acc.	prod. acc.	user acc.	prod. acc.	user acc.
First crop corn	**100.00**	84.13	*88.68*	97.92	*94.34*	98.04
Second crop corn	82.93	100.00	100.00	87.23	**100.00**	93.18
Wet soil	85.00	62.96	90.00	60.00	**90.00**	60.00
Moist soil	100.00	100.00	100.00	100.00	**100.00**	100.00
Dry soil	**70.59**	96.00	64.71	91.67	64.71	91.67
Well-developed cotton	**97.06**	89.19	91.18	100.00	91.18	100.00
Moderate developed cotton	90.00	85.71	100.00	83.33	**100.00**	83.33
Weak developed cotton	66.67	100.00	66.67	100.00	**66.67**	100.00
Water body	97.74	100.00	94.74	100.00	**94.74**	100.00

Even though the overall accuracies of minimum distance and SVM are close to each other and the difference is 0.70%, we will check the benefits of each classifier for individual class classification and compare the performances. The highest accuracies for individual class category (producer accuracy) are given in bold in Table 2 for each classification method. While minimum distance classify most accurately only three classes (first crop corn, dry soil and well developed cotton), WTA classified the remaining classes within producer accuracy. When we check the results in Table 2, we can not find any method that classify the all classes on highest accuracy. Producer accuracies of SVM and WTA are pretty close to each other however WTA outperformed SVM 5.7% (Italic) of producer accuracy for the first crop corn class as it is one of our investigation on this study.This 5.7% increase on the producer accuracy for first crop corn enables the WTA had higher overall accuracy than SVM as 1.74% (Table 2). Classification maps for the most accurate three methods are given in Fig. 3.

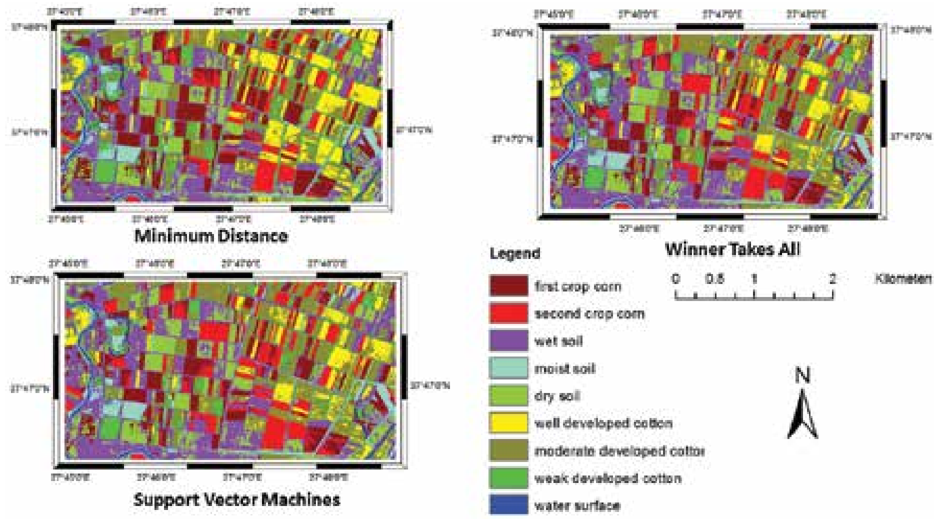

Fig. 3. Classification maps

CONCLUSIONS

In this study, we examined the sensitivity, applicability and comparative performance of six different supervised classification techniques and a classifier ensemble for the classification of crop types in Aydin Province, Turkey. Also the suitability of Rapideye imagery for crop mapping has been investigated.

It can be concluded that each type of classification method has different sensitivity and benefits on classes and classifier ensembles could increase the overall classification accuracy as well as individual class-based accuracy for this study area. Results demonstrate that WTA classification outperformed other classification methods whilst the Parallelepiped obtained the lowest classification accuracy 13.24%. Moreover SVM gave the second highest overall classification accuracy of 89.90%. Most accurate classification method (WTA in our study) can not have the highest accuracy (producer accuracy) for all classes. Results indicate that since the sensitivity of each classification method is different, it is possible to obtain high classification accuracy as well as low classification accuracy for crop classification even though same imagery and input data were used.

In future work, we are planning to assess the comparative classification performance of other advanced techniques such as rotation forest, relevance vector machines and object based SVM for our study area. We also plan to integrate the information by RapidEye and Sentinel-1 sensor that will be freely available and provide C-band that is commonly used in agricultural applications in remote sensing.

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