Testing the Sensitivity of Vegetation Indices for Crop Type Classification Using Rapideye Imagery

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SUMMARY

Several spectral vegetation indices that based on the combinations of spectral bands have been developed and widely used in remote sensing community for the environmental monitoring and assessment such as agriculture, vegetation and forestry. Sustainable management of the agriculture is the one of the key factors for the country's economy. Cutting-edge remote sensing technology provides us the information about the earth surface in different temporal and spatial domain hence is in efficient use for the monitoring and management of agricultural areas. Image classification is commonly performed to derive thematic information from the images therefore it has a great attention by remote sensing scientists to develop new classification methods. There are several factors affecting the accuracy of image classification such as training data and spectral bands. Moreover the integration of ancillary data can improve the image classification accuracy. In this study, three different vegetation indices of RapidEye imagery for the study area located in western part of the Turkey have been used on image classification as additional bands and the sensitivity of these additional bands on image classification accuracy has been investigated. The Normalized Difference Vegetation Index (NDVI), the Green Normalized Difference Vegetation Index (GNDVI), and the Normalized Difference Red Edge Index (NDRE) are the three vegetation indices used in this study. Support Vector Machines (SVM) and Maximum Likelihood Classification (MLC) have been implemented here as classifiers. Classified images have been assessed using overall classification accuracy and Kappa coefficient. Results demonstrated that the incorporation of these additional bands (three different vegetation indices) increase the classification accuracy for the SVM classification from 83,96% to 86,01 % as overall accuracy, however decrease the classification accuracy for MLC from 80,21% to 73,38%. Moreover it is proven than both classification methods with RapidEye data give satisfactory results for crop type mapping and analysis.

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1. INTRODUCTION

Since the increasing necessity of the food due to the high population growth and global climate change, the sustainable management of the agricultural resources is crucial especially for developing countries (Forkuor et al., 2014). The obtaining of the agricultural land use information using remote sensing has a significant role at the sustainable management of agricultural areas. Cutting-edge remote sensing technology provides us the accurate, up-to-date and cost-effective information about the crop types at the different temporal and spatial domains therefore the number of the remote sensing applications for agricultural purposes has been increasing in recent years.

To derive the thematic information from the images, the classification of the remotely sensed data for land use-cover mapping is one of the most common methods. The classification accuracy is for land cover mapping since it influences the quality of the information gathered by output maps (Foody 2004). Support Vector Machines (SVM) which is the kernel based machine learning algorithms has been implemented here for classification since it's superior performance on crop and land use/cover classification than other algorithms has been proven in many studies (Huang et al., 2002;Foody and Mathur, 2004; Löw et al., 2013). In addition, Maximum Likelihood Classification (MLC) which is one of the most common used classifier in remote sensing has been carried out here for the comparison.

Spectral vegetation indices in remote sensing have been widely used for the assessment and analysis of the biomass, water, plant and crops (Jackson and Huete, 1991). The key benefits of these indices are enhancing the spectral information and increasing the separability of the classes of interest therefore it influences the quality of the information derived from the remotely-sensed data. The Normalized Difference Vegetation Index (NDVI), the Green Normalized Difference Vegetation Index (GNDVI), and the Normalized Difference Red Edge Index (NDRE) are the three vegetation indices used in this study since all of these incorporated the near-infrared (NIR) band.

RapidEye is the first high-resolution multispectral satellite system incorporating the rededge band (Schuster et al. 2012). This satellite imagery has been successfully used for classification of vegetation, forestry and agricultural areas recently (Eitel et al. 2011, Kross et al. 2015, Kim and Yeom 2015). Eitel et al. (2011) investigated the broadband, red-edge information from the RapidEye satellites for the detection of early stress in conifer forests. Kross et al. (2015) examined the applicability of RapidEye vegetation indices for estimation of leaf area index and biomass in corn and soybean crops. Kim and Yeom (2015) tested the sensitivity of vegetation indices of RapidEye imagery for paddy rice detection on the study area in South Korea.

In this study, the sensitivity of three different vegetation indices of RapidEye imagery on crop type classification has been investigated. In classification, these indices have been added as an additional band to the original bands of RapidEye imagery. Moreover the applicability and performance of the classification methods for mapping the crops have been examined for the study area.

2. STUDY AREA AND DATA

The study area which is located in Aegean region of Turkey and comprised of approximately 17.3 km^2 of areas. (Figure 1). It 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. Agriculture is the one of the important sources of income in the region. Therefore the proper management of the agriculture is crucial for the region.

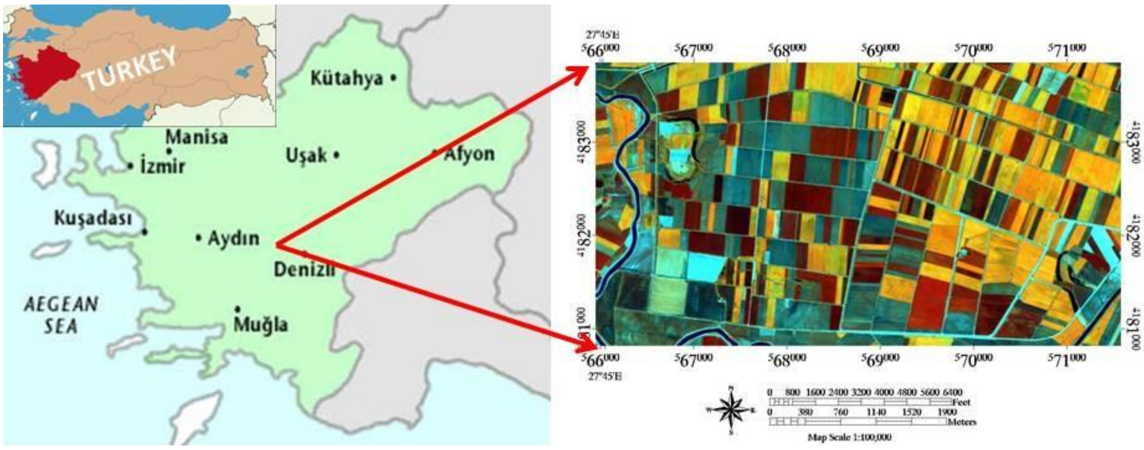

Figure 1: Study area

RapidEye which is the first high-resolution multispectral satellite system incorporating red-edge channel has been commonly preferred and successfully used for agricultural and forestry applications. Technical specifications of data are given as below.

Product Attribute	Description
Product Type	Level 3A (orthoproduct)
Pixel size (orthorectified)	5 m
Spectral Bands	Blue(440 – 510nm) Green(520 – 590nm) Red(630 – 685nm) Rededge(690 – 730nm) Near-Infrared(760 - 850)
Bit Depth	16-bit unsigned integers

Table 1: Technical Specifications

RapidEye imagery offers promising results in many applications due to incorporating the near-infrared and rededge spectral bands.

3. VEGETATION INDICES AND IMAGE CLASSIFICATION

The Normalized Difference Vegetation Index (NDVI), the Green Normalized Difference Vegetation Index (GNDVI), and the Normalized Difference Red Edge Index (NDRE) are selected here as the three different spectral indices in this study since all of these incorporated the near-infrared (NIR) band. The band numbers of 2,3,4,5 refer to green (520 – 590nm), red (630 – 685nm), rededge (690 – 730nm) and near-infrared (760 – 850nm), respectively in Table 2 below.

Vegetation Index	Equation
NDVI (Tucker,1979)	$NDVI = (R_{band5} - R_{band3}) / (R_{band5} + R_{band3})$
GNDVI (Gitelson et al,1979)	$GNDVI = (R_{band5} - R_{band2}) / (R_{band5} + R_{band2})$
NDRE (Barnes et al.,2000)	$NDRE = (R_{band5} - R_{band4}) / (R_{band5} + R_{band4})$

Table 2: Vegetation Indices

The Support Vector Machine (SVM) which is the kernel based machine learning algorithms is based on statistical learning theory. The most remarkable point of the SVMs is to be able to perform well with small set of training data. (Huang et al., 2002; Pal and Foody, 2010). Kernel functions could construct the optimal hyperplane for the separation of the classes in complex data (Huang et al., 2002). Radial Basis Function (RBF) as a kernel type was selected for SVM classification here. The optimum parameters of cost (C) and kernel width (σ) for the RBF kernel have been determined as 100 and 0,125, respectively.

Maximum Likelihood Classification (MLC) which is the most common used classifier in remote sensing is a supervised parametric method. In this method, the pixel is assigned to the class with highest probability.

Only very basic information on classification methods has been provided here and reader could reach the further details and theoretical background at Huang et al. (2002) for SVM and Richards, J.A. (1999) for MLC.

4. ACCURACY ASSESSMENT

The image classification accuracy was evaluated using overall accuracy and kappa coefficient. Classification results of the analysis are as given below in Table 3.

Analysis	Overall Accuracy (%)	Kappa coefficient
MLC_5 (5 spectral band)	80,21	0,77
MLC_8 (5 band+ 3 vegetation indices)	73,38	0,70
SVM_5 (5 spectral band)	83,96	0,82
SVM_8 (5 band+ 3 vegetation indices)	86,01	0,84

Table 3: Classification Results

It is demonstrated that the incorporation of these additional bands (three different spectral vegetation indices) increase the classification accuracy for the SVM classification from 83,96% to 86,01 % as overall accuracy, however decrease the classification accuracy for MLC from 80,21% to 73,38%. Classification maps for MLC_5, MLC_8 and SVM_5, SVM_8 can be seen on the Figure 2.

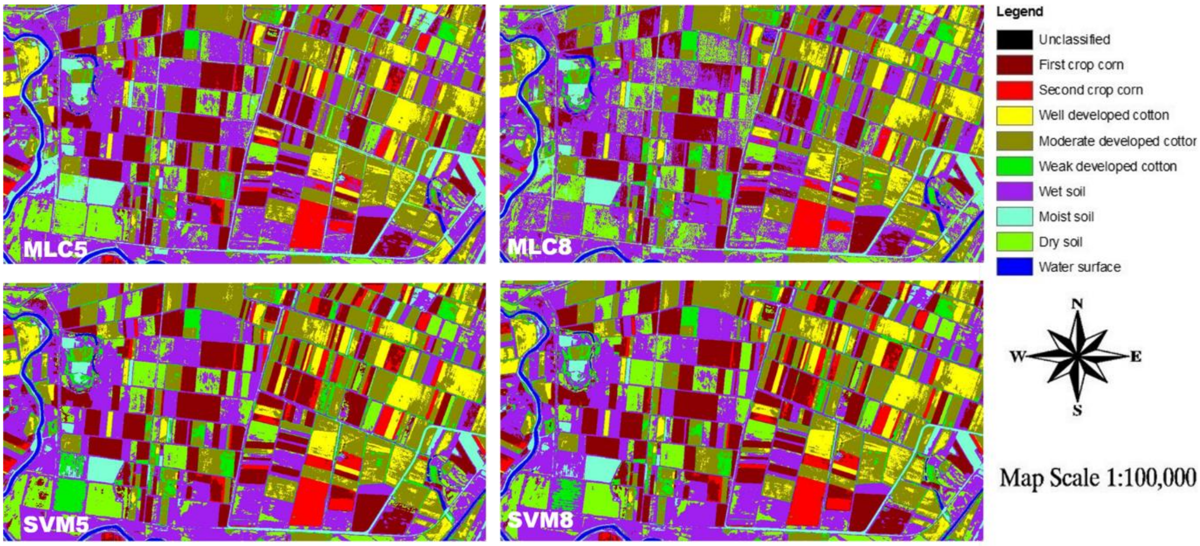

Figure 2: Classification Maps

5. CONCLUSION

The applicability and sensitivity of three different vegetation indices of RapidEye imagery for crop type mapping have been investigated using support vector machine and maximum likelihood classification. The results of this study indicate that vegetation indices derived from original spectral bands of RapidEye imagery have different sensitivity on classification methods as increasing the accuracy for SVM however decreasing for MLC. In addition SVM outperformed MLC for our study area. As proven and tested in several previous studies in recent years, using the RapidEye data with SVM classification for crop pattern mapping is in efficient use and gives satisfactory results. This study also proves that the combination of this data and classification method get satisfactory results.

In future work, we plan to evaluate the sensitivity of any other vegetation indices for the same purpose incorporating NIR and Rededge bands from RapidEye imagery using different classification techniques such as object based SVM or import vector machines as an addition to SVM. Also the integration of optical and synthetic aperture radar imagery for improving crop mapping using different classification methods for our study area with the different type of dataset is considered as the a follow-up of this study.

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BIOGRAPHICAL NOTES

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