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Proceedings

Greenhouse Detection from Color Infrared Aerial Image and Digital Surface Model †

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† Presented at the 6th International Electronic Conference on Sensors and Applications, 15–30 November 2019; Available online: https://ecsa-6.sciforum.net/

Published: 14 November 2019

Abstract: Greenhouse detection is important with respect to urban and rural planning, yield estimation and crop planning, sustainable development, natural resource management, risk analysis and damage assessment. The aim of this study is to detect greenhouse areas by using color and infrared orthophoto (RGB-NIR), topographic map and Digital Surface Model (DSM). The study was implemented in Kumluca district of Antalya, Turkey which includes intensive greenhouse areas. In this study, color and infrared orthophotos, normalized Digital Surface Model (nDSM), Normalized Difference Vegetation Index (NDVI) and Visible Red-based Built-up Index (VrNIR_BI) were used and the greenhouse areas were detected using Object Based Image Analysis (OBIA). In this process, the optimum scale parameter was determined automatically by the Estimation of Scale Parameter2 (ESP2) tool and Multi Resolution Segmentation (MRS) was used as the segmentation algorithm. In the classification stage, K-Nearest Neighbor (K-NN), Random Forest (RF) and Support Vector Machine (SVM) classification techniques were used and the accuracies of the classification results were compared. Obtained results showed that greenhouse areas can be determined from color and infrared orthophoto and DSM data successfully by using the OBIA. The highest overall accuracy was obtained when the SVM classifier was used with 94.80%.

Keywords: Greenhouse extraction; color and infrared orthophoto; Object Based Image Analysis (OBIA); nDSM; NDVI; VrNIR_BI; SVM

1. Introduction

Greenhouse extraction is important research area and creating and updating greenhouse information systems is vital for urban and rural planning, yield estimation, crop planning, risk analysis and damage assessment in case of natural disaster. The fast and accurate detection of greenhouses automatically from remote sensing imagery saves labor and time. With the development of digital image analysis and processing methods, the greenhouse detection process has become easier and faster when compared with traditional techniques. When the studies about greenhouse detection from remotely sensed data were examined, it can be stated that the classification techniques are widely used. The most widely used classification technique in the literature for greenhouse detection is the Maximum Likelihood Classification. Carvajal et al. [1, 2] used Artificial Neural Networks Classifier for greenhouse detection. In addition, there are studies that use machine learning algorithms [3-5] and unsupervised image classification [6, 7] for greenhouse extraction. On the other hand, there is a considerable amount of research about greenhouse detection using Object-Based Image Classification [8-12]. In these studies, generally K-Nearest Neighbor (K-NN) classifier was used as classification algorithm.

The aim of this study is to detect greenhouse areas from color infrared orthophotos and DEMs using Object Based Image Analysis (OBIA). Normalized Difference Vegetation Index (NDVI) and Visible Red-based Built-up Index (VrNIR_BI) were calculated using the bands of the orthophoto image. The obtained indices and the normalized Digital Surface Model (nDSM) were added to the orthophoto as additional bands and the greenhouse areas were obtained with OBIA. Three different machine learning algorithms were used in the classification stage and the results were compared.

3.1. Study Area and Data Sets

Antalya province is one of the most proper cities of Turkey for greenhouse farming with its climatic and ecological characteristics and geographical structure. The 37% of greenhouse areas of Turkey is located in Antalya province by the year 2018 [13]. In this study, Kumluca district of Antalya was selected as study area, because an important part of the greenhouses is located in this district. Kumluca is in the first rank in terms of greenhouse areas in Antalya [13]. The study area and its location was given in Figure 1.

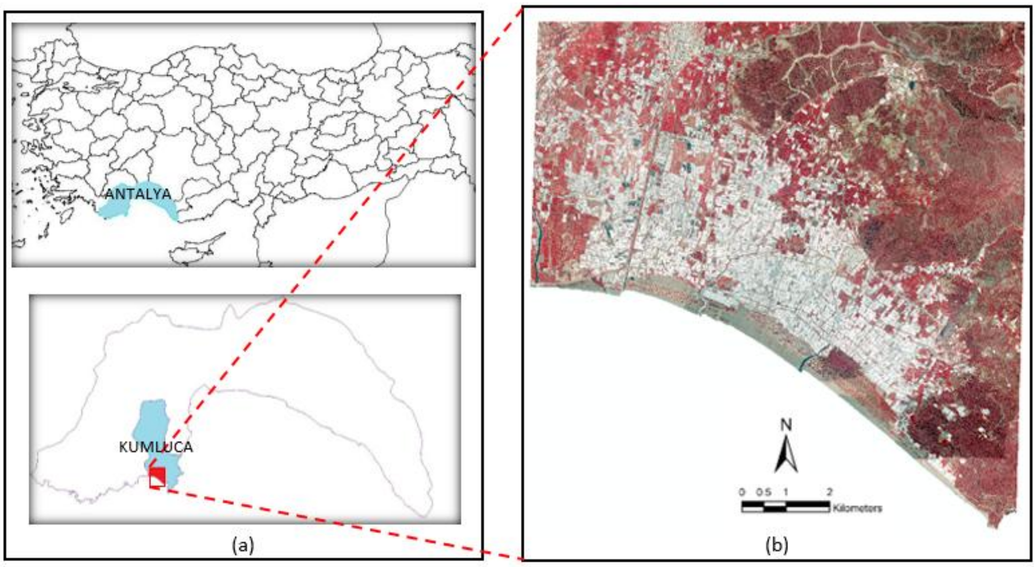

Figure 1. Study Area (a) The location of the Antalya in Turkey and Kumluca district in Antalya and (b) Color infrared orthophoto of the study area.

The data used in this study are (1) color infrared orthophoto, (2) Digital Elevation Models (DEM), and (3) topographic maps. Color infrared orthophoto and DSM data were obtained from General Directorate of Mapping. The orthophoto collected with 0.30 m Ground Sampling Distance (GSD) in 2012 having Blue, Green, Red and NIR bands. The DSM, which includes 3D man-made objects and topography, had been generated from stereo aerial images by automatic matching and its spatial resolution is 5m and in 90% confidence interval it has ±3m vertical accuracy. The topographic maps were used for DTM generation.

3. Methodology

In this study, there are basically two steps for greenhouse detection from color infrared orthophoto and DSM: (1) Preparation of additional bands and (2) Object based image classification. In the first stage the NDVI and VrNIR-BI indices were computed using the bands of the orthophoto and nDSM was generated by subtracting DTM from DSM. In the object based image classification stage initially Multi Resolution Segmentation (MRS) was performed and then machine learning algorithms namely K-Nearest Neighbour (K-NN), Random Forests (RF), and Support Vector Machines (SVM) were used for image classification.

3.1. Preparation of Additional Bands

The NDVI and VrNIR-BI images were computed utilizing the red and NIR bands of the orthophoto by the formulas (1) and (2), respectively. Threshold values that were determined Otsu thresholding were applied to these indices and threshold applied indices were used as additional bands in the classification process. The NDVI is an index that is used for determining the vegetation areas. On the other hand, VrNIR_BI is an index to detect built-up areas [14]

$$NDVI = (B_{NIR} - B_{RED}) / (B_{NIR} + B_{RED}) \quad (1)$$

$$VrNIR\text{-}BI = (B_{RED} - B_{NIR}) / (B_{RED} + B_{NIR}) \quad (2)$$

In addition, nDSM, which is an important data for detecting 3D objects, was used as additional band and it was generated by subtracting DTM from DSM. In this study, DTM was generated by using topographic maps.

3.2. Object Based Image Classification

The first stage of object based image classification is segmentation. It is an important stage that affect the classification result directly. There are different algorithms for segmentation, which are: Chessboard, Quadtree Based, Contrast Split, Multi Resolution, Spectral Difference, Multi-Threshold and Contrast Filter. When the literature on Object-Based Greenhouse detection is examined, it is seen that the most commonly used segmentation algorithm is (MRS) [12, 15]. Some parameters need to be set by the user during the segmentation. These parameters differ from image to image. The parameters used in segmentation are: scale, shape and compactness. The Estimation of Scale Parameter2 (ESP2) tool is available for automatic detection of the scale parameter. This tool was recommended by Dragut et al. in 2014 [15].

For the determination of the scale parameter, shape and compactness parameters should be determined. When the previous studies were examined, it was found that the compactness value was fixed to 0.5 and the shape value was adjusted not to be greater than the compactness value [16, 17]. Therefore, in this study the compactness value was fixed to 0.5 and the shape parameter value was given as 0.1, 0.3 and 0.5. Then, Local Variance (LV) graphs of the obtained results were examined and the lowest LV level was observed when the shape value was 0.5. As a result, the scale parameter was determined as 103 using both shape and compactness values as 0.5 (Table 1). In this study, since level1 has the most appropriate segments visually, level1 was used. The obtained MRS result using these parameters were quite successful, and it has been seen that the determined parameters were useful for greenhouse detection.

Table 1. The scale parameters obtained by ESP2 tool and shape and compactness parameters.

Shape	Compactness	Scale Parameter
0.1	0.5	117
0.3	0.5	113
0.5	0.5	103

After segmentation, in the classification stage three different machine learning algorithms were used: K-NN, RF, and SVM Classifiers. Initially, 6 classes were determined by analyzing the study area: Greenhouse, Building 1, Building 2, Road, Bareland and Vegetation. Then, 30 segments per class were collected for training, while 60 segments per class were collected for testing. Same training and testing samples were used for K-NN, RF and SVM classifications.

K-NN is one of the most popular machine learning classifiers. It is a non-parametric and supervised classification and the k parameter plays an important role in K-NN classification. In this study k value is determined as 1. The RF is an ensemble learning technique and uses a bagging-based approach. The maximum tree value was selected as 50 in this study. SVM is a machine learning algorithm that is generated for binary classification and then extended for multi-class problems [18]. It works quite well even using limited training areas. In this study, Radial Basis Function which is most popular kernel, was used. The C and gamma parameters were determined as 1000 and 0.00001, respectively.

Finally, for accuracy assessment error matrices were generated and the machine learning algorithms were compared for selecting the best result.

4. Results and Discussion

The obtained classification results indicate the success of the OBIA for greenhouse detection. The K-NN, RF, and SVM results were given in Figure 2. The K-NN, RF and SVM classification results were assessed using collected testing segments and error matrices were generated. The classification accuracies (Producer's Accuracies – PA; User's Accuracies – UA; Overall Accuracies) were given in Table 2. The overall accuracies were computed as 83.47, 81.46 and 94.80 for K-NN, RF, and SVM classifiers, respectively.

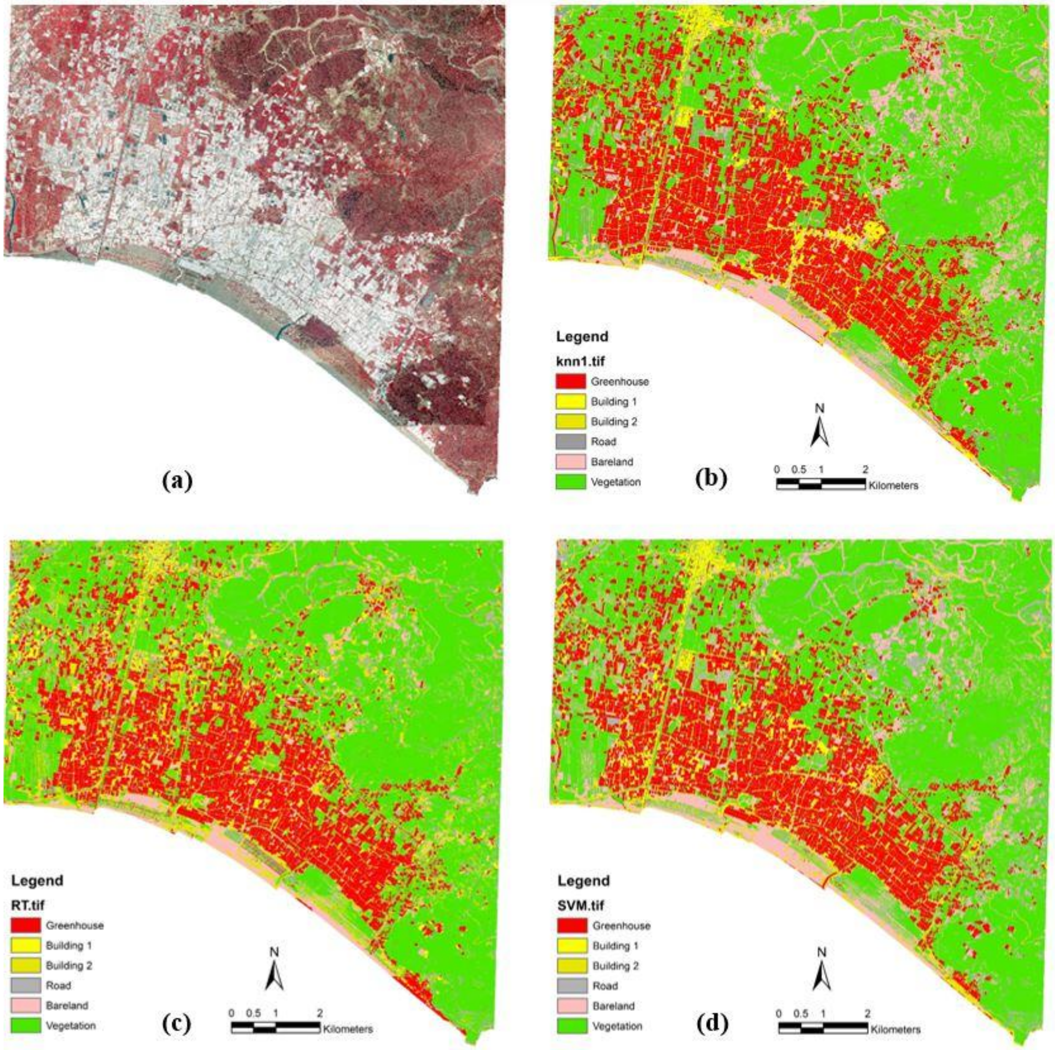

Figure 2. (a) Color infrared orthophoto of the study area and the OBIA results using (b) K-NN Classifier, (c) RF Classifier and (d) SVM classifier.

When the Producer's Accuracy values of Greenhouse class were analyzed, SVM classifier provided the highest accuracy with 96.88, RF classifier follows SVM with 82.51 and the lowest accuracy was obtained when K-NN classifier was used with 78.21%. When the User's Accuracy values were analyzed, similarly the highest accuracy was obtained when SVM classifier was used (98.10). However, the RF classifier gave the lowest User's Accuracy value with 88.90% for this time.

When the Producer's and User's Accuracies of classes were analyzed, for each classifier "vegetation" class has the highest accuracies and the lowest accuracies were obtained for the "road" class.

Table 2. The Producer's, User's and Overall Accuracies using K-NN, RF and SVM Classifiers.

Classes	K-NN		RF		SVM	
	PA	UA	PA	UA	PA	UA
Greenhouse	**78.21**	**91.84**	**82.51**	**88.90**	**96.88**	**98.10**
Building 1	**89.21**	**56.57**	**87.41**	**70.24**	**95.44**	**94.67**
Building 2	**92.43**	**71.34**	**85.98**	**61.98**	**82.63**	**97.47**
Road	**57.13**	**62.16**	**53.72**	**46.49**	**82.10**	**84.94**
Bareland	**83.49**	**84.14**	**74.83**	**83.75**	**94.99**	**90.80**
Vegetation	**100**	**100**	**100**	**100**	**100**	**100**
Overall Accuracy	83.47		81.46		94.80	

5. Conclusions

In this study, greenhouse areas were obtained from color and infrared orthophoto and nDSM images using Object Based Image Classification. The NDVI, VrNIR-BI and nDSM images were used in the classification process. In the segmentation stage ESP2 tool and MRS were used. In the classification stage K-NN, RF and SVM machine learning classifiers were used and their performances were compared. The obtained classification results indicated that greenhouse areas can be detected accurately and effectively from color and infrared orthophoto and nDSM using OBIA. Although, all three machine learning algorithms provided quite high accuracies, the highest overall accuracy was computed when SVM classifier was used.

Funding: This work was supported by the General Directorate of Mapping (HGM), Turkey. The data used in this study are provided by HGM for the project named as "Detection of Greenhouse Areas Using Color Infrared Orthophoto and Digital Elevation Model (in Turkish)"

Acknowledgments: We would like to thank Gokhan ARASAN (Lieutenant Engineer, HGM) for data acquisition.

Conflicts of Interest: The authors declare no conflict of interest.

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