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Object-based classification with rotation forest ensemble learning algorithm using very-high-resolution WorldView-2 image

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Machine learning algorithms reported to be robust and superior to the conventional parametric classifiers have been recently employed in object-based classification. Within these algorithms, ensemble learning methods that construct set of individual classifiers and combining their predictions to make final decision about unlabelled data have been successfully applied. In this study, performance and effectiveness of a novel ensemble learning algorithm, rotation forest (RotFor) aiming to build diverse and accurate classifiers, was investigated for the first time in object-based classification using a WorldView-2 (WV-2) satellite image. Also, the combination of satellite imagery and ancillary data (i.e. normalized difference vegetation index and principal components) were assessed. Random forest (RF), support vector machine (SVM) and nearest neighbour (NN) algorithms were also used as benchmark classifiers to evaluate the power of RotFor. The classification results confirmed that integration of ancillary data increased the classification accuracy in comparison to using solely spectral bands of WV-2. While RotFor and SVM generally produced similar results, they outperformed the RF and NN based on McNemar's and Wilcoxon's signed-rank test of statistical significance results.

1. Introduction

Land cover information about the Earth's surface features in terms of their quantity, diversity and spatial distribution has been identified as one of the crucial data components for many aspects of global change studies and environmental applications (Sellers et al. 1995). Remote sensing technologies provide an efficient tool for gathering this valuable information at various spatial and temporal scales (Huang, Davis, and Townshend 2002). The latest technological innovations in the design of remote sensing satellites and sensors offer new application opportunities in many fields including environmental monitoring and natural resource management.

With the availability of a new generation of remotely sensed data with higher spatial and spectral resolution, research efforts in classifying remote sensing data have shifted in the last decade from traditional pixel-based to object-based approaches (Blaschke 2010; Tzotsos, Karantzalos, and Argialas 2011). One of the main steps in object-based image analysis is to classify the image objects generated from the segmentation process into a specific land use and land cover class. Up to now, a variety of image classification algorithms, generally categorized into parametric and non-parametric classifiers, have been proposed and applied

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in the literature. In recent years, the use of non-parametric classifiers including support vector machines (SVM), decision trees and ensemble learning-based algorithms (e.g. boosting, bagging and random forest (RF)) in object-based classification has been a hot topic in remote sensing area (Wieland and Pittore 2014; Qian et al. 2015).

Rotation forest (RotFor), a recently introduced ensemble learning algorithm, has been successfully applied in numerous machine learning studies in the past few years and its generalization performance was found to be robust and efficient for different data sets (Rodriguez, Kuncheva, and Alanso 2006; Zhang, Zhang, and Wang 2008). Also, it has been recently used for remotely sensed image classification problems. For example, Kavzoglu and Colkesen (2013) compared the classification performance of RotFor algorithm with the six popular ensemble learning methods (e.g. boosting, bagging and RF) using Terra ASTER imagery. Xia et al. (2014) explored the use of RotFor algorithm for classifying hyperspectral remote sensing imageries. Classification performance of the algorithm was also compared with SVM, bagging, boosting and RF methods. Du et al. (2015) applied RotFor, RF, SVM and Wishart classifiers to PolSAR image. Reporting the effectiveness of RotFor algorithm, the above-mentioned comparative studies were performed for pixel-based classification with middle-resolution images. However, in the literature, the RotFor has not been applied to object-based classification with high-resolution satellite images. The objective of this study was to analyse the performances of RotFor ensemble learning algorithms in the context of object-based image classification using high-resolution WorldView-2 (WV-2) satellite imagery. In order to evaluate the algorithm's performance, widely used nearest neighbour (NN), RF and SVM methods were also applied to a data set.

2. Test site and data

The study area covers approximately 240 ha land located in Gebze district of Kocaeli province, Turkey. The land use and land cover of the study area mainly composed of six prominent classes: buildings, forest, soil, water, pasture and road. Study area covers about 25 ha forested land dominated by four types of tree species, namely stone pine (*Pinus pinea* L.), Turkish red pine (*Pinus brutia* Ten.), Cedrus (*Cedrus libani*) and plane trees (*Platanus orientalis* L.). In addition, buildings in the area were categorized into three subclasses according to main roofing materials in the study area as white-roofs, grey-roofs and tile-roofs.

A radiometrically corrected, geo-referenced, orthorectified 16-bit standard level 2 (LV2A) WV-2 image acquired on 7 July 2013 was used as a source data for classification. The WV-2 images provide eight spectral bands having 2 m spatial resolution and panchromatic band with 0.5 m spatial resolution. In order to improve the spatial resolution of multispectral bands from 2 to 0.5 m, panchromatic and multispectral bands were fused using the Gram–Schmidt pan-sharpening technique. Available pan-sharpened eight multispectral bands with 0.5 m spatial resolution were employed in object-based image analysis conducted in this study. In addition to pan-sharpened spectral bands, normalized difference vegetation index (NDVI) image calculated based on red and the first near-infrared band of the WV-2 and the first three principal components (3PC) accounting for about 98% of the variability in the data were produced and considered as ancillary data sets.

3. Methodology

In this study, the RotFor algorithm was adopted into object-based image classification to produce detailed land use and land cover classification using high-resolution satellite imagery. For this purpose, main processing steps of object-based image analysis including image segmentation, creating image object features (attributes), selecting training and testing data, classification of image objects and accuracy assessment were followed and employed, respectively.

3.1. Image segmentation

The first and the most important stage in object-based image analysis is the creation of image objects through the aggregation of pixels by image segmentation. In this study, image objects, the basic processing units of object-based classification, were generated through a bottom-up region-merging technique known as multiresolution segmentation algorithm proposed by Baatz and Schape (2000), and performed via Definiens eCognition Developer 9 software (Trimble GmbH, Munich, Germany). Scale, shape and compactness are the fundamental parameters available to users for controlling the algorithm. Among the others, scale parameter is considered as the most important one as it controls the relative size of the image objects, which has a direct impact on the subsequent classification steps (Kim et al. 2011; Kavzoglu and Yildiz 2014; Ma et al. 2015). In this study, the estimation of scale parameter tool was used to estimate optimum scale parameter providing better discrimination of the interested land use and land cover classes (Drăguţ, Tiede, and Levick 2010). It should be noted that only the spectral bands of WV-2 were used to create the image objects, with each band equally weighted. After visually analysing the segmentation results, the optimal scale parameter was chosen as 38 and the other parameters (i.e. shape and compactness) were set to 0.3 and 0.5, respectively, after an extensive trial process.

3.2. Creating images object and collecting training samples

In this study, five image object features, namely mean values, standard deviations, band ratio values, maximum and minimum pixel values of spectral bands of WV-2, NDVI and 3PC, were calculated for the created image objects, outputs of the segmentation process. In order to assess the relative classification performance of RotFor, SVM, RF and NN algorithms on different data sets, five combinations of the input variables were formed. The combinations included the following:

(1) WV-2 (40): data set contains five image objects features of eight spectral bands of WV-2.
(2) WV-2 + NDVI (45): data set contains five image objects features of eight spectral bands of WV-2 and NDVI.
(3) WV-2 + 3PC (55): data set contains five image objects features of eight spectral bands of WV-2 and 3PC.
(4) 3PC (15): data set contains five image objects features of 3PC.
(5) WV-2 + NDVI + 3PC (60): data set contains five image objects features of eight spectral bands of WV-2, NDVI and 3PC.

It is necessary to set some user-defined parameters for SVM, RF and RotFor algorithms to determine best performing classification models. For this purpose, training and testing data sets were formed considering the ground reference data. As a result, 604 objects were selected as training and 495 objects were selected as testing samples. In addition, apart from the training and testing data, a validation data set comprising 1740 pixels (145 pixels per class) was also created for the purpose of making objective and sound comparisons on the produced thematic maps.

3.3. Performance evaluation

As a standard operation in image classification, results were evaluated using a standard confusion matrix to calculate the overall accuracy. In addition to these standard metrics, two non-parametric tests, namely McNemar's and Wilcoxon's signed-rank tests, were also performed to determine statistical significance of the differences between method performances.

McNemar's test is a popular non-parametric test that is generally applied to compare the classification errors of two classifiers. The test statistic based on χ^2 distribution was calculated (Japkowicz and Shah 2011). If the calculated test value exceeds the distribution values for the desired level of significance, the null hypothesis is rejected. Wilcoxon's signed-rank test is another non-parametric test that has been limited use in remote sensing application for analysing matched pairs. The test ranks the differences in performances of two classifiers, ignoring the signs, and compares the ranks for positive (T_+) and negative differences(T_-). If the number of non-zero values (n) is up to 50, the statistics is distributed approximately normally and the following test statistic given in Equation (1) is calculated. If calculated test statistic z is smaller than the critical table value for desired level of significance, the null hypothesis is rejected (Japkowicz and Shah 2011):

$$z = \frac{\min(T_+, T_-) - \frac{n(n+1)}{4}}{\sqrt{\frac{n(n+1)(2n+1)}{24}}} \tag{1}$$

4. Classification algorithms

4.1. Nearest neighbour

NN classifier constructed on simple mathematical principles is one of the traditional distance-based algorithms that is widely used in both pixel-based and object-based classification problem. It determines the class label for the unknown sample considering its closest neighbour.

4.2. Support vector machine

SVM, one of the robust non-parametric classification algorithms, has been successfully used in a wide range of classification problems in remote sensing (Kavzoglu and Colkesen 2009; Mountrakis, Im, and Ogole 2011; Pal, Maxwell, and Warner 2013; Maxwell et al. 2014). The basic idea of SVM for any given classification problem is to find an optimal decision boundary (represented by a hyperplane in feature space) between two classes that minimize the classification error (Vapnik 1995). For linearly non-separable classes, the input data are mapped into a high-dimensional space using a non-linear kernel functions. Although numerous kernel functions exist in the literature, radial basis function was considered in this study due to its positive effects on classification accuracy (Kavzoglu and Colkesen 2009).

4.3. Random forest

RF algorithm has been a popular method of image classification applied to a wide range of problems (Kavzoglu and Colkesen 2013; Maxwell et al. 2015). RF algorithm consisting of a collection of decision trees is an ensemble learning technique developed by Breiman (2001). Each tree in the forest is trained using a bootstrap sample of training data and random subset of features sampled independently from the input features (Pal and Foody 2010). RF creates new training sets by randomly resampling two-third from the original data set n times, with replacement, n being the number of samples in the original training set (Breiman 2001). The remaining one-third is put down the tree to generate a test classification and to calculate the out-of-bag error. By means of a majority vote, the results of the individual RF trees are combined and the model output is determined (Löw et al. 2013). Use of RF requires the setting of certain parameters to determine two user-defined parameters, namely the number of trees and the number of features.

4.4. Rotation forest

RotFor algorithm, proposed by Rodriguez, Kuncheva, and Alanso (2006), is a new ensemble learning technique based on a similar principle to RF, in which the training set for each base classifier is formed by applying feature extraction. The main idea of RotFor is to simultaneously encourage diversity and individual accuracy within an ensemble classifier (Zhang and Zhang 2010). Specifically, diversity is promoted by using principal component analysis (PCA) to do feature axis rotation for each base classifier; accuracy is sought by keeping all principal components and also using the whole data set to train each base classifier. Original input data set is randomly split into K subsets to create the training data for a base classifier and PCA is applied to each subset. Due to their sensitivity to rotation of the feature axes, decision trees have been suggested as the base classifier (Rodriguez, Kuncheva, and Alanso 2006). The number of iterations and the number of splits are the two main user-defined parameters of RotFor algorithm. In this study, a decision tree classifier was used as a base classifier in RotFor.

5. Results and discussion

The performance of the RotFor algorithm in comparison to SVM, RF and NN was analysed for the object-based classification using the five different band combinations. NN and SVM, RF and RotFor classification models constructed with optimum parameter configurations were applied to the segmented image objects and LULC thematic maps of the study area were produced for each classification method. The optimized parameter settings for the RotFor, RF and SVM algorithms for variable each combination are listed in Table 1. For RotFor, the number of iterations (t) took values ranging from 50 to 100. When comparing the results obtained by selecting different number of splits (K), it was found that the results vary slightly, and none of the parameters take obvious advantage. In other words, there is no consistent relationship between the classification accuracy and K, which was also pointed out in Kuncheva and Rodríguez (2007) and Liu and Huang (2008). Therefore, K parameter was set to 10 in all experiments in this study. For the RF algorithm, while the number of trees (k) took values between 50 and 150, the optimal number of feature (m) varied between 2 and 3. For SVM, the optimal setting for kernel-width (γ) and cost parameter (C) were selected as different for all considered band combinations.

Table 1. Optimized parameter settings for SVM, RF and RotFor.

Band combination	Parameter setting for classifiers		
	SVM (γ, C)	RF (m, k)	RotFor (K, t)
WV-2	0.01, 600	2, 150	10, 50
WV-2 + NDVI	0.12, 500	2, 125	10, 70
WV-2 + 3PC	0.02, 900	3, 80	10, 80
3PC	0.11, 1000	2, 50	10, 60
WV-2 + 3PC + NDVI	0.01, 400	3, 125	10, 100

Table 2. Performance of the classifiers with different variable combinations in terms of the overall accuracy (OA) and computation time (CT).

Band combination	Summary measure	Classifier			
		NN	RF	RotFor	SVM
WV-2	OA (%)	81.21	83.16	90.11	90.00
	CT (s)	0.08	0.14	0.76	0.17
WV-2 + NDVI	OA (%)	81.90	83.33	91.38	90.69
	CT (s)	0.17	0.16	1.76	0.28
WV-2 + 3PC	OA (%)	81.55	83.22	90.75	88.51
	CT (s)	0.14	0.09	1.56	0.27
3PC	OA (%)	79.89	82.01	87.24	83.22
	CT (s)	0.06	0.08	0.69	0.17
WV-2 + 3PC + NDVI	OA (%)	80.40	82.87	91.72	91.38
	CT (s)	0.19	0.13	2.51	0.17

Ground-truth data were used to analyse the accuracy of the thematic maps and to perform further comparisons about the classification performances of the methods. For this purpose, overall accuracies estimated from confusion matrices and required computation time for training phase of each algorithm are shown in Table 2. It should be noted that computation time indicates measured runtimes calculated for each method using a personal computer having Core i7 quad core (3.40 GHz) processor with 16 GB of RAM. Some important conclusions can be drawn from the accuracy results presented in the table. Firstly, it was clearly seen that the highest classification accuracies were estimated by the RotFor algorithm for all band combinations considered in this study. Within these, the RotFor algorithm yield the best classification performance (91.72%) using the band combination including five image objects features of spectral bands of WV-2, NDVI and 3PC. Also, when band combinations of WV-2 and WV-2 + 3PC + NDVI were considered, it was seen that the estimated accuracies between RotFor and SVM were slightly different. Furthermore, the overall accuracies of RF were lower than the RotFor and SVM, ranges from 2% to 7%. On the other hand, the worst classification performance was calculated for the NN classifier for all five band combinations. In addition, with the use of RotFor, RF and SVM the improvement in the accuracy was about 2% compared with the NN algorithm. This clearly indicated that the machine learning algorithms outperformed the traditional NN algorithm for object-based classification. Secondly, when the classification results were analysed with respect to the considered band combinations, overall accuracy slightly increased with addition of image object features related to NDVI and principal components into classification process. On the other hand, the worst classification performances were produced with the band combinations that included only image object features of 3PC. This could be the result of the limited spectral information contents of the band combination. When the band combination consisting of all calculated image object features of WV-2, NDVI and 3PC was used, the use of all data set decreased the classification accuracy of NN and RF, RotFor and SVM produced the highest classification performances. Decrease in classification performance of NN and RF could be the result of the increasing number of image object features. On the other hand, this result suggests that there was a merit in combining the ancillary data sources and using the RotFor and SVM algorithms.

The classification algorithms considered in this study were also compared in terms of their computational costs required for the training phase (Table 2). It was found that the RotFor algorithm required the highest time for all band combinations. In addition, the required computation time increased parallel to the size of image object features (bands). The main reason for this outcome can be related to the PCA in the modelling stage. On the other hand, while the NN algorithm was the fastest for the band combinations having small data set size (i.e. WV-2 and 3PC), RF is the fastest for all other band combinations.

In order to analyse whether the differences in the classification accuracies produced by the classifiers were statistically significant, McNemar's and Wilcoxon's signed-ranks tests were performed (Table 3). It should be noted that both statistical tests were two-tailed and results were interpreted at 95% confidence interval. Within this confidence level, if the calculated statistic is smaller than the critical value shown in bold in the table, it was concluded that there is no statistical significance between the

Table 3. Statistical comparison of the results produced by the classifiers.

	SVM	RF	NN
(a) Comparison of classification algorithms using WV-2 data only			
RotFor	**0.30/0.15**	5.68/8.90	4.77/9.59
SVM		4.93/8.19	4.92/9.43
RF			2.34/5.51
(b) Comparison of classification algorithms using WV-2 + NDVI data			
RotFor	**1.47/1.04**	6.04/10.05	3.88/9.61
SVM		5.27/8.26	3.49/9.36
RF			2.04/4.20
(c) Comparison of classification algorithms using WV-2 + 3PC data			
RotFor	2.30/3.90	5.17/10.81	5.00/10.97
SVM		3.23/5.73	4.01/9.00
RF			2.17/4.74
(d) Comparison of classification algorithms using 3PC data only			
RotFor	5.83/4.98	2.49/6.24	5.09/7.02
SVM		**1.21/1.18**	3.79/8.63
RF			2.53/5.49
(e) Comparison of classification algorithms using WV-2 + NDVI + 3PC data			
RotFor	**1.39/0.48**	5.45/12.18	4.95/11.55
SVM		4.47/9.48	4.70/11.27
RF			3.09/6.73

Notes: While the first value shows Wilcoxon's signed-rank test result, the second shows McNemar's test result. Note that the bold values indicate calculated statistics smaller than the critical values ($\chi^2_{0.05} = 3.84$ and $z_{0.05} = 1.96$).

two classification results at 95% confidence interval. When the statistical test analysed with respect to the comparison of classification algorithms, only four of the all possible combinations were not to be statistically different, and both Wilcoxon's signed-rank test and McNemar's test statistics were lower than the critical table values. In other words, RotFor and SVM classifier produced a statistically similar classification results for the three combinations. All remaining statistical tests results indicated that the RotFor algorithm showed a better performance than the other classifiers with respect to the considered band combinations. In addition, the SVM algorithm produced better classification results than the RF and NN algorithms for all band combinations except for the combinations that included only the 3PC-related image object features. For this data set, SVM and RF yielded a statistically similar classification result. In summary, both statistical test results showed that generally RotFor and SVM classifier showed similar classification performances, superior to the RF algorithm. Also, statistical test results verified that the RotFor, RF and SVM algorithms in all cases outperformed traditional NN algorithm and there were statistically significant differences in overall accuracies between RotFor-NN, SVM-NN and RF-NN.

6. Conclusions

In this study, potential use of the RotFor algorithm, a recently introduced non-parametric ensemble learning algorithm, was analysed in the context of an object-based image analysis and its performance was compared with well-known classification algorithms, namely SVM, RF and NN. For this purpose, combining multiple data sources including WV-2 imagery, NDVI and 3PC were used as a source data. Five data set combinations were created from the multiple data sources, and classification performances of the algorithms were analysed thoroughly.

Results of this study led to some important conclusions. Firstly, for all five data set combinations, the RotFor algorithm showed a superior classification performance than the RF and NN when the estimated overall accuracies were compared. Secondly, although RotFor is a variant of RF method, it produced more accurate classification results. This can be resulting from the training strategy of RotFor that each individual tree in the ensemble is trained on complete data set in a rotated feature space derived from PCA transformation. Thirdly, from the analysis of overall accuracy results, it was observed that two of the five combinations, RotFor and SVM, produced similar accuracies which were confirmed by McNemar's and Wilcoxon's signed-rank tests. Statistical tests also verified the previous findings that the RotFor, RF and SVM algorithms could improve the level of interpretation accuracy in the identification of LULC in object-based classification compared with the traditional NN algorithm. Furthermore, out of the three data combinations, RotFor produced significantly better results than SVM, RF and NN at 95% confidence level. On the other hand, computational cost time measures showed that RotFor required the longest time for the training phase, which is the main drawback of this method. Lastly, it was inferred from the accuracy results that combining both NDVI and 3PC data with WV-2 imagery increased the accuracy of RotFor and SVM while decreasing the accuracy of the RF and NN algorithms. All in all, the results showed that RotFor was found to be an effective and robust classification algorithm for performing object-based image analysis, especially compared with the popular NN and RF when the data set in this study was considered. However, further investigations are needed to validate the performance of RotFor in different types of data sets.

Disclosure statement

No potential conflict of interest was reported by the authors.

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