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Classification of multispectral images using Random Forest algorithm

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Abstract

Random Forest (RF) algorithm is known to be one of the most efficient classification methods. Due to its inherent interdisciplinary nature, it draws researchers from different backgrounds. This study aims at investigating the performance of RF algorithm using multispectral satellite images having different spatial resolutions and scene characteristics. The satellite images used include Ikonos and QuickBird images with four multispectral bands. Ikonos image taken in 2003 covers mainly urban area, whereas QuickBird images acquired in 2005 and 2008 covers both urban and rural areas, respectively. QuickBird image taken in 2005 also contains noisy patterns over Black Sea due to waves resulting from windy weather. To evaluate the performance of RF, the classification results are compared with the results obtained from Gentle AdaBoost (GAB), Support Vector Machine (SVM) and Maximum Likelihood Classification (MLC) algorithms. Preliminary results indicate that RF gives higher classification accuracies than other methods. For Ikonos image over urban area, the results show that RF algorithm gives 10% higher classification accuracy than SVM, whereas GAB algorithm has the lowest classification accuracy (14 % lower than RF). For QuickBird image (taken in 2008) of rural area, RF gives the best result compared to the others. Also, for QuickBird image containing noisy pattern, RF has around 11% higher overall accuracy than SVM.

Keywords
Image classification, Random forest algorithm, Accuracy assessment, Land use.

Özet

Rastgele Orman algoritması kullanılarak çok bantlı görüntülerin sınıflandırılması

Rastgele Orman (RO) algoritması en başarılı sınıflandırma yöntemlerinden biri olarak bilinir. Doğası gereği çok farklı disiplinlere hitap etmesinden dolayı, RO farklı alanlarda çalışan araştırmacıların dikkatini çekmektedir. Bu çalışma, farklı konumsal çözünürlüğe ve karakteristiğe sahip çok bantlı uydu görüntüleri kullanarak RO algoritmasının performansını incelemeyi amaçlamaktadır. Kullanılan uydu görüntüleri dört bantlı Ikonos ve QuickBird görüntüleridir. 2005 ve 2008 yıllarında elde edilen QuickBird görüntüleri sırasıyla hem kentsel hem de kırsal alanları kapsarken, 2003 yılında alınan Ikonos görüntüsü, özellikle kentsel alanı içermektedir. Ayrıca, 2005 yılında alınan QuickBird görüntüsü rüzgarlı havanın yol açtığı dalgalar nedeniyle Karadeniz üzerinde gürültülü örüntüler içermektedir. RO'nun performansını değerlendirmek için sınıflandırma sonuçları, Gentle AdaBoost (GAB), En Çok Benzerlik (EÇB) ve Destek Vektör Makineleri (DVM) algoritmalarından elde edilen sonuçlarla karşılaştırılmıştır. Elde edilen sonuçlar RO'nun diğer yöntemlerden daha yüksek sınıflandırma doğruluğu verdiğini göstermektedir. Kentsel alan üzerinde çekilen Ikonos görüntüsüne ait sonuçlar, RO algoritmasının, DVM' den %10 daha yüksek sınıflandırma doğruluğu verdiğini, GAB algoritmasının ise en düşük sınıflandırma doğruluğuna sahip olduğunu (RO'dan %14 daha düşük) göstermektedir. Kırsal alan üzerinde alınan QuickBird görüntüsüne (2008 yılında alınan)ait sonuçlar diğer yöntemlerden elde edilen sonuçlarla karşılaştırıldığında RO' nun daha iyi sonuç verdiği görülmüştür. Gürültüye benzer örüntüler içeren QuickBird görüntüsü için de RO'nun, DVM'den yaklaşık %11 daha yüksek sınıflandırma doğruluğu verdiği gözlenmiştir.

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1. Introduction

Image classification is the process of converting Digital Number (DN) values to significant land cover information at every pixel location in the image. In other words, image classification assigns pixels of an image to many classes according to statistical decision rules in spectral domain or logical decision rules in spatial domain. Spectral domain uses decision rules, which are based on spectral values of pixels; whereas, decision rules in spatial domain are based on neighborhood information of pixels and spatial contexts such as shape, texture and pattern (Gao 2009).

The most common image classification approaches in the literature are in the category of pixel-based and object-based methods. Pixel-based classification approaches use only spectral information, namely spectral vectors, at each pixel location and ignore spatial context. One of the most widely used pixel-based approaches is Maximum Likelihood Classification (MLC) algorithm. The MLC method assumes that the image data for each class in each band is normally distributed. In the MLC procedure, a given pixel has a probability to belong to a specific class. Hence, the probability of each pixel is calculated and each pixel is assigned to the class that has the highest probability (ENVI 2005).

Contrary to the pixel-based approaches, object-based classification methods consider pixels as group of pixels based on their spatial characteristics to provide more reliable results. Object-based classification methods use different object features such as shape and texture, and spectral values as well. These methods segment the image according to objects that represent groups of pixels obtained with criteria such as shape, compactness and scale factor. Then, these segments are classified (Dronova et al. 2011). This approach is based on fuzzy theory. Using different membership values, one object may be assigned to more than one class (Matinfar et al. 2007).

As an alternative to the traditional pixel-based and object-based approaches, various learning-based algorithms have been developed to obtain more accurate and more reliable information from satellite images. The most widely used learning based algorithms can be listed as Random Forest (RF), Bagging, Boosting, Decision Tree, Artificial Neural Network, Supported Vector Machine (SVM) and K-Nearest-Neighbor. These algorithms are also known as machine-learning methods. Contrary to the statistical approaches, machine-learning methods are non-parametric since they do not rely on any assumption about data distribution. These methods are data driven and they learn the relationship between predictor and response data (Breiman 2001). Using sufficient size data set and parameters, the machine learning methods aim to find the best model for the data using decision rules created from input data.

The SVM, which has widely been used as a machine-learning based classifier in recent years, aims to find a linear discriminate function with maximum margin to separate each class. If samples are not linearly separated from each other, they are transferred to a higher dimensional space where they can be linearly separated and then, the samples are classified in that space (Kaban and Diri 2008). Essentially, SVM is first developed for binary classification, since multi-class problems require complex optimization. However, many pattern recognition applications need more than two classes. Multi-class SVM problems are solved by constructing many binary classifiers (Yavuz and Çevikalp 2008). One Against One (OAO) and One Against All (OAA) are two commonly used methods to solve multi-class problems. For each class, OAA uses one binary SVM to separate members of that class from members of other classes. On the other hand, OAO also uses one binary SVM not for each class, but for each pair of classes to separate members of one class from members of the others. Although OAO would be somewhat slower than OAA, it produces more accurate results on the data (Aisen 2006). This solution makes the classification process very complicated. RF, in this sense, is an alternative method to SVM since RF can classify many variables and classes without using complex parameters and models. The RF classification algorithm is superior to many tree-based algorithms since it is not sensitive to noise and is not subject to overfitting (Watts and Lawrence 2008).

There are many studies to test the performance of RF classifier by comparing the classification results with the ones obtained from other classification algorithms. Jay et al. (2009) state that RF method classifies successfully both complex and homogeneous plant groups with an overall classification accuracy of 88.37%. Waske and Braun (2009) classify temporal SAR images using learning-based (RF and boosting) methods and MLC. Their study shows that learning-based methods give higher classification accuracy (around 10%) than MLC. Prasad et al. (2006) generate plant cover maps for the four species using Regression Tree Analysis (RTA), RF, Bagging Trees (BT) and Multivariate Adaptive Regression Splines (MARS). They compare these four methods by assessing the outputs through multiple statistical evaluation indicators: correlation, Kappa and its variants, variable importance, and the output maps. Results show that BT and RF are superior to other methods, yet the RF gives slightly better performance. Also, Watts and Lawrence (2008), Waske et al. (2007), Gislason et al. (2004), Pal (2003) and Akar et al. (2010) emphasize high accuracy and speed of RF in their studies.

This paper examines the performances of RF algorithm, which is known as a voting based ensemble classification method. Classification results of RF are compared with the results obtained from Gentle AdaBoost (GAB), Support Vector Machine (SVM) and Maximum Likelihood Classification (MLC) algorithms for rural and urban areas using satellite images with different spatial resolutions. Since RF is both an ensemble method and a machine-learning algorithm, it is compared with GAB as an ensemble method and compared with SVM as a machine-learning algorithm. RF can also be counted among pixel-based classification algorithms since it considers individual pixels, not groups of pixels as in the case of object-based algorithms. Therefore, it is also compared with MLC method, which is widely used as a traditional pixel-based classification algorithm.

2. Random forest

Ensemble classification methods are learning algorithms that construct a set of classifiers instead of one classifier, and then classify new data points by taking a vote of their predictions. The most commonly used ensemble classifiers are Bagging, Boosting and RF.

In Bagging algorithm, many bootstrap samples are drawn from a training data set with replacement to learn a classifier and a tree is constructed for each bootstrapped sample such that successive trees are constructed independently from earlier trees, and a simple majority vote is taken for prediction (Liawand Wiener 2002). On the other hand, Boosting uses iterative re-training, and the weights of incorrectly classified samples are increased as the iterations progress to make them more important in the next iterations. Boosting generally reduces both the variance and the bias of the classification, and in most cases, it is considerably more accurate than Bagging; however, it has some disadvantages. It is slow, it can overtrain and it is sensitive to noise (Gislason et al. 2006).

RF classifier can be described as the collection of tree-structured classifiers. It is an advanced version of Bagging (Breiman 2001) such that randomness is added to it. Instead of splitting each node using the best split among all variables, RF splits each node using the best among a subset of predictors randomly chosen at that node. A new training data set is created from the original data set with replacement. Then, a tree is grown using random feature selection. Grown trees are not pruned (Archer 2008; Breiman 2001). This strategy makes RF unexcelled in accuracy (Breiman and Cutler 2005). RF is also very fast, it is robust against overfitting, and it is possible to form as many trees as the user wants (Breiman and Cutler 2005).

To initialize RF algorithm, the user must define two parameters. These parameters are ***N*** and *m*, which are the number of trees to grow and the number of variables used to split each node, respectively. First, ***N*** bootstrap samples are drawn from the 2/3 of the training data set. Remaining 1/3 of the training data, also called out-of-bag (OOB) data, are used to test the error of the predictions. Then, an un-pruned tree from each bootstrap sample is grown such that at each node *m* predictors are randomly selected as a subset of predictor variables, and the best split from among those variables is chosen. It is crucial to select the number of variables that provides sufficiently low correlation with adequate predictive power (Horning 2010). Breiman (2002) suggests that setting number of variables (*m*) equal to the square root of *M* (number of overall variable) gives generally near optimum results. RF uses Classification and Regression Tree (CART) algorithm to create the trees (Beriman 2001). At each node, split is performed according to a criterion (e.g., GINI index) in CART algorithm. GINI index measures class homogeneity and can be written as the equation below (1):

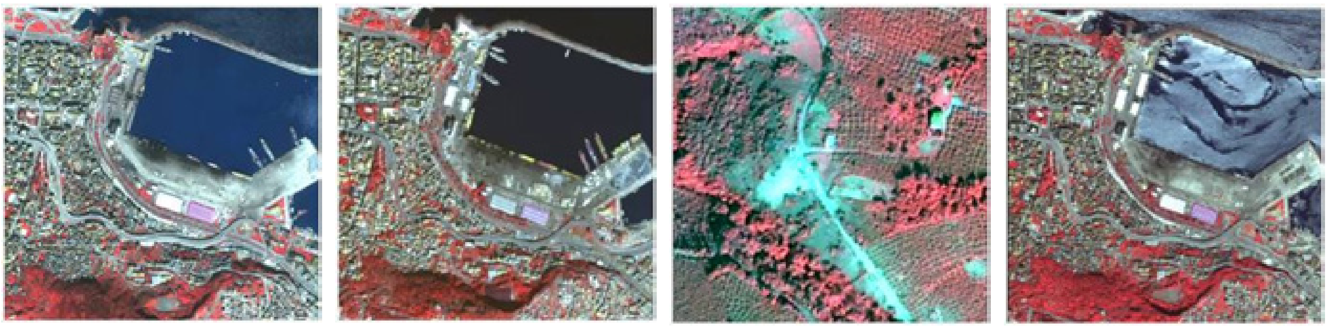
$$\sum\sum_{j\neq i}\left(f\left(C_i,T\right)/\left|T\right|\right)\left(f\left(C_i,T\right)/\left|T\right|\right) \tag{1}$$

where T is a given training set, C_i is the class that a randomly selected pixel belongs to, and $f\left(C_i,T\right)/\left|T\right|$ is the probability that the selected case belongs to class C_i (Pal 2005). As GINI index increases class heterogeneity also increases; however, as GINI index decreases, class homogeneity increases. If a child node of GINI index is less than a parent node, then the split is successful. Tree splitting is terminated when GINI index is zero, which means only one class is present at each terminal node (Watts et al. 2011). Once all N trees are grown in the forest, the new data is predicted based on the outcome of the predictions of N trees (Liaw and Wiener 2002).

RF algorithm explained above works for image classification as follows. Suppose N is chosen as 1000. RF algorithm generates 1000 trees that mean 1000 different classification results for a particular pixel. Suppose that a particular pixel is classified as forest in 800 trees, as land in 100 trees and the same pixel is classified as water in 100 trees. The predicted output for this pixel will be forest.

3. Study area and data

This study is carried out using high resolution multiple images over the city of Trabzon, Turkey and its vicinity with both urban and rural features. Image data used include QuickBird pan-sharpened multispectral (0.6 m) images acquired in 2005 and 2008, and Ikonos multispectral image (4 m) taken in 2003 (Figure 1). Training data set is selected on each image by visually identifying and manually digitizing multiple polygons for each class. For urban area, training areas are selected on the image for eight different land use classes namely, Sea, Vegetation, Soil, Urban Structure 1, Urban Structure 2, Urban Structure 3, Oil Residue and Shadow. For rural area, training areas are also selected for eight different land use classes, i.e., Forest 1, Forest 2, Orchard, Grass, Soil, Road, Urban Structure and Shadow. Once training areas are created, training and test data sets are then generated using Random Feature Selection Method in Matlab. These training areas then used to classify the image data with RF and GAB methods. Total number of training data for Ikonos, QuickBird (2005), QuickBird (2008)-Urban, and QuickBird (2008)-Rural images are 6381, 15092, 12021 and 7716 pixels, respectively. Approximately equal numbers of training pixels are collected for each class. One half of the training data set is used for training and the remaining ones are used



a b c d

Figure 1: Study Areas. a) Ikonos multispectral image over urban area, b) QuickBird pan-sharpened image over urban area (acquired in 2008), c) QuickBird pan-sharpened image over rural area (acquired in 2008)d) QuickBird pan-sharpened image (acquired in 2005), which has noisy patterns.

for testing. The same training areas are also used for SVM and MLC methods. Classification results for RF and GAB algorithms are obtained using a Matlab code; however, ENVI software is used for SVM and MLC.

4. Results and discussion

Classification accuracy of RF method depends on user-defined parameters *N* and *m*; hence, optimal selection of these parameters increases classification accuracy. To find the optimum values for *N* and *m*, multiple combinations are tested and assessed to obtain more reliable thematic maps for the study areas. For different *N* and *m* combinations, OOB error, test accuracy, kappa and computational time results for the training set are given in Table 1.As seen in Table 1, $N = 100$ and $m = 2$ is selected for Ikonos image over urban area. For QuickBird image taken over urban area $N = 350$ and $m = 2$ is chosen; whereas $N = 500$ and $m = 2$ is selected for QuickBird image of rural area.

Images are classified using RF algorithm once optimal parameters for each image are determined. Thematic maps showing classification results are presented in Figure 2 and Figure 3 below. The accuracy of each classification result is evaluated using error matrix, which is one of the most widely used post classification accuracy assessment method. Utilizing this matrix, the relationship between the known reference data (ground truth) and the corresponding results of an automated classification can be compared on category-by-category basis (Lillesand et al. 2004).

For accuracy assessment 240 points are randomly distributed on the images such that the number of points for each class is stratified to the distribution of all thematic layer classes. Accuracy of each thematic map is tested using the same 240 points. Table 3 shows the error matrices of RF method for urban and rural areas.

To evaluate the performance of RF algorithm, classification results of RF are compared with the results obtained from GAB, SVM and MLC algorithms. Similar to RF algorithm, SVM method also requires optimum parameter selection. ENVI's implementation of SVM uses the pairwise classification strategy, also known as one against one, for multi-class classification. Radial Basis Function kernel, among the ones provides most accurate classification results for SVM (Kavzoğlu and Çölkesen 2010), is used for SVM method. Optimal penalty parameter (*C*) is also identified for each study area and different *C* parameter combinations are given in Table 2.

When error matrices of all classification methods and all images are investigated, it can be concluded that classes having similar spectral properties are most likely to be confused. In Ikonos image over urban area, Urban Structure 2, Urban Structure 3, Vegetation and Soil classes are the ones most confused since they have similar spectral characteristics. Oil Residue and Shadow classes have also similar spectral properties as well. From Table 4, it can be concluded that RF has ~22% higher producer's accuracy than GAB, SVM and MLC particularly for vegetation class. According to user's accuracy of the same class, RF has higher accuracy than GAB (~28%), SVM (~12%) and MLC (~4%). SVM has the best performance for Urban Structure 3 class since it has 1% higher performance than RF. For the Soil class, RF has higher producer's accuracy than SVM(~19%)and MLC (~13%). User's accuracy of the same class shows that MLC has the lowest performance (43% lower than RF).

In QuickBird-2005 image, which has a higher spatial resolution than the Ikonos image, RF gives the highest overall classification accuracy (83.75%). When both user's and producer's accuracies are considered, Table 4 reveals that RF separates Vegetation, Soil, Urban Structure 2, Urban Structure 3 and Shadow classes better than other methods. In terms of producer's accuracies, RF has better performances for Soil, Urban Structure 3, Shadow, Oil Residue and Vegetation classes.

Classification results for rural area indicate that RF algorithm is more successful than GAB, SVM and MLC (see Table 5). Forest, Grass and Orchard classes have similar spectral characteristics. For class name Forest 1, RF has higher producer's accuracy values than GAB (~29%), SVM (~21%) and MLC (~38%). RF also improves user's accuracies of SVM and MLC around 17% and 29%, respectively for the same class. Grass class also has similar results. Although MLC shows the best performance for producer's accuracy of Orchard class, RF has the highest user's accuracy value for this class.

The reason of selecting QuickBird 2005 image is to test the performance of RF algorithm with an image that has noisy effects in it. This image was taken on a windy weather; therefore, the surface of the Black Sea was not smooth. Rough sea surface, as a result of waves, created shadows and white sea-foam patterns (just like noise added intentionally to the image data), which are considered as noise in this paper. As a result, pixels belong to this noisy pattern in the Sea class are misclassified as Urban Structure 1. As seen in Table 7 and Table 8, noisy pattern in sea class adversely affects the performance of classifiers; however, RF algorithm is less affected from this unfavorable situation and offered best performance among other classifiers with a 83.75% overall classification accuracy. With this image, GAB demonstrates the poorest performance with 68.54% overall classification accuracy. Hence, it can be concluded that GAB method is the one most affected from the noise. Urban Structure 1 and Sea classes are heavily affected from noise; however, RF and SVM methods have a better performance than GAB and MLC when these classes are considered (Table 6).

Table 1: Parametersof RF test results for Ikonos image

N	*m*	OOB Error (%)	Accuracy (%)	Kappa	Computational Time (sn)
95	2	0.0536	78.33	0.7521	34.2965
100	2	0.0465	87.08	0.8524	36.2796
125	2	0.0444	80.42	0.7757	42.2122
233	2	0.0486	78.75	0.7563	69.9202
250	2	0.0465	77.92	0.7477	78.1638
500	2	0.0514	81.67	0.7891	144.4255

Table 2: Different C Parameters of SVM test results for 2008 QuickBird image over rural area

C	Test Accuracy (%)	Kappa
50	66.40	0.5836
60	66.80	0.5884
70	67.20	0.5937
80	68.00	0.6038
90	68.00	0.6044
100	67.60	0.5992

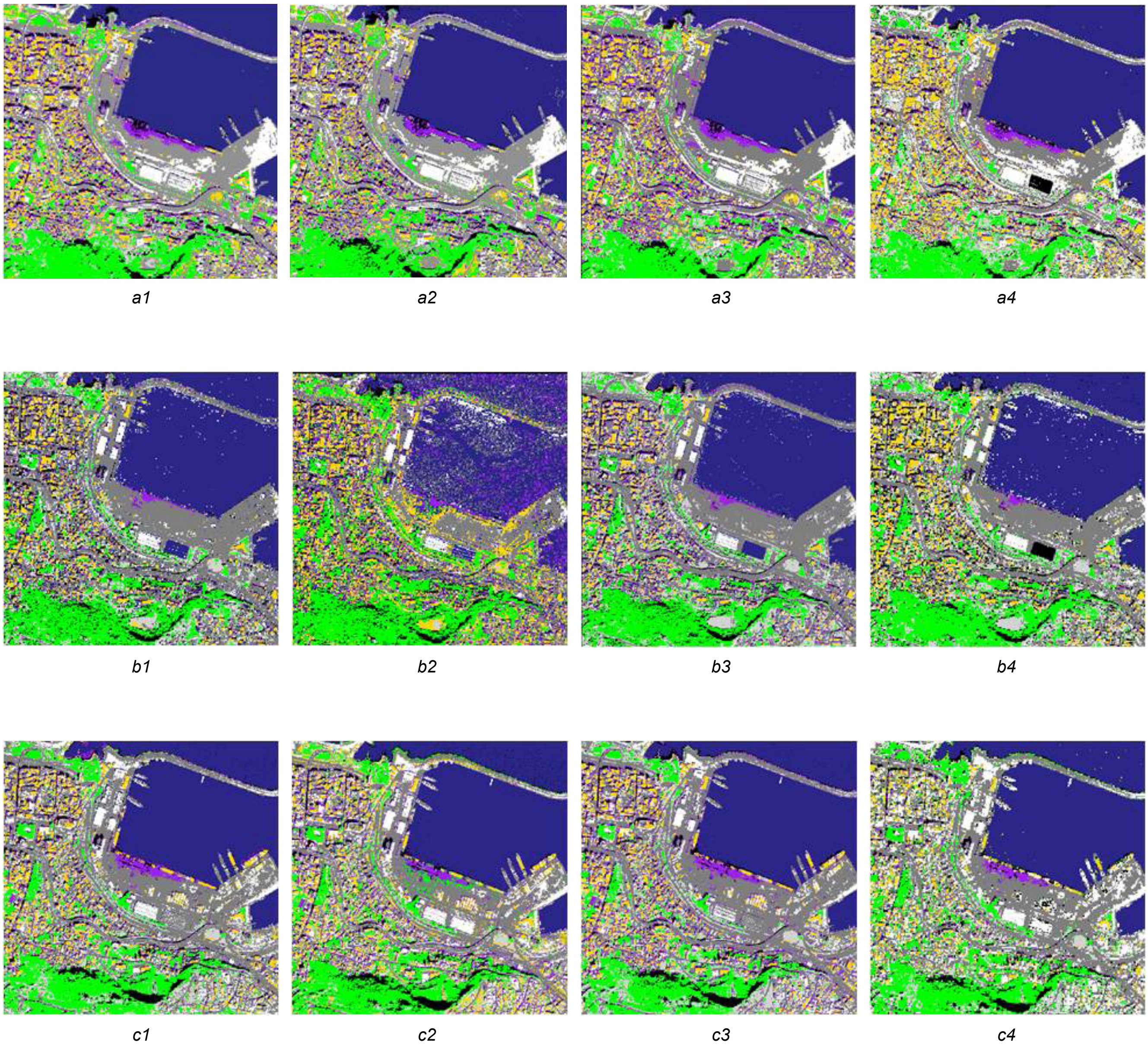


Figure 2: Classification results of the images over urban area. Classification results for Ikonos image: RF(a1), GAB (a2), SVM (a3) and MLC (a4). Classification results for QuickBird-2005 image, which has noisy pattern: RF(b1), GAB (b2), SVM (b3) and MLC (b4). Classification results for QuickBird-2008 image: RF(c1), GAB (c2), SVM (c3) and MLC (c4)

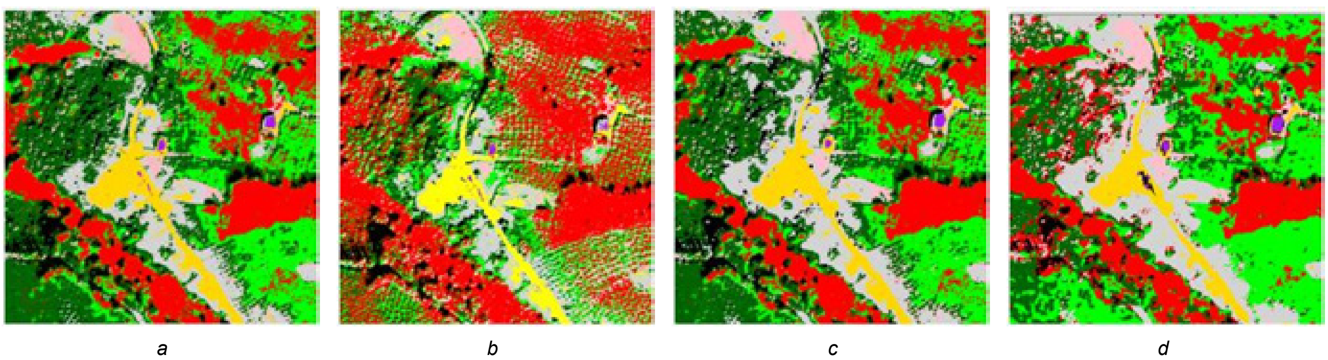


Figure 3: Classification results of the QuickBird-2008 image over rural area: RF (a), SVM (b), GAB (c) and MLC (d) methods.

Table 3: Error Matrix of RF for a) Urban Area (Ikonos), b) Rural Area (QuickBird-2008)

		Classes										
		Sea	**Vegetation**	**Soil**	**Urban Structure 1**	**Urban Structure 2**	**Oil Residue**	**Urban Structure 3**	**Shadow**	**Row Totals**	**Producer's Accuracy(%)**	**User's Accuracy(%)**
Classes	**Sea**	30	0	0	0	0	0	0	0	30	100.00%	100.00%
	Vegetation	0	30	0	0	0	0	0	0	30	93.75%	100.00%
	Soil	0	0	30	0	0	0	0	0	30	96.77%	100.00%
	Urban Structure 1	0	0	0	30	0	0	0	0	30	93.75%	100.00%
	Urban Structure 2	0	1	0	1	27	0	0	1	30	77.14%	90.00%
	Oil Residue	0	0	1	0	7	7	2	13	30	87.50%	23.33%
	Urban Structure 3	0	0	0	1	1	0	27	1	30	93.10%	90.00%
	Shadow	0	1	0	0	0	1	0	28	30	65.12%	93.33%
	Column Totals	30	32	31	32	35	8	29	43	240		

Overall accuracy = 87.08%   Kappa = 0.8524
a)

		Classes										
		Forest 1	**Forest 2**	**Orchard**	**Grass**	**Soil**	**Road**	**Urban Structure**	**Shadow**	**Row Totals**	**Producer's Accuracy(%)**	**User's Accuracy(%)**
Classes	**Forest 1**	21	0	5	1	0	0	0	3	30	87.50%	70.00%
	Forest 2	0	19	8	0	0	0	0	3	30	70.37%	63.33%
	Orchard	0	7	22	1	0	0	0	0	30	62.86%	73.33%
	Grass	3	1	0	26	0	0	0	0	30	89.66%	86.67%
	Soil	0	0	0	0	24	5	0	1	30	92.31%	80.00%
	Road	0	0	0	1	2	27	0	0	30	84.38%	90.00%
	Urban Structure	0	0	0	0	0	0	30	0	30	100.00%	100.00%
	Shadow	0	0	0	0	0	0	0	30	30	81.08%	100.00%
	Column Totals	24	27	35	29	26	32	30	37	240		

Overall accuracy= 82.92%   Kappa= 0.8048
b)

Table 4: The user's and producer's accuracies for images over urban areas

	Ikonos								QuickBird-2008							
	RF		GAB		SVM		MLC		RF		GAB		SVM		MLC	
Classes	Producer's Accuracy(%)	User's Accuracy(%)	Producer's Accuracy(%)	User's Accuracy(%)	Producer's Accuracy(%)	User's Accuracy(%)	Producer's Accuracy(%)	User's Accuracy(%)	Producer's Accuracy(%)	User's Accuracy(%)	Producer's Accuracy(%)	User's Accuracy(%)	Producer's Accuracy(%)	User's Accuracy(%)	Producer's Accuracy(%)	User's Accuracy(%)
Sea	100.00	100.00	100.00	83.33	96.67	96.67	100.00	90.91	93.75	100.00	96.88	93.94	96.88	96.88	93.75	100.00
Vegetation	93.75	100.00	71.88	71.88	71.88	88.46	71.88	95.83	81.08	100.00	70.27	61.90	62.16	95.83	81.08	81.08
Soil	96.77	100.00	38.71	80.00	77.42	77.42	83.87	56.52	81.48	73.33	48.15	61.90	74.07	54.05	62.96	68.00
Urban Structure 1	93.75	100.00	90.63	93.55	87.50	93.33	84.38	87.10	93.33	93.33	93.33	93.33	80.00	96.00	96.67	63.04
Urban Structure 2	77.14	90.00	85.71	54.55	80.00	59.57	74.29	74.29	90.00	90.00	80.00	82.76	90.00	81.82	76.67	56.10
Oil Residue	87.50	23.33	62.50	20.83	75.00	18.75	87.50	50.00	100.00	36.67	72.73	33.33	81.82	29.03	72.73	57.14
Urban Structure 3	93.10	90.00	62.07	81.82	72.41	91.30	72.41	65.63	96.00	80.00	64.00	55.17	92.00	82.14	52.00	76.47
Shadow	65.12	93.33	48.84	84.00	44.19	90.48	41.86	94.74	62.50	100.00	62.50	93.75	58.33	93.33	54.17	92.86

Table 5: The user's and producer's accuracies for QuickBird-2008 image over rural area

	RF		GAB		SVM		MLC	
	Producer's Accuracy(%)	User's Accuracy(%)	Producer's Accuracy(%)	User's Accuracy(%)	Producer's Accuracy(%)	User's Accuracy(%)	Producer's Accuracy(%)	User's Accuracy(%)
Forest 1	87.50	70.00	58.33	1.62	66.67	53.33	50.00	41.38
Forest 2	70.37	63.33	85.19	41.82	70.37	57.58	55.56	38.46
Orchard	62.86	73.33	14.29	50.00	57.14	68.97	71.43	53.19
Grass	89.66	86.67	75.86	68.75	89.66	83.87	55.17	80.00
Soil	92.31	80.00	69.23	48.65	75.00	63.16	78.13	100.00
Road	84.38	90.00	75.00	68.57	88.46	63.89	100.00	65.00
Urban Structure	100.00	100.00	30.00	100.00	60.00	100.00	76.67	100.00
Shadow	81.08	100.00	67.57	96.15	67.57	100.00	27.03	100.00

Table 6:The user's and producer's accuracies forQuickBird-2005 image, which has noisy effects

	RF		GAB		SVM		MLC	
	Producer's Accuracy(%)	User's Accuracy(%)	Producer's Accuracy(%)	User's Accuracy(%)	Producer's Accuracy(%)	User's Accuracy(%)	Producer's Accuracy(%)	User's Accuracy(%)
Sea	90.63	96.67	84.38	79.41	90.63	96.67	87.50	96.55
Vegetation	85.71	100.00	94.29	73.33	85.71	85.71	85.71	78.95
Soil	95.00	63.33	25.00	41.67	95.00	41.30	85.00	53.13
Urban Structure 1	96.55	93.33	75.86	91.67	79.31	95.83	65.52	76.00
Urban Structure 2	80.56	96.67	41.67	65.22	63.89	82.14	69.44	67.57
Oil Residue	100.00	23.33	100.00	20.59	100.00	25.00	100.00	50.00
Urban Structure 3	96.67	96.67	96.67	65.91	73.33	100.00	80.00	70.59
Shadow	58.82	100.00	45.10	95.83	50.98	96.30	52.94	96.43

Table 7: Overall accuracy assessment of RF, SVM, GAB, and MLC methods for all four image sets

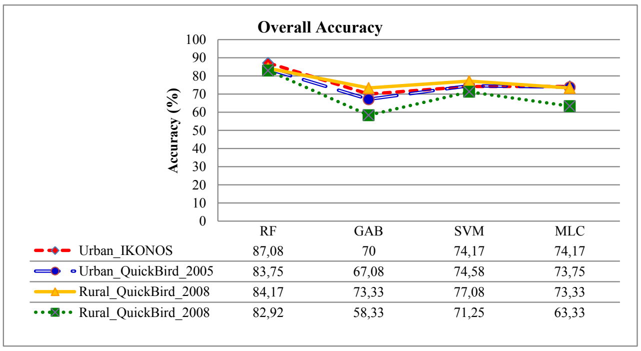


Table 8: Average overall accuracies of RF, SVM, GAB, and MLC methods with/without noisy effect

Noisy Effect	Area	RF (%)	GAB(%)	SVM(%)	MLC(%)
No	**Urban**	85.63	71.67	75.63	73.75
	Rural	83.75	67.08	74.58	73.75
Yes	**Urban**	85.42	68.54	74.38	73.96

5. Conclusion

This study examines the performance of RF algorithm using satellite images with different resolutions and areas with different characteristics. The results of RF algorithm are compared with the ones obtained from SVM, GAB and MLC methods. Two types of images are used; one is composed of Ikonos and QuickBird images covering urban areas; whereas other one is a QuickBird image taken over rural area. Additionally, the effect of noisy patterns to the classification accuracy in an image is investigated with a QuickBird image, which contains noisy patterns. Results show that RF gives the best performance in urban area with 85.63% overall classification accuracy. RF also has 10% and 15% better performances when compared to the corresponding SVM results for urban and rural data, respectively. These results reveal that SVM has the second best performance among four classifiers, as it follows the best performance of RF in rural and urban areas. With noisy urban data, RF method also improves the overall accuracies of the SVM and MLC methods around 11% and the GAB method around 17%, which indicates that RF is also successful when working with image having noisy effects. It is also seen that RF method is successful at discriminating the classes having similar spectral characteristics. Future research will focus on integrating texture, slope and other non-spectral information to the RF method to further improve its performance in satellite image classification.

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