RECENZIRANI ČLANKI | PEER-REVIEWED ARTICLES

PRIMERJAVA DREVESNIH ALGORITMOV RAZVRŠČANJA PRI ZAJEMU OBMOČIJ POGORELIH GOZDOV

COMPARISON OF TREE-BASED CLASSIFICATION ALGORITHMS IN MAPPING BURNED FOREST AREAS

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IZVLEČEK

V študiji primerjamo rezultate različnih drevesnih algoritmov razvrščanja območij za zajem pogorelih gozdov v sredozemskem delu Turčije, to so naključni gozd (angl. random forest*), rotacijski gozd (angl.* rotation forest*), J48, izmenično odločitveno drevo (angl.* alternating decision tree*), gozd z izločanjem atributov (angl.* forest by penalising attributes*), logična analiza podatkovnih algoritmov (angl.* logical analysis of data algorithm*) in funkcionalni gozd (angl.* functional forest*). Izvedli smo objektno analizo (OBIA, angl.* object-based image analysis*) izostrenih satelitskih podob Landsat 8. V študijo so bila vključena štiri pogorela območja oziroma regije, to so Kumluca, Adrasan, Anamur in Alanya. Kumluca, Anamur in Alanya so bili izbrani za učenje, medtem ko je bil Adrasan uporabljen kot študijsko območje. Rezultate smo ovrednotili z matriko razvrstitev in statističnimi analizami. Rezultati so bili najboljši pri uporabi algoritmov funkcionalnih dreves in rotacijskih dreves, pri čemer so se rezultati izkazali tudi statistično značilni, medtem ko so bili pri drugih algoritmih slabši.*

ABSTRACT

In this study, we compared the performance of tree-based classification algorithms – Random Forest (RF), Rotation Forest (RotF), J48, The Alternating Decision Tree (ADTree), Forest by Penalising Attributes (Forest PA), Logical Analysis of Data Algorithm (LADTree) and Functional Trees (FT) – for mapping burned forest areas within the Mediterranean region in Turkey. Object-based image analysis (OBIA) was performed to pan-sharpened the Landsat 8 images. Four different burned areas, namely Kumluca, Adrasan, Anamur, and Alanya, were used as study areas. Kumluca, Anamur, and Alanya regions were used as training areas, and Adrasan region was used as the test area. Obtained results were evaluated with confusion matrix and statistically significant analysis. According to the results, FT and RotF produced more accurate results than other algorithms. Also, the results obtained with these algorithms are statistically significant.

KLJUČNE BESEDE

drevesni algoritmi, strojno učenje, daljinsko zaznavanje, nadzorovana klasifikacija, Landsat

KEY WORDS

tree-based algorithm, machine learning, remote sensing, dupervised vlassification, Landsat

1 INTRODUCTION

Forest fires threaten the forest ecosystems in the Mediterranean region as well as in forest ecosystems all over the world (Gonçalves and Sousa, 2017). Although the fires in the Mediterranean ecosystem are an expected consequence due to climatic effects (hot and dry summers), it has been observed that they have increased dramatically in recent years. Only in 2017, a total of 50,727 fires occurred in countries located in the Mediterranean climate zone (Italy, Portugal, France, Greece, Turkey, Spain), which nearly 1 million hectares of forest were damaged (San-Miguel-Ayanz, 2019). As a result of increasing fire events, the Mediterranean ecosystem may expose to loss of biodiversity, desertification and soil erosion. Fires also cause economic losses, human life losses, and greenhouse emissions (Vilén and Fernandes, 2011).

After a forest fire, rapid mapping of the burned area is an important task to determine the effects of fires and to plan and manage the reforestation activities (Palandjian, Gitas and Wright, 2009; Vallejo, Arianoutsou, and Moreira, 2012; Chen et al. 2017; Meng et al., 2017). Also, burned area maps can be used as input to produce future fire risk maps (Filippidis and Mitsopoulos, 2004). Satellite imagery has provided very important contributions in the mapping of burned areas since the 1980s (Flannigan and Haar, 1986). The most commonly used method for extracting information from satellite images is image classification. Many image classification algorithms have been applied in mapping burned areas from past to present (Pereira, 1999; Chuvieco Martin and Palacios, 2002, Epting, Verbyla and Sorbel, 2005; Loboda, O'neal and Csiszar, 2007; Escuin, Navarro and Fernandez, 2008; Palandjian, Gitas and Wright, 2009; Petropoulos et al., 2010; Bastarrika, Chuvieco and Martín, 2011; Mitrakis et al., 2012). These studies were generally based on classical classification algorithms such as rule-based classification or change detection. On the other hand, Machine learning algorithms that can successfully classify many variables in large data sets have become more popular in remote sensing applications (Lary et al. 2016). A limited number of machine learning algorithms such as Random Forest (RF), Support Vector Machine (SVM), Neural Networks (NN) and a well-known decision tree algorithm (C5.0) were used for mapping burned areas from satellite images (Petropoulos, Kontoes, and Keramitsoglou, 2011; Dragozi et al., 2014; Ramo and Chuvieco, 2017; Pereira et al., 2017; Ramo et al., 2018; Çömert, Matcı, and Avdan, 2018).

In recent years, fast and efficient classification algorithms have been developed for classifying data in complex data sets, particularly in the classification of satellite images for the production of thematic maps. Among these methods, tree-based classification algorithms are proposed as an effective classification algorithm which is used to solve many application problems (Pal and Mather, 2001; Tan, Dowe and Dix, 2007; Al Snousy et al., 2011; Sothe et al., 2018). Tree-based machine learning algorithms are effective algorithms for accurate classification of large datasets with many variables. These algorithms have been successfully implemented in different field of data mining applications (Nithya and Santhi, 2015; Estuar et al., 2017). Rotation Forest (RotF), J48, and RF were the algorithms currently used in the classification of satellite images (Vieira et al., 2012; Sharma, Ghosh and Joshi, 2013; Kavzoglu, Colkesen and Yomralioglu, 2015; Du et al., 2015; Belgiu and Drăguţ, 2016). On the other hand, there are many tree-based algorithms that can be used successfully in satellite image classification. Forest by Penalizing Attributes (Forest PA) (Adnan and Islam, 2017), Alternating Decision Tree (ADTree) and Logical Analysis of Data Algorithm (LADTree) have not been used in remote sensing applications.

This study aims to investigate the success of the different tree-based classifiers that can be used for mapping burned areas with medium spatial resolution and no-cost satellite image. For this aim, seven tree-based classification algorithms (RF, RotF, J48, ADTree, Forest PA, LADTree, FT) were compared on the Landsat 8 images of burned forest areas within the Mediterranean region in Turkey. The accuracy of the results was evaluated according to the confusion matrix. Then, Mcnemar's test was performed to compare the classification algorithms based on the accuracy results.

2 STUDY AREA AND DATASETS

The study areas are located in the Mediterranean region of Turkey (Figure 1). Kumluca, Adrasan and Alanya are within the province of Antalya, and Anamur is within the province of Mersin. These cities are the Mediterranean cities which have a first-degree fire risk potential. Mediterranean climate characteristics such as unfavourable meteorological conditions, flammable Mediterranean vegetation, and rugged topographic structure, increase the forest fire risk in these areas. Most of the forest areas in Antalya and Mersin provinces consist of red pine forests (*Pinus brutia* Ten.). 65 % of the forests in the province of Antalya, and 79 % of the forests in the province of Mersin consist of red pine forests. There is a long dry period, characterised by high temperatures and relatively low humidity in the summer months, in areas where red pine forests are spread. During this period, since the moisture content of both the living vegetation cover and the dead vegetation cover is decreased significantly, the risk of fire is extremely high (Küçükosmanoğlu, 1990; Duran, 2014). The four burned forest areas selected as the study area consist of red pine forests.

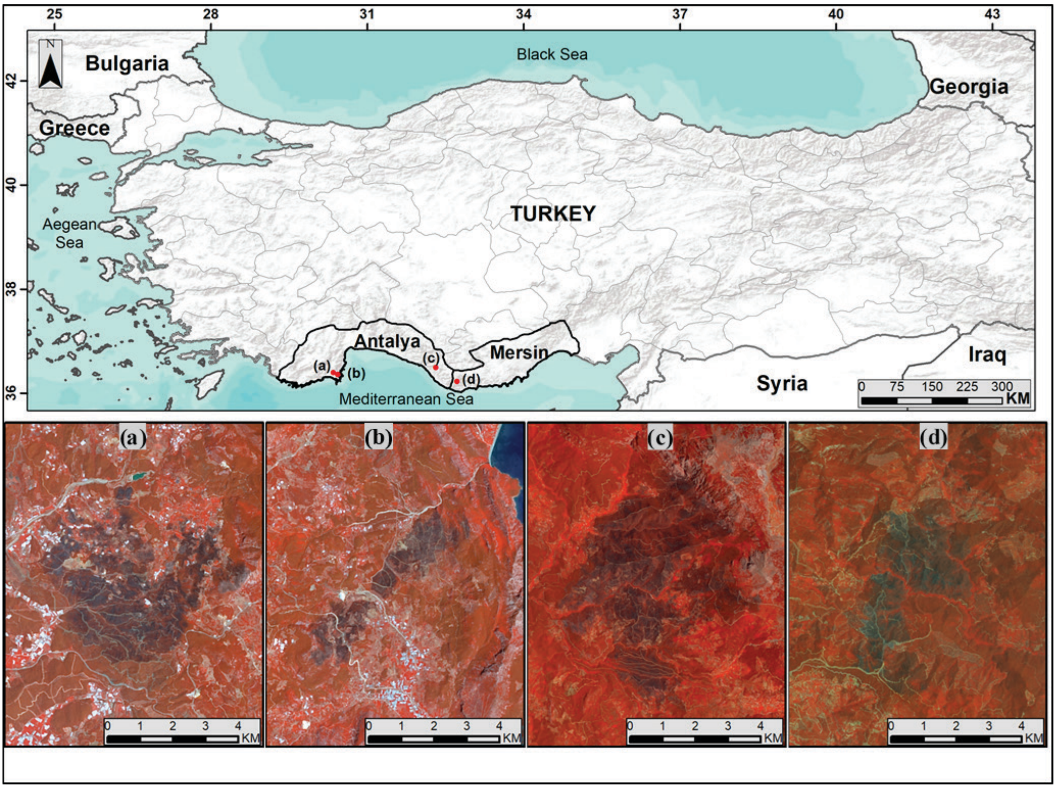

Figure 1: Study areas a) Kumluca (The First Training Area) b) Adrasan (Test Area) c) Alanya (The Second Training Area) d) Anamur (The Third Training Area).

The Adrasan and Kumluca fire events occurred on 24–27 June 2016. During these events, 1320 ha forest area in Kumluca and 520 ha forest area in Adrasan were burned. The Alanya fire event occurred on 31 June-2 July 2017. In this event, 1 500 hectares of forest area were damaged. The Anamur fire event occurred on 1-3 July 2017, and during this event, 200 hectares of forest area were burned.

The USGS Landsat mission is one of the longest moderate- resolution free satellite image resources for agriculture, geology, forestry, regional planning, education, and mapping resource all over the world. Landsat 8 that is the last satellite of Landsat mission has two sensors that are Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). In this study, OLI Level-1 Processing Terrain Precision (L1TP) post-event satellite images (08 July 2016 for Adrasan and Kumluca, 4 July 2017 for Anamur and Alanya) were used. The Landsat L1TP collection is radiometrically calibrated and orthorectified using ground control points and digital elevation model (DEM) data, to correct for relief displacement (URL 2). In this study, six multispectral bands (Blue, Green, Red, NIR, SWIR 1, SWIR 2) of Landsat 8 were used for burned forest area mapping using tree-based algorithms. Also, the panchromatic band was used for the pan-sharpening of these spectral bands.

3 METHODS

Object-based image analysis approach was used to compare the success of tree-based classification algorithms. Training and test datasets were generated for comparison. The training data was used to determine the optimal classification models by testing different parameters for every classification algorithm. Then, the optimal classification models were applied to the test data set. The accuracy analysis of the results was performed according to the confusion matrix. Mcnemar's test was applied to the comparison of the classification algorithms. Applied methods of this study consist of six steps which are pan-sharpening, image segmentation, calculation of image objects attributes, creating training and test data, classification with tree-based algorithms, accuracy assessments and comparison (Figure 2).

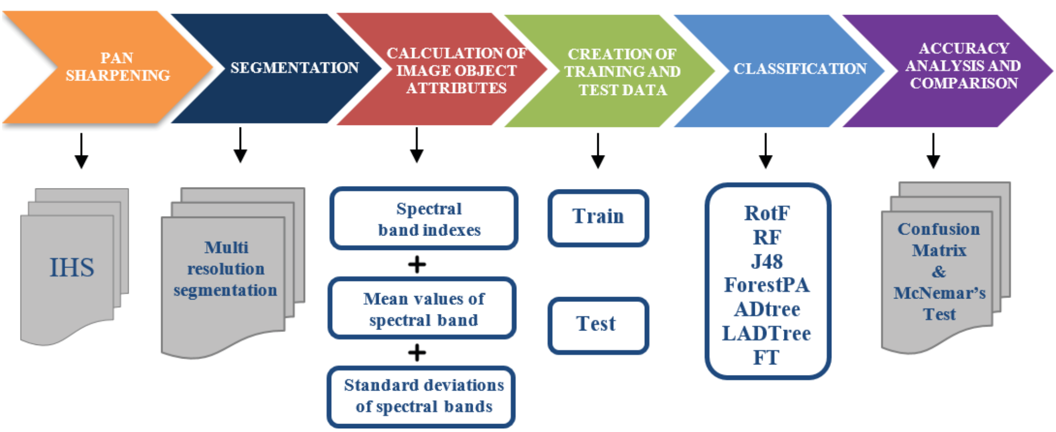

Figure 2: Applied methodology for comparison of tree-based classification algorithms.

a. Pan-Sharpening

During pan-sharpening steps, 6 multispectral bands were pan-sharpened using a 15-meter spatial resolution panchromatic band. During the pan-sharpening phase, the intensity–hue– saturation (IHS) algorithm was applied to spectral bands. In this method, the image is converted from RGB colour space to IHS colour space. The Intensity band is replaced by a panchromatic image, assuming that the band is equivalent to a panchromatic image. A high-resolution multi-band image is obtained by reverse IHS conversion (Rahmani et al., 2010).

b. Image Segmentation

Pixel-based image analysis (PBIA) and object-based image analysis (OBIA) are two main image classification approaches in remote sensing applications. Many studies have compared the performance of these two approaches. OBIA gives more accurate results when applied to very high-resolution images (Ghosh and Joshi, 2014; Sertel and Alganci, 2015; Kavzoğlu and Erdemir, 2016), it gives almost close or slightly outperforming results with PBIA when applied to medium resolution images (Esetlili et al., 2018). In this study, OBIA was preferred because the two approaches were not statistically different in medium resolution images.

Image segmentation is the first stage of the OBIA. The main aim of this stage is the creation of homogeneous and meaningful image objects for image classification. The multi-resolution segmentation (MRS) that were commonly used algorithm in OBIA was preferred as image segmentation (Baatz and Schape, 2000). The MRS is a region enhancement algorithm that combines pixels or existing image objects. The method starts at the one-pixel level and combines neighbouring pixels depending on a spectral and geometric homogeneity criterion. In the study, MRS was implemented using Ecognition Developer (version: 9.0) software. In the segmentation process, six pan-sharpened spectral bands were used. To obtain optimal image objects, the scale parameter, shape, compactness and layer weight were specified by the trial and error method (Benz et al., 2004).

c. Calculation of image object metrics

The forest fires directly affect the vegetation. There are many studies on burned area mapping and burned severity assessment, which used burned area indices and vegetation indices for the increasing success of the methods (Fraser, Li, and Cihlar, 2000; Chuvieco, Martin, and Palacios, 2002; Loboda, O'neal, and Csiszar, 2007; Schepers et al., 2014).

Table 1: Spectral bands indices using for the classification process.

Band İndex	Formulation	References
Brightness values (B)	$B = \left(\frac{1}{n}\right) * \sum_{i=1}^{n} ci$ n= indicates of number band ci: sum of the object mean values in the bands	(Stumpf and Kerle,2011)
Burned Area Index (BAI)	$1/((0.1\text{-Red})^2 + (0.06 - \text{NIR})^2)$	(Chuvieco Martin, and Palacios, 2002)
Normalized Burn Ratio (NBR)	(NIR –SWIR 2) / (NIR + SWIR 2)	(Key and Benson, 2006)
Normalized Burn Ratio 2 (NBR2)	(SWIR 1 –SWIR 2) / (SWIR 1 + SWIR 2)	(USGS)
Normalized Difference Vegetation Index	(NIR-Red) / (NIR+Red)	(Tucker, 1979)
Soil-adjusted Vegetation Index	((NIR – Red) / (NIR + Red + 0.5)) * (1.5)	(Huete, 1988).

The eighteen object attributes were used in the classification. These attributes consist of six spectral bands mean values (Blue, Green, Red, NIR, SWIR 1, SWIR 2), six standard deviations of spectral bands and six band indices The mean values of the bands are obtained by dividing the total value of the pixels falling into an image object by the number of pixels. When calculating the standard deviation values of the bands, firstly, the sum of the differences of each pixel value forming the image object from the average value is calculated. The calculated value is divided by one minus the total number of pixels, and the square root of that value is calculated. The names and formulas of the band indices used are given in Table 1.

d. Classification

Seven tree-based algorithms were tested in this study. The common feature of these algorithms is that they are the tree-based supervised classification methods. In this context, training and test data are needed. Within the scope of the study, we collected the training data from the different parts of the Mediterranean region. The common characteristics of these regions are that they have similar geographical specifications and vegetation types as the test area. These training data collected from the regions affected by the fires occurred in the Kumluca, Alanya and Anamur regions (Figure 1a, 1c, 1d). Adrasan burned area was used as the test dataset (Figure 1b).

In this study, one of the methods used for mapping burnt areas is the random forest (RF) method. The random forest method developed by Breiman (1996), creates multiple decision trees and combines them to get a more accurate and stable forecast (Breiman, 2001). Random Forest adds additional randomness to the model as it grows trees. Rather than searching for the most important feature when splitting a node, it looks for the best feature among a random subset of features. This results in a wide variety that often results in a better model.

In the rotation forest algorithm (RotF), more than one tree is used as it is in the random forest algorithm. Unlike the random forest algorithm, the data set to be used in the training of each decision tree in the forest is determined by the main component analysis. With the rotation forest algorithm, the training data set is randomly divided into subgroups during the training of the decision trees in the forest and feature extraction is performed by applying the analysis of the main components to each subgroup (Rodriguez, Kuncheva and Alonso, 2006).

The J48 classifier begins with the tree structure, dividing the trees and selecting the best root variable for the tree, and constructing from top to bottom. J48 is able to do an effective pruning to cut weak branches. One of the reasons is that the purpose of the decision trees is not to discover data but to create a simple classification model on the data (Patil and Sherekar, 2013).

The Alternating Decision Tree (ADTree) applies boosting procedures to produce accurate classifiers. The algorithm consists of decision nodes and prediction nodes. Decision states indicate an action result. Classification for a record is made by following the correct path of each prediction node, and all decision nodes passed through it (Freund and Mason, 1999).

The Forest by Penalizing Attributes (ForestPA) algorithm generates a very precise set of decision trees using all out-of-class attributes present in a data set. At the same time, penalties are imposed on the attributes of the most recent tree to form the next trees (Adnan and Islam, 2017).

Logical Analysis of Data Algorithm (LADTree) is a decision tree for the multi-class produces. So, it has the ability to enter more than one class. The modelling for a given set of data is based on creating large group patterns and choosing subgroups within each group by specific requirements in terms of prevalence and homogeneity (Boros et al., 2000).

Functional trees (FT) use the information of all input properties in both the nodes and leaves. The decision nodes in functional decision trees include a test data set based on attribute combination, and leaf nodes are in estimates due to a combination of attributes. The decision tests for multiple variables are performed in internal nodes, while class estimates are carried out using approximation curves in leaf nodes (Gama, 2004).

e. Accuracy Assessment

The classification results were evaluated using a confusion matrix, that summarises the classification performance of a classifier to test data (Table 2). The performance measures that are sensitivity, precision, f-score and overall accuracy were calculated from the confusion matrix (eq. 1-4) (Sokolova and Lapalme, 2009).

Table 2: Confusion matrix parameters.

	Predicted Class	
Actual Class	(TP) True Positive	(FN) False Negative
	(FP) False Positive	(TN) True Negative

$$Sensitivity = \frac{TP}{TP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$F - score = \frac{2 * sensitivity * precision}{sensitivity + precision} \tag{3}$$

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} \tag{4}$$

In order to calculate performance measures of tree-based classification algorithms according to the confusion matrix, 626 control points were randomly assigned to the test area (Figure 3). The ground truth class of the control points were determined using Google Earth software as they provide high-resolution images of the test area. Obtained results were evaluated using McNemar's statistically significant test. This method used to analyse whether the two methods applied to the same data set are different (McNemar, 1947).

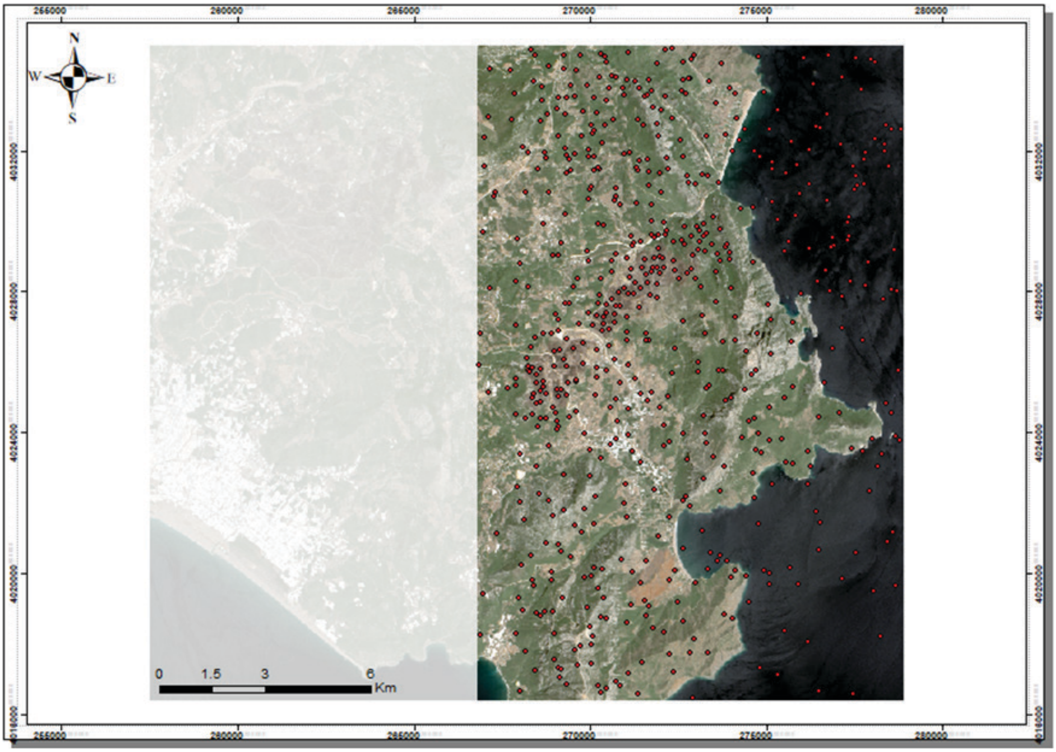

Figure 3: Red dots indicate the control points that were used at accuracy assessment.

4. RESULTS AND DISCUSSION

During the segmentation process, to obtain optimum MRS segmentation parameters, the trial and error method was applied. As a result of the trial and error method, the appropriate parameter values for the data set were determined as scale factor 100, shape 0.3 and compactness 0.5. The equal weight values were assigned to all bands. These parameters were used for both training and test areas when creating image objects. After the segmentation process, image object attributes were calculated. Using image objects and their attributes, training and test datasets were generated for the classification step. In the training areas, image segments were defined in two classes, burned area (BA) and non-burned area (NBA). The classification models for each forest algorithms were developed by using the training database. These developed classification models were applied to the test data set, which cover the Adrasan burned area region to evaluates their success (Figure 1b). The obtained result maps for each classifier are shown in Figure 4.

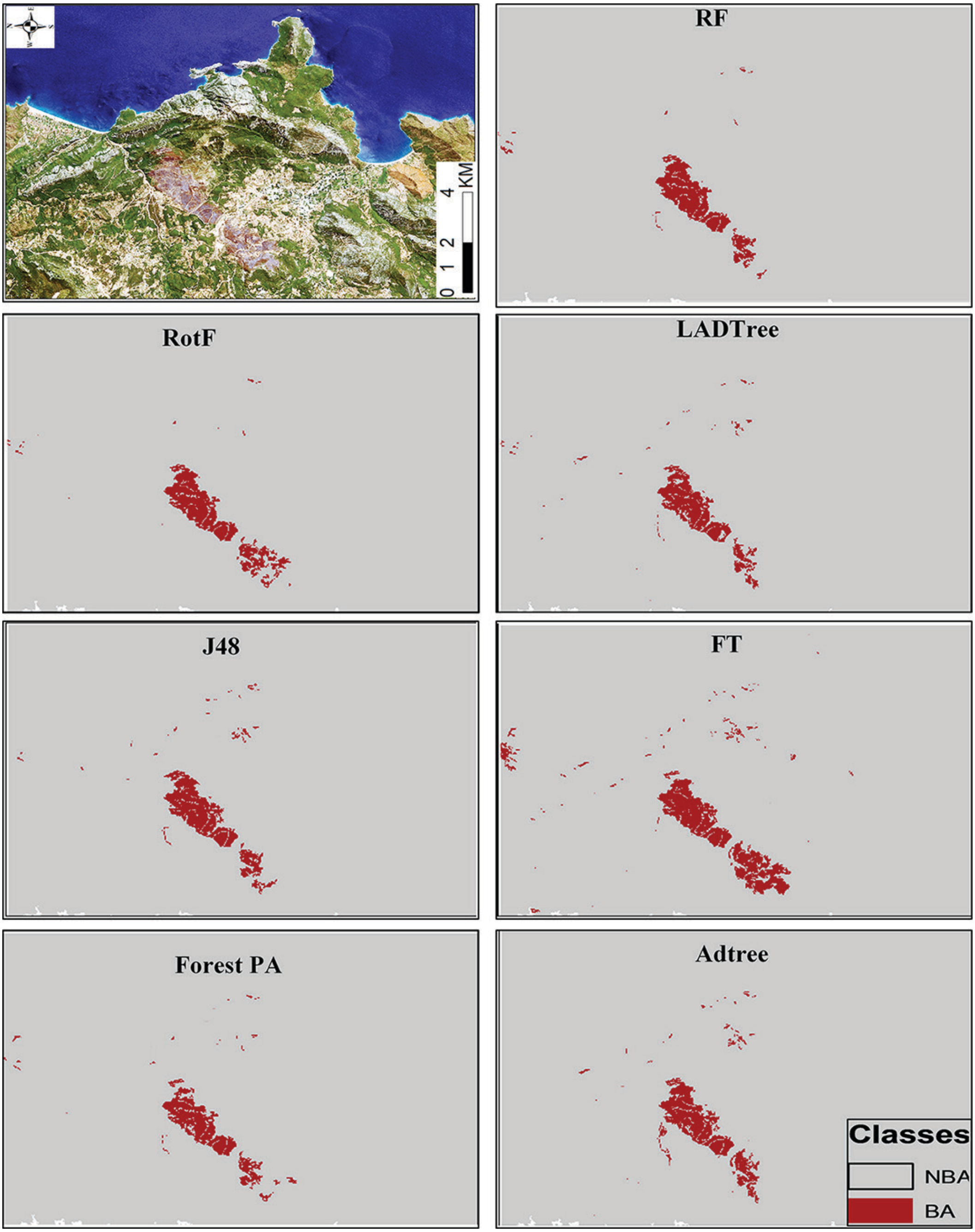

Figure 4: Result Maps of the applied tree-based algorithms. Red colour indicates the burned area (BA) and grey colour shows the non-burned area (NBA).

The confusion matrix of the results is given in Table 3. According to the sensitivity values, the best results were obtained by the FT algorithm, and the worst results were obtained by the Forest PA algorithm.

Furthermore, high accuracy value was produced by the RotF algorithm. It is seen that the precision values of all algorithms are high. According to the F-score, which are the harmonic balancer of precision and sensitivity, the highest results were obtained by FT and RotF algorithms. All these algorithms give higher overall accuracy results.

Table 3: Performance measures for all classifier.

Algorithms	RF	RotF	J48	ADTREE	FOREST PA	LADTREE	FT
Sensitivity	0.62	0.73	0.67	0.64	0.59	0.60	0.89
Precision	**1**	**1**	**0.98**	0.98	**1**	0.96	**0.98**
F-Score	0.76	0.84	0.79	0.77	0.74	0.74	0.93
Overall Accuracy	0.95	0.96	0.95	0.95	0.95	0.95	**0.98**

To estimate statistical significance of the results obtained with the applied classifiers, McNemar's test was used to compare the classifiers in two subset combinations (Table 4 and Table 5). McNemar's tests were performed at %95 confidence interval. Also, the p-value was calculated according to the significance level of $\alpha = 0.05$. The results obtained with the FT algorithm according to Table 4 and Table 5 were found to be statistically significant compared to all other algorithms. Also, the RotF algorithm was found to be statistically significant compared to other algorithms except for the J48 algorithm.

Table 4: McNemar's test results for all classifiers.

	J48	LADTREE	RotF	FT	RF	FORET PA
ADTREE	0.17	1.50	**4.90**	**15.04**	0.00	0.44
J48		3.125	1.76	**13.14**	0.80	1.45
LADTREE			**10.08**	**18.89**	0.80	0.00
RotF				**6.72**	**7.11**	**7.69**
FT					**14.81**	**19.36**
RF						0.17

Table 5: p-values of the classifiers according to McNemar's test.

	J48	LADTREE	RotF	FT	RF	FORET PA
ADTREE	0.34155	0.11034	**0.01343**	**0.00005**	0.5	0.25249
J48		0.03855	0.09072	**0.00014**	0.18555	0.1139
LADTREE			0.00075	**0.00001**	0.18555	0.5000
RotF				**0.00476**	**0.00383**	**0.00277**
FT					**0.00006**	**0.00001**
RF						0.34155

When the result maps were evaluated visually, the FT algorithm extracted some small areas as burned area according to the RotF algorithm. Although the RotF algorithm produces less noisy results, it was unable to extract some areas within the burned area. This has led to a decrease in the accuracy of the RotF algorithm. RotF algorithm is a method used in the classification of satellite images in different studies (Akar, 2017; Zhang et al., 2018; Pham et al., 2019) FT algorithm can be used in the mapping of burned forest areas. In this study, the FT algorithm provided better results than the RotF algorithm. The results showed that FT can be used for mapping burned areas.

5 CONCLUSION

This study aimed to compare the performance of seven tree-based classification algorithms for mapping burned areas using Landsat 8 images. As the study area, the Antalya and Mersin cities were selected, because these areas are one of the most affected regions from the summer fires in Turkey. In the implementation of the seven algorithms used in this study, the same data sets, including 18 variables (6 spectral indexes, 6 mean values of spectral bands, and 6 standard deviations of spectral bands) were used. In order to evaluate the ability of these algorithms to map burned areas, confusion matrices were created, and the statistical indicators were calculated based on these matrices. Also, McNemar's test statistics were used to compare to evaluate the results. The result of the evaluation process indicated that the FT algorithm gives more accurate results than the other tree-based algorithms. These results show that FT can be used as a classifier for burned forest area mapping. Future studies will be based on the comparison of these algorithms more complex datasets and different satellite images.

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