Using Machine Learning for Land Suitability Classification

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Abstract

Artificial intelligence and machine learning methods can be used to automate the land suitability classification. Multiple Classifier System (MCS) or ensemble methods are rapidly growing and receiving a lot of attention and proved to be more accurate and robust than an excellent single classifier in many fields. In this study a dataset based land suitability classification is addressed. It is done using a newly proposed ensemble classifier generation technique referred to as RotBoost, which is constructed by combining Rotation Forest and AdaBoost, and it is known to be the first time that RotBoost has been applied for suitability classification. The experiments conducted with the study area, Shavur plain, lies in the northern of Khuzestan province, southwest of Iran. It should be noted that suitability classes for the input data were calculated according to FAO method. This provides positive evidence for the utility of machine learning methods in land suitability classification especially MCS methods. The results demonstrate that RotBoost can generate ensemble classifiers with significantly higher prediction accuracy than either Rotation Forest or AdaBoost, which is about 99% and 88.5%, using two different performance evaluation measures.

Introduction

Agriculture is important as a source of food and income, but how, where and when to cultivate are the main issues that farmers and land managers face every day. Land suitability is carried out to estimate the suitability of land for a specific use such as arable farming or irrigated agriculture. Land evaluation can be carried out on the basis of biophysical parameters and, or socio-economic conditions of an area (FAO, 1976). In order to carry out land suitability forecasting, a number of methods are used, including system-dynamics modeling, scenario analysis, input–output design and land-transformation simulation (Pijanowski *et al*., 2002; Tang *et al*., 2005; Yong *et al.*, 2007; Yu *et al*., 2003). However, the amount of computations in common land suitability methods is too over whelming. Due to this excessive amount of calculations accurate results require automatic computer controlled calculations. Many computational tools have been applied in this field up to now. One of the main important techniques used is Artificial intelligence and machine learning based approaches. Artificial intelligence and machine learning methods can be used to automate the acquisition of ecological knowledge, i.e. automate the construction of ecological models. Classifiers and statistical learning methods, Artificial Neural Networks

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(ANN), Fuzzy systems are examples of Artificial intelligence tools.

One single classification system can not always lead to high classification accuracy. Instead, multiple classifier system (MCS) or ensemble methods, for example (Banfield *et al.,* 2007; Breiman 1996; Breiman 2001; Salkhordeh Haghighi *et al.*, 2011; Rodríguez *et al.,* 2006; Skurichina & Duin, 2002) are rapidly growing and enjoying a lot of attention and proved to be more accurate and robust than an excellent single classifier in many fields. MCS is the method which uses a set of individual classifiers. These techniques generally work by means of firstly generating an ensemble of base classifiers by applying a given base learning algorithm to different alternative training sets, and then the outputs from each ensemble member are combined in a suitable way to create the prediction of the ensemble classifier. The combination is often performed by voting for the most popular class. Examples of these techniques include Bagging, AdaBoost, Rotation Forest and Random Forest (Rodríguez, 2006).

AdaBoost is a method which constructs an ensemble of subsidiary classifiers by applying a given base learning algorithm to successive derived training sets that are formed by either resampling from the original training set (Breiman, 1998; Freund & Schapire, 1996) or reweighing the original training set according to a set of weights maintained over the training set (Freund & Schapire, 1997). Rodríguez *et al.* (Rodríguez, 2006) proposed a new ensemble classifier generation technique, Rotation Forest. Its main idea is to simultaneously encourage diversity and individual accuracy within an ensemble classifier. In view of the fact that both Adaboost and Rotation Forest are successful ensemble classifier generation techniques and they apply a given base learning algorithm to the permutated training sets to construct their ensemble members, with the only difference lying in the ways to perturb the original training set, it is plausible that a combination of the two may achieve even lower prediction error than either of them.

RotBoost is constructed by integrating the ideas of Rotation Forest and AdaBoost (Zhang, 2008). Some experimental studies conducted with data consisting of Topography, Wetness, Soil fertility, salinity and alkalinity and soil physical characteristics show that RotBoost can create ensemble classifiers with significantly lower prediction error than either Rotation Forest or AdaBoost more often than the reverse. There has been no study on the application of RotBoost to the land suitability classification so far. This study, therefore, was carried out to investigate the ability of the RotBoost Method to land suitability classification and comparison of this method with other methods such as Bagging, Rotation Forest and Boosting techniques to find the best method for land suitability classification.

Material and methods

The paper proposes an approach for the construction of accurate and diverse ensemble members by means of learning from a land suitability dataset for which suitability classes for the input data were calculated according to FAO methodology (FAO, 1976). The method in this paper is to apply an ensemble classifier generation method using a combination of Rotation

Forest and AdaBoost algorithms and evaluate the generalization ability of various ensemble non-ensemble classifier systems. The details are discussed in the following sections.

FAO framework method

The land suitability model was constructed using GIS capabilities and modeling functions. In order to classify the lands, Sys *et al*. (Sys, 1991) parametric method was used. In parametric method land and climate characteristics are defined using different ratings. In this method impressive feature in land suitability is ranked between a minimum and maximum value (usually between 0 and 100) according to Sys table. If a feature is so effective, it is scored 100 and if it isn't effective zero will be assigned to that feature. These rankings are shown with A, B, C …, etc.

To determine different characteristics and land indexes the following equation is used (Sys, 1993):

$$I = R_{\min} \times \sqrt{\frac{A}{100} \times \frac{B}{100} \frac{C}{100} \times ....} \qquad (1)$$

where I is the specified index, $R_{\min}$ is a parameter with a minimum rank, and A, B, C … are parameter ranks influencing the land suitability. After determined index, land suitability classes were calculated according to Table 1.

Rotboost technique

RotBoost is an ensemble classifier generation technique, which is constructed by combining Rotation Forest and AdaBoost. Before describing the RotBoost algorithm, the ensemble methods AdaBoost and Rotation Forest were briefly reviewed as follows. AdaBoost (Freund & Schapire, 1996; Freund & Schapire, 1997) is a sequential algorithm in which each new classifier is built by taking into account the performance of the previously generated classifiers. In this ensemble method, a set of weights $D_t(i)$ (i=1, 2,…,N) are maintained over the original training set L, and initially they are set to be equal (namely all training instances have the same importance). In subsequent iterations, these weights are adjusted so that the weight of the instances misclassified by the previously trained classifiers is increased whereas that of the correctly classified ones is decreased. In this way, these ''hard" instances can be better predicted by the subsequently trained classifiers.

The training set L_t used for learning each classifier C_t can be obtained by either resampling from the original training set L (Breiman, 1998; Freund & Schapire, 1996) or reweighting the original training set L (Freund & Schapire, 1997) according to the updated probability distribution D_t maintained over L. In the current research, the former is chosen due to its simple implementation. Furthermore, each base classifier C_t is assigned to a weight in the training phase and the final decision of the ensemble classifier is obtained by weighted voting of the outputs from each ensemble member. Note that in the above algorithm, the iteration is carried out until T classifiers are generated or until a classifier achieves an error zero or accuracy below 0.5, in which cases the weight updating rule fails and the algorithm stops (Zhang *et al.*, 2008).

Rotation Forest is another newly proposed successful ensemble classifier generation technique (Rodríguez, 2006), in which the training set for each base classifier is formed by applying principal component analysis (PCA) to rotate the original feature axes. Specifically, to create the training data for a base classifier, the feature set F is randomly split into K subsets (K is a parameter of the algorithm) and PCA is applied to each subset. All principal components are retained in order to preserve the variability information in the data. Thus, K axis rotations take place to form the new features for a base classifier. The main idea of Rotation Forest is to simultaneously encourage diversity and individual accuracy within the ensemble: diversity is promoted through doing feature extraction for each base classifier and accuracy is sought by keeping all principal components and also using the whole data set to train each base classifier (Salkhordeh Haghighi *et al.*, 2011).

For describing the RotBoost algorithm let's consider a training set $L = \{(x_i, y_i)\}_{i=1}^{N}$ consisting of N independent instances, in which each case (x_i, y_i) is described by an input feature vector $X_i = (X_{i1}, X_{i2},....X_{iP})$ εR^P and a class label y_i which takes value from the label space $\Phi = \{1,2,....,J\}$. In a classification task, the goal is to use the information only from L to construct classifiers that have good generalization capability, namely perform well on the previously unseen data which are not used for learning the classifiers. For simplicity of the notations, let X be an N×p matrix composed of the values of p input features for each training instance and Y be an N-dimensional column vector containing the outputs of each training instance in L. Put in another way, L can be expressed as concatenating X and Y horizontally, i.e., L = (X Y). Denote by C_1, C_2, …, C_T the base classifiers included into an ensemble classifier, say, C^*. And let $F = (X_1, X_2, \ldots, X_p)^T$ be the feature set composed of p input features. Appendix 1 gives the pseudocodes of this algorithm.

For solving a classification task using RotBoost algorithm, some parameters included in it should be specified in advance. As with the most ensemble methods, the values of the parameters S and T, respectively, specify the numbers of iterations done for Rotation Forest, and AdaBoost can be subjectively determined by the user and the value of K (or M) can be chosen to be a moderate value according to the size of the feature set F (Zhang *et al.*, 2008). Since the good performance of an ensemble method largely depends on the instability of the used base learning algorithm (Breiman 1996; Breiman, 1998; Dietterich, 2000), it can, therefore, be selected to be either a classification tree or a neural network (Hansen & Salamon, 1990), which is instable in the sense that small permutations in its training data or in its construction can lead to large changes in the constructed predictor (Breiman, 1996; Breiman, 1998).

For a better comparison, some classifier combination methods including RotBoost, Bagging (Breiman, 1996), AdaBoost (Freund & Schapire, 1997), and Rotation Forest (Rodríguez, 2006) were used and compared for land suitability evaluation. At the same time, the results computed with the base learning algorithm were also considered for a complete comparison. In order to simplify the notations, Rotation Forest was abbreviated as RotForest. In all the ensemble methods, a classification tree was always adopted as the base learning algorithm because it is sensitive to the changes in its training data and can still be very accurate.

APPENDIX 1

Input:

L: a training set, L= { (x_i , y_i)}$^N_{i=1}$ = [X Y] where X is an N×p matrix containg the input values and Y is an N-dimensional column vector containing the class labels

K: number of attribute subsets (or *M*: number of input attributes contained in each sbset)

W: a base learning

S: number of iterations for Rotation Forest

T: number of iterations for AdaBoost

X: a data point to be classified

Training Phase

For s= 1, 2, …. , S

1. Use the teps similar to those in Rotation Forest to compute the Rotation matrix, say, R^a_s and let L^a = [X R^a_t Y] be the training set for classifier C_s.
2. Initialize the weight distribution over L^a as D_1 (i) = 1/N (i=1,2, … , N).
3. For t= 1, … , T

(a) According to distribution D_t perform N extractions randomly from L^a with replacement to compose a new set L^a_t.

(b) Apply w to L^a_t to train a classifier C^a_t and then compute the error of C^a_l as $€_t$ = $Pr_{i\sim Dt}$ (C^a_t (x_i)‘“y_i) = “$^N_{i=1}$ Σ^NI(C^a_t (x_i) ≠y_i) D_t (i)

(c) If $€_t$ > 0.5, then set D_t(i) = 1/N (*i*= 1, 2, …. , N) and go to step (a); if $€_t$ = 0, then set $€_t$ = 10^{-10} to continue the following iterations.

(d) Choose α_t = ½ ln (1-$€_t$/$€_t$).

(e) Update the distribution D_t over L^a as D_{t+1} = (i) = D_t(i) / Z_t × $\begin{cases} e^{-\alpha_t} & if\ C^a_t\ (x_i) = y_i \\ e^{\alpha_t}, & if\ C^a_t\ (x_i) \neq y_i \end{cases}$

Wher Z_t is a normalization factor being chosen so that D_{t+1} is a probaility distribution over L^a.

4. End for
5. Let C_s (*x*) = argmax $_{ye\ddot{O}}$ $\Sigma^T_{t=1}$ α_t I (C^a_t (*x*)= y).

End for

Output

The class lable for *x* predicted by the final ensemble C^* as C^* (*x*) = argmax $_{ye\ddot{O}}$ $\sum_{s=1}^{S} I(C_s$(x)

For the techniques Bagging, AdaBoost, and RotForest, 100 trees were trained to constitute the corresponding ensemble classifiers. With respect to RotBoost, the number of iterations done for Rotation Forest and AdaBoost were both taken to be 10 so that an ensemble classifier created by it also consists of 100 trees. As for the parameter M (namely the number of attributes contained in each attribute subset) included in RotForest and RotBoost, the value of it was taken to be 3.

To evaluate the performance of the algorithms, two various errors estimation methods .632+ bootstrapand and 10-fold cross validation have been used. The .632+ bootstrap involves sampling a training set with replacement from the original dataset. The test set is formed by those samples omitted from the training set. The .632+ bootstrap is repeated K times, and the final bootstrap error estimator b.632 are defined as

$$b.632 = \frac{1}{K}\sum_{i=1}^{K}(0.368\alpha i + 032\beta_\iota) \qquad (2)$$

where and β_i are the training error and test error on the ith resampling. Following the work in (Freund & Schapire (1996)), the bootstrap samples are formed with K = 20 replicates. Each instance in the original dataset is made to appear exactly 20 times in the balanced bootstrap training samples. Feature selection is then performed on the whole dataset. Finally, the test error is estimated on the unseen test samples. The classification accuracy is then estimated using Equation (2).

In 10-fold cross-validation, the original sample is randomly partitioned into 10 subsamples. Of the 10 subsamples, a single subsample is retained as the validation data for testing the model, and the remaining nine subsamples are used as training data. The cross-validation process is then repeated 10 times (the folds), with each of the 10 subsamples used exactly once as the validation data. The 10 results from the folds then can be averaged to produce a single estimation.

Study area and data used

The study area, Shavur plain, is located in the Khuzestan province, in the southwest of Iran, between latitudes 31° 00' 30" N – 32° 30' 00"N and longitudes 48° 15' 00" E – 48° 40240" E with an area of 774 km^2 (Fig.1). Data used for the case study are consisting of: topography (Primary slope, Secondly slope and Micro relief), wetness (Groundwater depth and Coroma depth), salinity and alkalinity (EC and ESP), soil texture, soil depth, $CaCO_3$, *p*H (H_2O) and gypsum in 63 points that were selected in the total zone of study area randomly. A summary of the data used for this study is shown in the Table 2 (Khuzestan Soil and Water Research Institute, 2009).

TABLE 1

Numerical values of index for the various classes [Sys (1976)]

Class	*Index*
S_1	75-100
S_2	50-75
S_3	25-50
S1 (highly suitable)	S2 (moderately suitable)
S3 (marginally suitable)	N (not suitable)

TABLE 2

Summary of effective parameters for land suitability in the study area (Khuzestan Soil and Water Research Institute, 2009)

Parameters	*Minimum*	*Maximum*
*p*H (H_2O)	8.32	7.9
Gypsum	0	2.94
CaCO3 (%)	17.74	39.16
Soil depth(cm)	150	200
Soil texture*	7.2	9.75
Salinity and Alkalinity	1	62.98
EC (ds/m)		
ESP (%)	1	49.99
Wetness		
Groundwater depth(cm)	0	200
Coroma depth (cm)	0	100
Primary slope (%)	0	3.5
Topography		
Secondly slope (%)	0	1.5
Micro relief(cm)	0	45

* Contents of Table 3 were used for replacing the number value instead of quality value for soil texture.

Results

The land suitability maps based on the parametric (FAO) method is shown in Fig. 2. The results of the FAO land suitability evaluation method in the study area (Fig. 2) showed that 26% of the lands are moderately suitable (S2 class), 25% as marginally suitable (S3 class) and 49% as not suitable (class N).

Fig. 3 demonstrated the mean prediction accuracy of RotBoost, Bagging, AdaBoost,

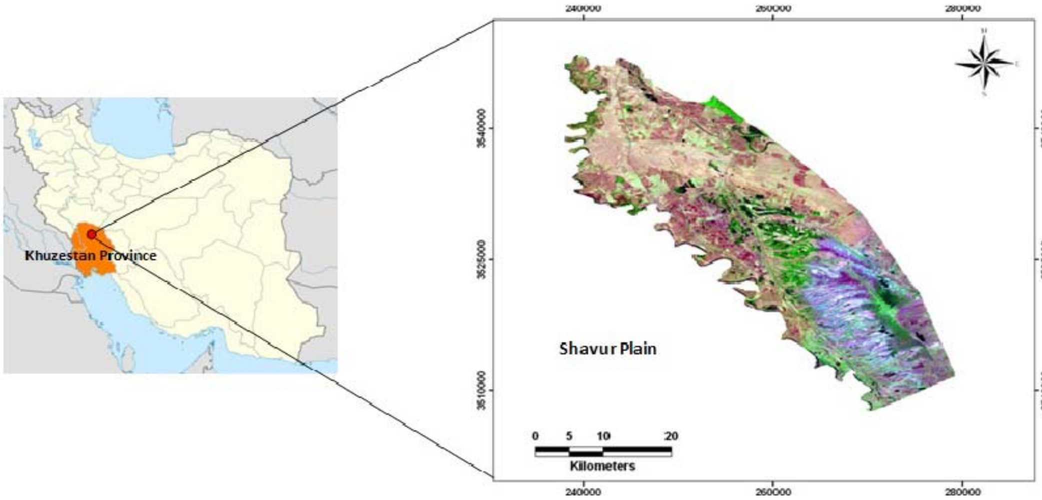

Fig. 1. Location of the study area in Iran.

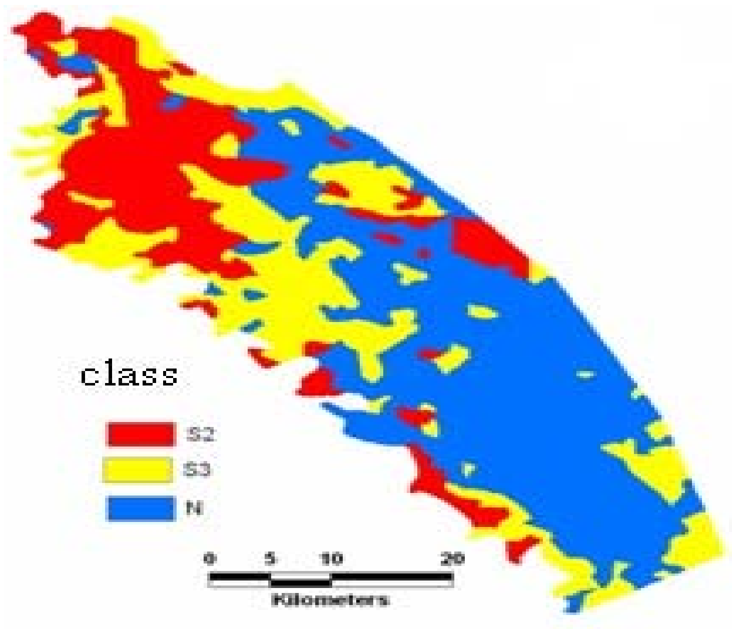

Fig.2. Land suitability map for wheat (FAO method)

and Rotation Forest and a single tree. Table 4 reports the means of prediction accuracy (expressed in %) for each classification method on the considered data sets, where the values following "±" are their respective standard deviations. In order to see whether RotBoost is significantly better or worse than other methods from the statistical viewpoint, a one-tailed paired t-test was performed with method. An open circle next to a result denotes that RotBoost performs significantly worse than the corresponding method. As the results show, both error estimation methods agreed to assert that RotBoost has shown better performance than single classifier and all other ensemble methods.

In order to evaluate and present the better method between these methods, five different

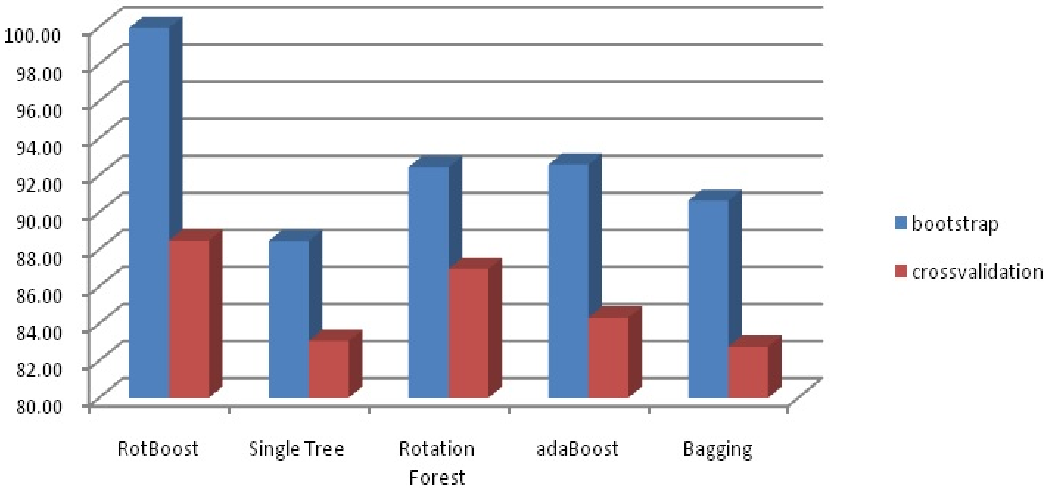

Fig.3. prediction accuracy (expressed in %) for all algorithms

TABLE 3
Using of number value instead of quality value for soil texture (Sanchez Moreno, 2007)

Number	*Soil texture*
9.5-10	SiCL, SiCs, SiL, SCL, L
8.5-9.5	SL
6-8.5	LS, Cm, SiCm
4-6	S

TABLE 4
Means and standard deviations of prediction Accuracy (expressed in %) for all algorithms

Methods	*Bootstrap*	*Cross validation*
RotBoost	99.95±0.13	88.49±3.36
Single Tree	88.47±0.90%	83.07±4.30%
Rotation Forest	92.45±0.88%	86.95±2.7%
AdaBoost	92.58±0.64%	84.32±2.27%
Bagging	90.64±0.81%	82.76±4.32%

significance level a $\alpha = 0.05$ and the results for which a significant difference with RotBoost was found are marked with a bullet or an open circle next to them. A bullet next to a result indicates that RotBoost is significantly better than the corresponding cultivation fields were randomly chosen. The points are plotted on the prepared comparison map and are shown in Fig. 4 (for better compare, soil map was used) and their information is given in Table 5, and shows

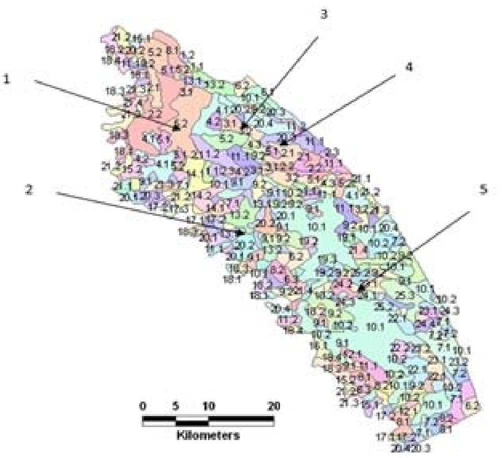

Fig.4. Sampling locations for comparison of the methods (Table 3, shows the information of the points).

the corresponding classes of the locations randomly selected locations. Also predicted classes using different methods are shown in Table 6.

According to Table 5, factors affecting land suitability such as slope primacy (%), slope secondary (%), water table depth (cm), micro relief (cm), depth of chroma (cm), gypsum me/100, ESP (%),Ec, (%), texture, *p*H, $CaCO_3$ were measured randomly for five points. Land suitability classes based on FAO method for five points were classified S2, S3, N, S2 and N, respectively (Table 6). The results of Single Tree, Rotation Forest, AdaBoost, Bagging methods showed that RotBoost algorithm was more accurate than the other method. The Single Tree, Rotation Forest, AdaBoost, Bagging method could not predict land suitability class for total points precisely. So for determination of land suitability RotBoost algorithm class can be used instead of FAO and other methods. The RotBoost algorithm has more accuracy and

Table 5

Information of the sampling points for comparison of the results data mining

Parameter Location	*X*	*Y*	*Slope primacy (%)*	*Slope secondary (%)*	*water table (cm)*	*Micro relief (cm)*	*Depth of depth*	*Gypsum me/100 (cm)*	*ESP (%)*	*EC(%)*	*PH*	*caco3*	*Texture*
1	249476	3539574	1	1	100	0	100	0.04	5	2.13	CL	7.1	32
2	255364	3527325	2	2	70	0	75	0.01	25	10.4	L	7.9	35
3	256693	3538530	2	2	70	0	50	0.1	28	11	L	7.89	30
4	260017	3535966	2	1	120	0	97	0.05	5	2.5	CL	7	30
5	263245	3524476	5	2	20	0	0	0.32	17.3	16.5	SiL	8.2	32

TABLE 6
Predicted classes using different methods

Parameter/location	*FAO*	*RotBoost*	*Single tree*	*Rotation forest*	*AdaBoost*	*Bagging*
1	S2	S2	S2	S1	S1	S2
2	S3	S3	S2	S3	S2	S1
3	N	N	S2	S2	N	S2
4	S2	S2	S2	S2	S1	S2
5	N	S3	N	N	N	S2

faster than the other methods for the determination of landform classification.

Conclusion

In this paper, RotBoost algorithm was applied to tackle the land suitability classification problem and this ensemble classifier generation method is a combination of Rotation Forest and AdaBoost. In this way, a set of diverse and accurate trees is obtained to build a robust ensemble classifier. In the experiments, RotBoost algorithm was operated on the data. To evaluate the performance of RotBoost algorithm, other techniques such as Bagging, Rotation Forest and Boosting techniques were applied for comparison. Here decision tree is applied as a basis classifier. Results demonstrate that RotBoost algorithm can generate ensemble classifiers with significant higher prediction accuracy than either Rotation Forest or AdaBoost, which is about 99% and 88.5% using two different performance evaluation measures. So for determination of land suitability class can use RotBoost algorithm instead of other methods. The RotBoost algorithm has more accuracy and faster than the other method for determination of landform classification. To achieved the high classification accuracy by using RotBoost algorithm, this method can be suggested as a robust one for land suitability classification.

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