Suitable Artificial Intelligence Techniques for Multispectral Image Classification

Ritica Thakur and V. L. Manekar

Abstract Hydrologic modelling is a complicated process depending on various factors. Since the evaluation of factors are exposed to high uncertainty due to high spatial variation. Hence, the precision of each factor becomes essential for modelling. Multispectral images are a highly informative set of data. It holds details of spectral characteristics and spatial structure of the objects in the image. Such data is beneficial to identify and classify the land covers on the bases of spectral signatures. Machine learning and AI techniques have made this work more efficient. This paper aims to understand the ability and suitability of AI techniques such as maximum likelihood classification (MLC), random trees (RT), and support vector machine to classify the image correctly. This paper discusses the basic principles of these AI techniques for land use classification. Accuracy assessment was considered as the criteria of comparison. Based on the obtained results, the performance of the SVM technique is found better than MLC and RT based on overall and Kappa coefficient (>0.80) for training and Kappa (0.64) for testing.

Keywords Artificial intelligence techniques · Support vector machine · Maximum likelihood classification · Random trees · LULC classification

1 Introduction

Quantification of Land Use and Land Cover (LULC) is always a tedious task. LULC is the basic information needed to plan, execute, and analyse the area. With the high-resolution satellites and multispectral data sensors, image processing becomes the most important part of information. This information can be used for many purposes. Nowadays, remotely sensed images are widely used for mapping and monitoring the

R. Thakur (✉) · V. L. Manekar
Civil Engineering Department, S.V. National Institute of Technology, Surat 395007, India
e-mail: riticathakur15@gmail.com

V. L. Manekar
e-mail: vlm@ced.svnit.ac.in

P. V. Timbadiya et al. (eds.), *Geospatial and Soft Computing Techniques*, Lecture Notes in Civil Engineering 339, https://doi.org/10.1007/978-981-99-1901-7_46

area. Image classification is the one of the data analyses used for extracting information to take decisions by many authorities. This study focusses on the LULC level 1 classification. Many LULC classification techniques are present in the literature. The classification can be broadly classified into supervised and unsupervised classification. However, supervised classification is tedious process, but more reliable than unsupervised classification. With new area of artificial intelligence techniques (AI), new classification and segregation techniques have become very efficient in classifying humongous complex pixel data sets. The most challenging nature of this job is the classification of the pixels in different classes produced from nearly similar spectral signatures. Different techniques have different working principles and techniques to refine the classified data. Many researchers have applied and studied techniques like support vector machine (SVM), K-means, and the maximum likelihood for the pixel-based classification of images [1, 2, 7, 9]. Al-doski et al. [2] studied the performance of SVM and k-mean method and recommended SVM over k-mean method. A classical approach of supervised image classification is maximum likelihood. It is a parametric approach of classification based on the training of model [9]. Though SVM is a nonparametric-based approach to segregating data sets in classes, another popular AI technique is Random Forest. It is a decision tree-based technique of generating rules from of nodes and leaves. This approach is also nonparametric and has high success rate of segregating data sets in the classes [6]. Thus, this study focuses on the applying these techniques to classify multispectral data sets into five classes. The main objective of this study is to find out the performance of the random tree (RT), maximum likelihood (ML), and support vector machine (SVM) for classification of Sentinel satellite image. Classification is restrained to level 1 classification using basic five classes: water, barren land, agriculture, forest and built up. The performance was evaluated using the classic approach of making a confusion matrix, commission and omission error, over all accuracy and kappa coefficient.

1.1 Materials and Methods

1.1.1 Random Forest Classifier

In Random Forest, each classifier is built using a random vector sampled independently from the input vector. It is made up of many tree classifiers. Each tree provides the most prevalent class to categories an input vector [3]. By integrating randomly selected elements or elements at each node, the random forest classifier creates a tree. To create a training data set for bagging, a method of random selection with alternative N examples—where N is the size of the first training set—was used for each feature/feature combination that was selected. The qualities used in decision tree induction can be chosen in a variety of ways, and most of these ways assign a quality measure directly to the attribute. Each time the maximum depth of a tree is reached using a mix of features and new training data. These old trees have not undergone pruning. This is one of the main advantages the random forest classifier has over other decision tree methods. According to the research, using the correct pruning techniques rather than the proper attribute selection techniques affects how effective tree-based classifiers are. Breiman [3] asserts that the Strong Law of Large Numbers avoids overfitting because the generalization error always converges as the number of trees increases, even if the tree is not trimmed (Feller). The quantity of features used at each node to generate a tree and the number of trees to be developed are two user-defined factors required to create a random forest classifier. Only a few attributes are considered at each node to determine the ideal split. The random forest classifier is composed of N trees since N is the number of trees to be created, which can be any number provided by the user. To categorize a new data set, the cases of each data set are passed down to each of the N trees. In that case, the class with the most N votes is selected by the forest.

1.2 Maximum Likelihood Classification (MLC)

MLC is popular parametric classification algorithm among researchers in many fields. This is a supervised classification technique. Basic principle of MLC is Bayes' classification. Initially, the algorithm is trained using supervised data sets. Then, further the image is classified on the basses of the likelihood of the pixels belonging to the trained group mean or covariance. For figuring the weighted distance or likelihood P of unclassified pixels measurement vector Y belong to one of the known classes N_c is based on the Bayesian equation [8, 9].

$$P = \ln(a_c) - [0.5 \ln(|\text{cov}_c|)] - [0.5(Y - N_c)\, T(\text{cov}_c - 1)\,(X - N_c)]$$

The Y vector is assigned to the class in which it has the maximum likelihood of belonging. The benefit of the MLC is a parametric classifier as it considers the variance–covariance within the class allocations and for normally distributed data [5].

1.3 SVM

A group of supervised algorithms used for regression and classification are called support vector machines (SVMs). SVMs are nonparametric classifiers as well. SVM was initially proposed by Vapnik and Chervonenkis (2015) and Vapnik (1999) [10, 11]. SVM performance is based on the training of the model. Most adopted linear separable classes are kernel density functions. This kernel density function is used to create hyperplanes. For the P number of data sets signified as $\{X_i, y_i\}$, $i = 1, \ldots, P$, where $X \in R^N$ is an N-dimensional space and $y \in \{-a, +a\}$ is no of class.

If a vector W exists perpendicular to the linear hyper-plane, these classes are regarded as linearly and hyperbolically separable. Two hyper-planes can be used to distinguish the data points in the two classes, i.e. class $+a$ represented as a and class 2 represented as $+a$. The design of these hyper-planes maximizes the separation between the two groups. When compared to traditional methods, SVMs yield more accurate results. However, the outcomes vary depending on the kernel used, the parameters selected for the chosen kernel and the SVM generation process [4].

2 Study Area and Data Source

2.1 Data Collection

For this study, a multispectral spectral image of Sentinel-2B has been used. Sentinel-2B is an optical imaging European satellite launched on 7 March 2017. The Sentinel-2B is the second satellite launched after Sentinel-2A as part of the European Space Agency's Copernicus Programme. The Sentinel-2B orbits will be placed phasing 180° opposite to Sentinel-2A. The Sentinel-2B has a wide, high-resolution multi-spectral imager with 13 spectral bands. Table 1 shows the details of the band properties.

Table 1 Shows the feature of each band of Sentinel-2B satellite

Sentinel-2B					
S. No	Sentinel 2 bands	Name of bands	Band width (nm)	Central wavelength (nm)	Spatial resolution (m)
1	1	Coastal aerosol	21	442.2	60
2	2	Blue	66	492.1	10
3	3	Green	36	559	10
4	4	Red	31	664.9	10
5	5	Vegetation red edge	16	703.8	20
6	6	Vegetation red edge	15	739.1	20
7	7	Vegetation red edge	20	779.7	20
8	8	NIR	106	832.9	10
9	8a	Narrow NIR	22	864	20
10	9	Water vapour	21	943.2	60
11	10	SWIR – Cirrus	30	1376.9	60
12	11	SWIR	94	1610.4	20
13	12	SWIR	185	2185.7	20

The data was downloaded by Earth Explorer (usgs.gov) https://earthexplorer.usgs.gov/ website

ArcMap 10.3 software is used for the present study for image processing. It provides the facility for pre-processing of the satellite image. Initially, the Sentinel 13 band data was read, and radiometric and atmospheric correction were given to each band before compositing the image. ArcMap 10.3 also provides the capability of performing AI-based image classification techniques. All the AI methods were performed using ArcMap 10.3 only. A random image of the location is selected for this study of 12,000 km^2.

2.2 Methodology

This study aims to understand the best supervised AI technique among parametric and nonparametric classifiers. The most popular maximum likelihood classifier, SVM, and random tree method were chosen for this analysis. Figure 1 shows the methodology adopted for the study. This classification was performed on the multispectral satellite data having 12 bands. A common training sample and testing samples were used to measure the classifier's capability.

Initially, a sets of signature files of around about 1800pixel per class using 330 shape files (sample count vary for each class to cover up the spatial variation in whole image) for water, built up, forest, agriculture and barren is used as training data. Figure 2 gives the detail of the training data. Three different classifiers were trained using the training data, and three images was generated using trained classifier of the random tree, maximum likelihood, and SVM. 499 Random points evenly distributed spatially across the image were generated, and ground truth data was generated using google earth image. Figure 3 represents all the training and testing data sets.

The testing and training point shape files were extracted from the image produced using random forest, maximum likelihood, and SVM. The data extracted were analysed against the ground truth data for the accuracy analysis. Commission error omission error, user accuracy, and producer accuracy were analysed for both training and testing points. Further, overall accuracy and Kappa coefficient were calculated to compare the classifier's performance.

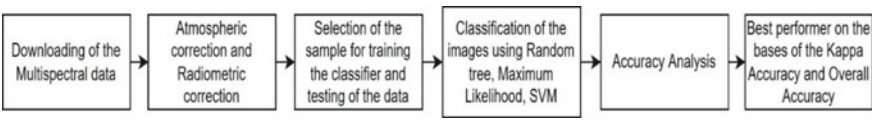
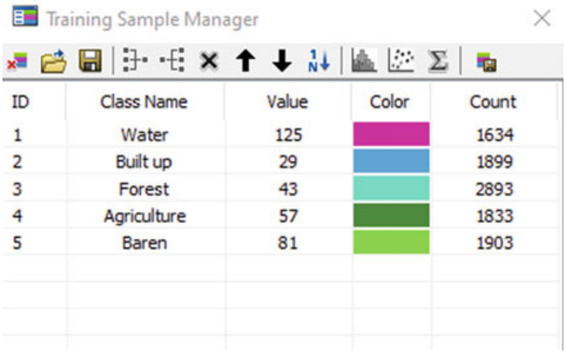


Fig. 1 Methodology adopted


Training Sample Manager

ID	Class Name	Value	Color	Count
1	Water	125		1634
2	Built up	29		1899
3	Forest	43		2893
4	Agriculture	57		1833
5	Baren	81		1903

Fig. 2 Training samples

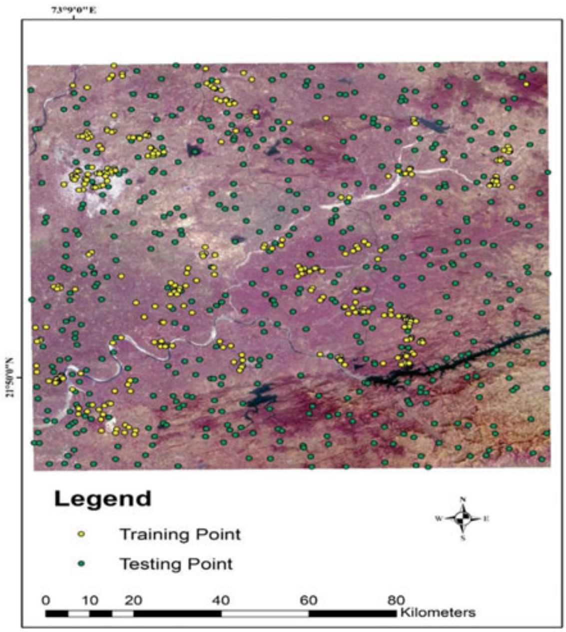


Fig. 3 Training and testing points

3 Results and Discussions

This study aimed to understand the best AI image classifier for the Sentinel multispectral satellite image. Among most popular supervised image classification technique, this study was constrained to random tree, maximum likelihood, and SVM techniques. Figure 4 shows the ground truth image from Google Earth, classified image from the random tree, maximum likelihood, and SVM. Training points and testing point data was extracted from the classified image, and confusion matrix was

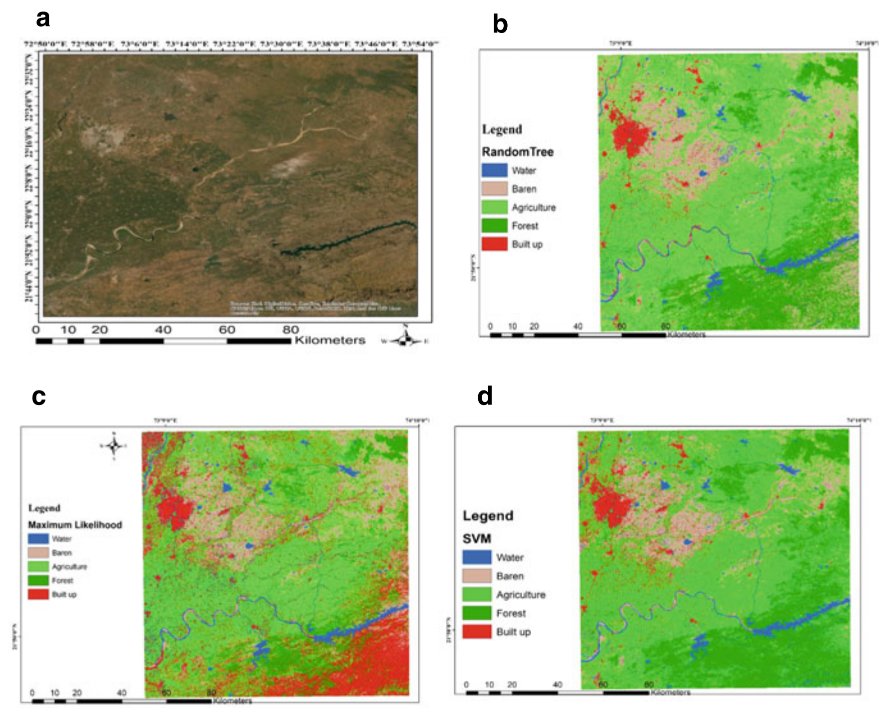


Fig. 4 **a** Google Earth image of the selected study area. **b** Classified image using random tree. **c** Classified image using maximum likelihood. **d** Classified image using maximum likelihood

prepared. Table 1 shows the confusion matrix for training point of a random tree, maximum likelihood, and SVM.

3.1 Confusion Matrix for Training Data

The confusion matrix is a 2D matrix with identity classes on both dimensions. It helps to understand the classification of the identity classes and accuracy related to them. Table 1 shows the confusion matrix for signature file given at the time of training of models. The confusion matrix based on the signature file (training data sets) represents how well the model is trained to classify the image. The confusion matrix (Table 2) of a random tree, maximum likelihood, and SVM representing well-trained models with training sample pixels is accurately classified in their classes. The Least error is present in SVM, and maximum error is present in maximum likelihood.

Table 3 shows the confusion matrix of the testing sample points. These are the randomly generated evenly spatially distributed point shape files with ground truth

Table 2 Confusion matrix training sample points

	Random tree						Maximum likelihood						SVM					
		A	B	C	D	E		A	B	C	D	E		A	B	C	D	E
Water	A	39	1	1	0	0	A	39	0	1	0	1	A	41	0	0	0	0
Barren	B	0	43	0	0	2	B	0	39	0	0	6	B	0	44	0	0	1
Agriculture	C	0	0	83	0	0	C	0	0	83	0	0	C	0	0	83	0	0
Forest	D	0	0	0	53	0	D	0	0	4	49	0	D	0	0	0	53	0
Built-up	E	0	1	0	0	107	E	2	10	0	0	96	E	0	1	0	0	107

Table 3 Confusion matrix testing sample points

	Random tree						Maximum likelihood						SVM					
		A	B	C	D	E		A	B	C	D	E		A	B	C	D	E
Water	A	11	0	1	2	0	A	10	0	1	0	3	A	12	1	1	0	0
Barren	B	3	95	19	11	3	B	2	66	17	1	45	B	3	75	27	17	9
Agriculture	C	5	22	187	37	5	C	16	9	193	7	31	C	8	5	208	28	7
Forest	D	1	6	8	66	0	D	0	5	15	51	10	D	3	0	5	73	0
Built-up	E	1	4	2	0	10	E	1	0	3	0	13	E	1	2	1	1	12

classes to test the predicted class. Hence, confusion matrix from testing sample point gives the real performance of the classifier. SVM seems to classify more accurately than random tree and maximum likelihood.

To account the errors in the image classification, commission and omission error is calculated.

3.2 Commission and Omission Error

Commission error is ratio of wrongly classified pixel to the total of classified pixel in that class. Similarly, the omission error is the ratio of omitted pixel from the class to the total number of assigned pixels in that class. The confusion matrix generated using training point shows least commission and omission errors. Figure 5 represents the commission and omission errors in the classified image using the training data set. It is evident from the graphs that the commission error (0–0.21) of the classifier is more than the omission error (0–0.13). ML classifier is shows the tendency of mostly wrong commissioned pixels in the classes, followed by RT. Forest class has no commissioned error by any of the classifiers. However, Fig. 5b shows that many pixels from the forest have been missing from ML-classified images. In omission error, the ML again having a high scorer of the errors following RT and SVM. It is concluded that SVM is best-trained classifier among RT and ML. Similarly, Fig. 6a shows the commission and omission error found in testing points.

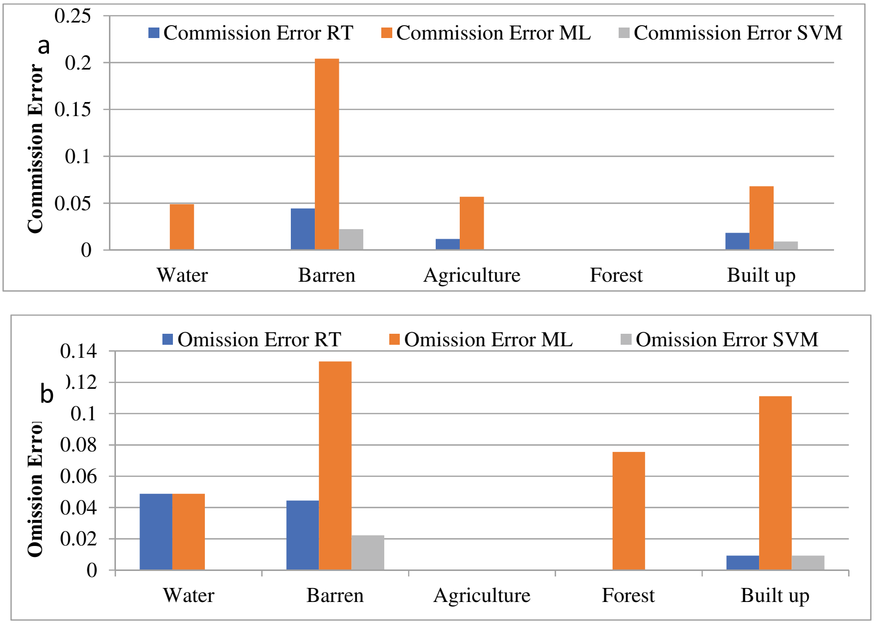


Fig. 5 **a** Commission error and **b** omission error of the classifier using training data set

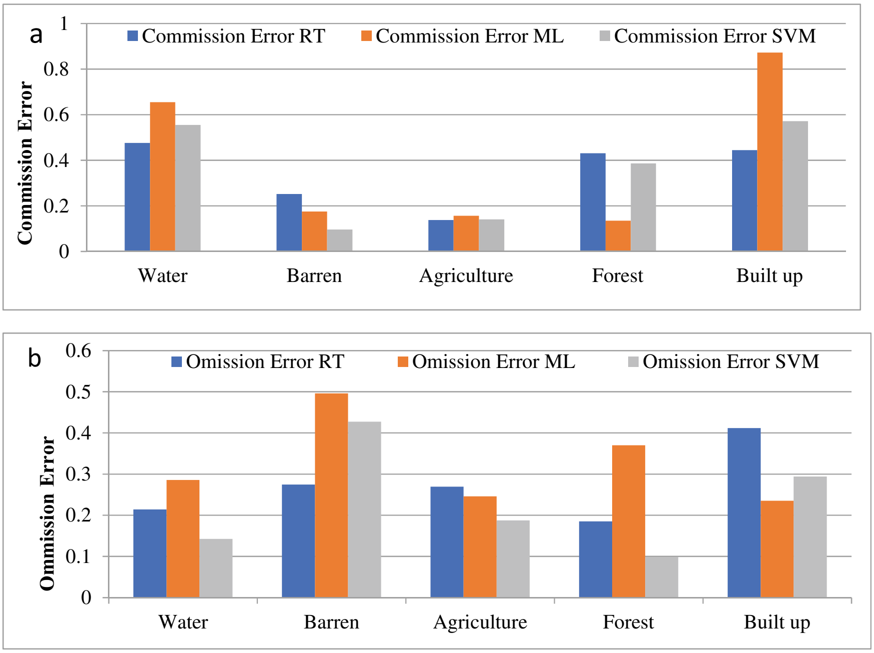


Fig. 6 **a** Commission error and **b** omission error of the classifier using testing data set

Commission error and omission error in classification of testing points show the real performance of the classifier. Number of wrongly commissioned pixels are more than the number of omitted pixels. Commission and omission error is significant in the ML classifier, though the commission and omission error in the water class are high for the ML classifier. For the barren land, commission error is high for RT, but omission error is high for the ML classifier. From the confusion matrix, it is evident that most of the pixel of the barren land has been classified under agriculture land. It happens due to the reflection of vegetation surrounding the barren land. From the confusion matrix, it is clear that SVM and RT have quite successfully commissioned the barren land and built-up pixel separately. RT has shown the least omission error for barren land. Maximum number of barren land pixels have been omitted in the classified image by RT classifier. For agriculture, commission error was low concerning to the omission error. Large number of the pixel are commissioned to other classes. SVM commissioned the maximum number of pixels within the class. With the least commissioned error and least omission error, SVM made a better classification than another classifier. The classified pixels of the forest of the testing sample, shows the least commissioned error and maximum omission error for ML classifier. It represents under prediction of the forest area by the ML. RT shows high commission error and higher omission error for the forest. SVM shows a high commission error and low omission error making it over predicting the forest area. For the built-up area, the ML classifier shows high commission and low omission errors, making it over predicting the built-up area. RT has nearly same number of omission and commission errors under this scenario though the pixel placement to the classes is inaccurate. For SVM, omission error is low, and commission error is high, which represents again over prediction of built-up area.

3.3 Producer Accuracy and User Accuracy

Producer and user accuracy are complementary to the commission and omission errors. It is essential to consider user accuracy to understand the classifier's performance. Figure 7 shows the producer and user accuracy of the training sample, and Fig. 8 shows the producer and user accuracy of the testing samples. From the figures, the producer and user accuracy of the training samples are very high and acceptable range. The user accuracy of the ML classifier is very low, being less accurately classified pixels. RT and SVM have a better performance.

The accuracy of the randomly generated point with ground truth gives a better picture of the accuracy of the classifier, though the training shows more than 0.9 accuracy. The testing shows all together a different accuracy. ML classifier is showing high user accuracy for the built-up only. SVM has performed better than RT in both accuracies in many classes. For the water class, SVM has a high rate (0.85) of accurately classified pixels with average producer accuracy. Water pixels are accurately classified with high producer accuracy using the RT classifier. Similarly, RT is classifying the barren pixel with 0.7 user accuracy, but the producer accuracy is low.

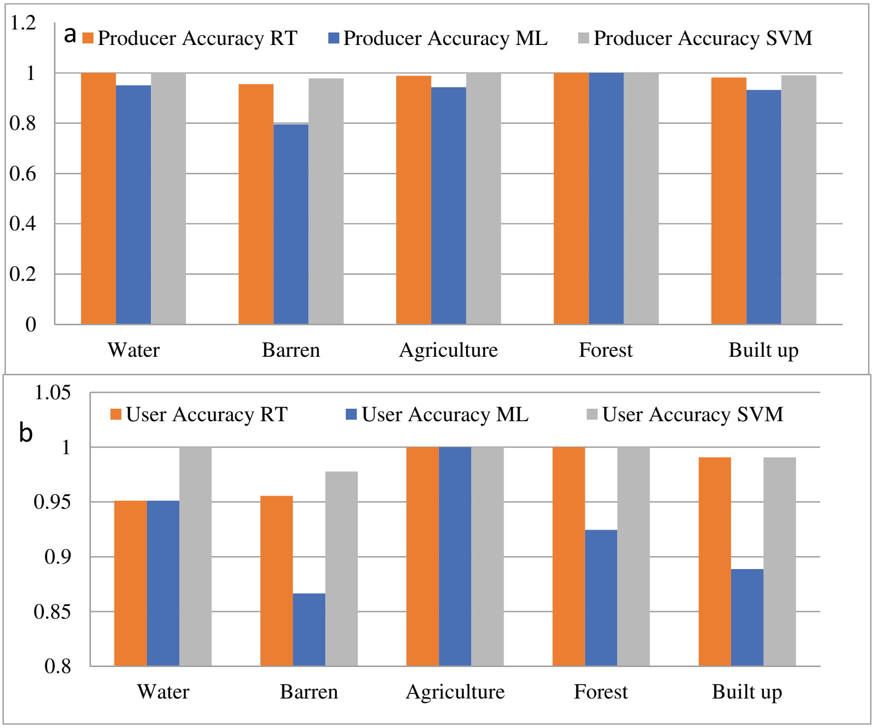
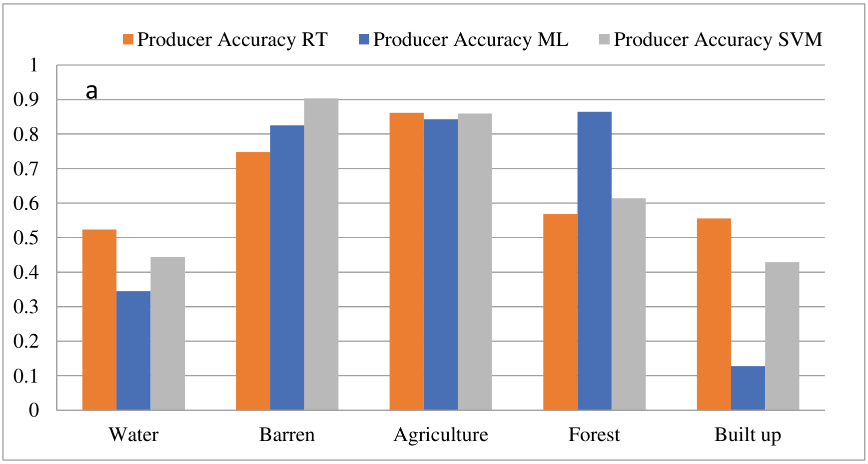


Fig. 7 **a** Producer accuracy of training samples. **b** User accuracy of the training samples

SVM gives user accuracy of 0.57 with high producer accuracy for barren land. All three classifiers have accurately classified agriculture class. Forest was classified most accurately by SVM then by ML and RT. Built up is accurately classified by the ML classifier, but the producer accuracy of ML classifier is very low.

3.4 Overall Accuracy and Kappa Coefficient

Overall accuracy and Kappa coefficient give the efficiency of the classifier. Table 3 shows the overall accuracy and Kappa coefficient of RT, ML, and SVM on trained and testing samples. From the training data sets of the classifier, SVM has performed best among RT and ML in overall accuracy and Kappa coefficient. It signifies that the SVM is the best trained among the three classifiers. SVM performs best on the testing data set among all the classifiers, followed by RT and ML. Table 4 shows the overall accuracy of the training and testing of samples.



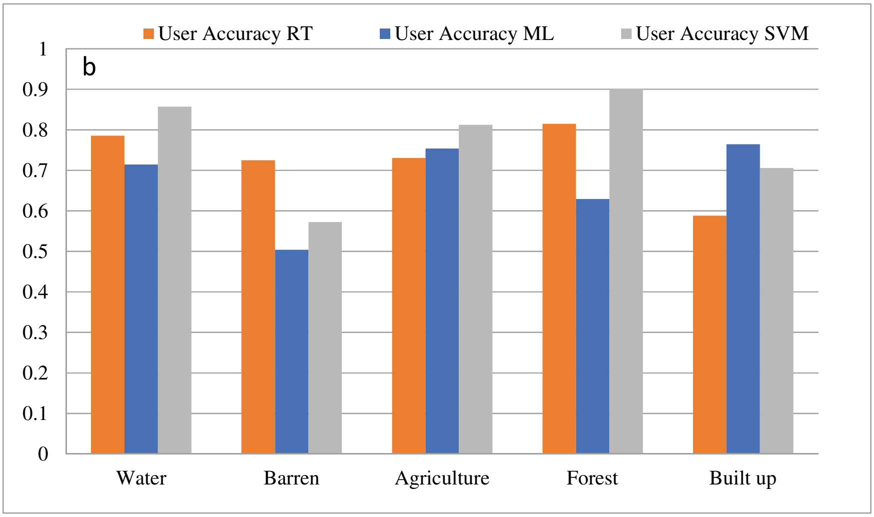


Fig. 8 **a** Producer accuracy of testing samples. **b** User accuracy of the testing samples

Table 4 Results obtain at the time of training and testing

Method	Training		Testing	
	Overall accuracy	Kappa coefficient	Overall accuracy	Kappa accuracy
Random tree	0.98	0.98	0.74	0.61
Maximum likelihood	0.93	0.91	0.67	0.52
SVM	0.99	0.99	0.76	0.64

4 Conclusions

This study was conducted to understand the performance of the supervised AI classifier to classify the multispectral Sentinel satellite data set. The Image was classified into four elementary class water, barren, agriculture, forest, and built-up. All the tree technique shows acceptable classified image with an overall accuracy more than 90 per cent in the training phase and more than 67 per cent in the testing phase. SVM and RT being a nonparametric classifiers, performed well than a parametric classifier. Among all, the SVM performed best as a classifier. Sentinel image is a high resolution to the resolution of 10 m giving a clear image and better LULC classification of the area.

References

1. Abburu S, Babu Golla S (2015) Satellite image classification methods and techniques: a review. Int J Comput Appl 119(8):20–25
2. Al-doski J, Mansor SB, Zulhaidi H, Shafri M (2013) Image classification in remote sensing. 3(10):141–148.
3. Breiman L (1999) Random forests. UC Berkeley TR567
4. Huang C, Davis LS, Townshend JRG (2002) An assessment of support vector machines for land cover classification. Int J Remote Sens 23(4):725–749
5. Inc E (1999) Erdas field guide. Erdas Inc. Atlanta
6. Jagannathan G, Pillaipakkamnatt K, Wright RN (2009) A practical differentially private random decision tree classifier. In 2009 IEEE international conference on data mining workshops. IEEE, pp 114–121
7. Jog S, Dixit M (2016) Supervised classification of satellite images. In: Conference on advances in signal processing, CASP 2016, X, pp 93–98
8. Otukei JR, Blaschke T (2010) Land cover change assessment using decision trees, support vector machines and maximum likelihood classification algorithms. Int J Appl Earth Obs Geoinf 12:S27–S31
9. Sisodia PS, Tiwari V, Kumar A (2014) Analysis of supervised maximum likelihood classification for remote sensing image. In: International conference on recent advances and innovations in engineering (ICRAIE-2014). IEEE, pp 1–4
10. Vapnik VN (1999) An overview of statistical learning theory. IEEE Trans Neural Netw 10(5):988–999
11. Vapnik VN, Chervonenkis AY (2015) On the uniform convergence of relative frequencies of events to their probabilities. In: Measures of complexity. Springer, Cham, pp 11–30