International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-8 Issue-10, August 2019

Object-Based and Rule-Based Classification of Synthetic Aperture Radar Images

Aishwarya Rastogi, Amit Doegar

Abstract: *Since thousands of years, the land is the basic and very important requirement for humans to survive and grow. The surface area of the earth provided by nature contains many different geographical locations divided into oceans, mountains, rivers, barren land, fertile land, ice caps and many more. The huge land masses and water bodies need to be observed and analyzed for optimum utilization of resources. Remote sensing is the best possible way to observe the earth's surface from a distance through different satellites and sensors. But most of the satellite images are not clear up to the extent to classify different terrain features accurately. Hence classification of image is needed to observe different terrain features in original images. In this study, the aim is to propose a branch of natural computation for SAR image classification into different terrain features with better information retrieval and accuracy measures as compared to traditional methods for satellite image classification. The object-based analysis has been used to extract spectral reflectance of five texture measures namely urban, rocky, vegetation, water and barren to generate training set. Minimum distance to mean classifier has been used with one of the Nature Inspired computation technique i.e. bacterial foraging optimization algorithm for the satellite image classification, to extract the more accurate information about land area of Alwar district, Rajasthan, India. In the proposed study a high-quality thematic map has been generated with the 7-band multi-spectral, medium-resolution satellite images. This approach provides the greater speed and accuracy in its computation with 97.43% overall accuracy (OA) and 0.96 Kappa co-efficient.*

Keywords: *Synthetic Aperture Radar (SAR) Image, Land use land cover (LULC), Object-based image analysis (OBIA), Bacterial Foraging Optimization Algorithm (BFOA)*

I. INTRODUCTION

In human civilization, the land is the fundamental requirement. This valuable offering cannot be extended or demolish by nature. We require a good realistic understanding of the land and its attributes to make optimum utilization of land and its innate resources. A precise understanding of land-utilization is most important for systematic and productive land use. Monitoring of different land cover area with urban growth, vegetation growth, natural hazards needs attention [1].

Manuscript published on 30 August 2019.
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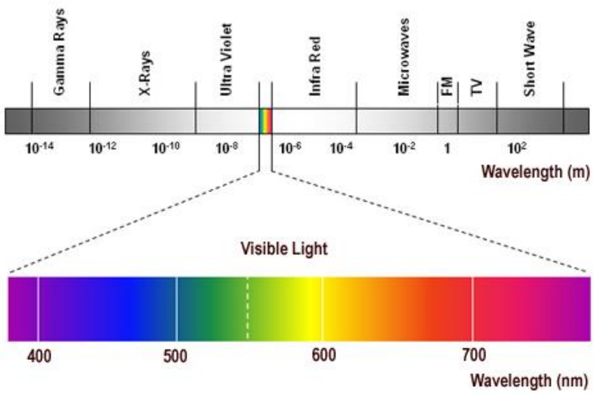

Fig. 1. Electromagnetic Spectrum [5]

Also, continuous renewal of land cover maps at micro and macro scales helps the government in monitoring of affected area after natural hazards [2]-[4].

Basic principle sources which could capture the temporal dynamics of this knowledge are satellite images. These are the fundamental tools needed to extract information from the surface of the earth for land cover classification. Thus, to analyze land cover changes, satellite images are used. The multi-spectral optical sensor generally works in the visible and near-infrared portion of the electromagnetic spectrum (Fig. 1.) and alone it could not provide enough accurate information due to the similar spectral pattern of ground and building material. Hence, it is not easy to increase the land cover classification accuracy of built-up and bare-land areas from multi-spectral optical imageries. Therefore, SAR sensor that works in the microwave portion [6], is one of the advanced technologies which is better option to acquire images of land surface with optical sensor.

II. SYNTHETIC APERTURE RADAR

This study is using an object-based and ruleset-based supervised classification approach based on computational intelligence to classify a SAR imagery of Alwar city into different terrain features and generates a thematic map out of it. Like other radar, SAR depends on the emitted and reflected radio waves to find out interesting properties of the area of interest [7]–[9]. SAR uses a very clever approach in which the SAR sensor while looking at a certain view, which is hundreds of km wide and simultaneously orbiting around the earth due to satellite movement imaged certain objects. Illuminated objects in that view backscatter the light received from a sensor whose position relative to the object changes with time. After integrating the successive light pulses received from those objects and recorded by sensor at multiple positions, a synthetic aperture can be created, which greatly increases the resolution of the sensor.

Fig. 2a. and Fig. 2b shows working principal of SAR

Some of the strong points of SAR are 1) It can observe under all weather conditions.

2) Being an active sensor, it does not depend on sunlight, it works day or night.

3) In consideration with a spectral resolution, it also provides polarimetric observations [6].

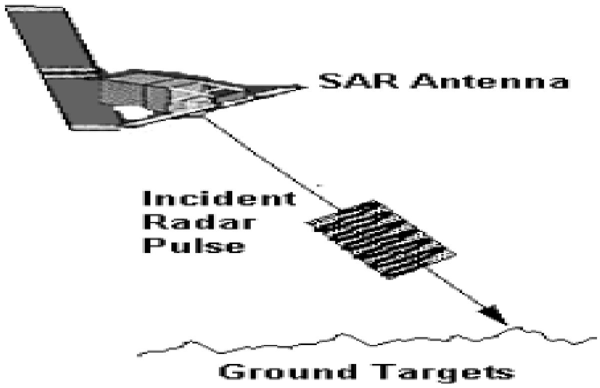

Fig. 2a. A radar signal is transmitted from the satellite to the ground. [10]

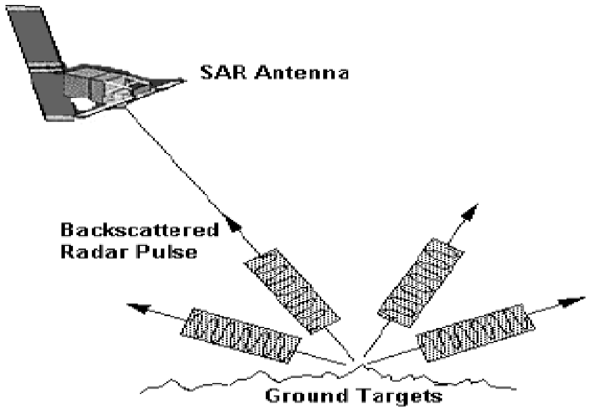

Fig. 2b. The radar signal is scattered back from ground to satellite. [10]

4) SAR also has coherency information, which is important while looking at land deformation around volcanoes due to landslides, earthquakes and tectonic shifts.

For satellite images like SAR, many researchers are using OBIA over other approaches like pixel-based or Principal Component Analysis (PCA) as it increases the accuracy of classification tremendously. To perform OBIA, the first step is image segmentation which provides the spectrally homogeneous image objects. With these objects, spatial, textural and contextual features of the image can be extracted easily by using the direct spectral observation which highly improves the classification accuracy.

Hence, accuracy of OBIA greatly depends on the accuracy of segmentation process [11]. Depending on the need of work, few attributes are selected from the extracted attributes from image objects. As addition of irrelevant attributes decreases the classification accuracy and increases the computational cost.

III. RELATED WORK

Importance of LULC maps can be seen in so many applications, therefore, this research area attracts a lot of research scholars from the past few decades. Y. Guo [12] proposed an approach for multitemporal image classification based on SVM Sequential Classifier Training (SCT -SVM). Tests were conducted over agricultural land in Australia with Sentinel-2A multitemporal data. The outcome showed, when training data was not sufficient, the final classification correctness of new image was enhanced.

In his study C. D. Man [13] offered a classification technique for areas having continual clouds with excessive earthly dynamics of land-cover types. The resulting composite images were clean with 99.78% pixels free from clouds and were 20.47% superior to their actual images. In comparison to single composite classifications, utilizing time series of composites remarkably enhance classification.

A. Sewnet and G. Abebe [14] studied the land use land cover (LULC) change in Koga watershed. Outcome unveiled that exceptional LULC change takes place in the observed area for the last thirty-eight years. Land of settlement and cultivation was expanded by 7054.6 ha, whereas, bush and grasslands reduced by 3376 and 4846.5 ha respectively. Also, wetland shrinks from 580.2 ha to 68.3 ha.

M. I. Sameen [15] shows how the accuracy reduced with increase in the number of features. Considering a total of 20 features from which the best subset comprising 12 features was selected via ACO. Using a decision tree algorithm, these features were utilized to generate rule sets, and a LULC map was developed for a given area.

H. Zakeri [1] proposed a technique to categorize the land cover of Tehran city, Iran by using dual-polarized data. With spatial texture analysis, eight texture measures were selected. After principal component analysis, it was found that a large number of features reduces the classification accuracy. With dimensionality reduction, few features were selected for classification. To find out bare land, vegetation, and three dissimilar built-up classes, two supervised classification techniques were used. Value of kappa coefficient lies in the range 0.25 to 0.58 which shows that PCA approach is not so effective to increase accuracy.

IV. STUDY AREA AND DATASET

A. *Study Area*

Planet earth contains very diversified physical features. But most of the portion of this giant planet has similar spectral and spatial features for hundreds or thousands of kilometers, for example vastly spread oceans or forest area which does not have any significance for this study as there is no diversity in terrain features. Hence to visualize the difference between backscattering values of different terrain measures and to observe the effectiveness of proposed work, a very diversified land area of Alwar district, state of Rajasthan, India is selected. Geographically it is located at 27° 34' North Latitude and 76° 35' East Longitude. Its height is 270 m from sea level. It acquires 8380 sq. km area, which consists of varied terrain regions. It is surrounded by beautiful Aravalli ranges contributes to rocky structures and divides the plateau into fragments.

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DOI: 10.35940/ijitee.J9534.0881019
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Two major rivers namely, river Arvari and Ruparal are flowing in this area. Because of these rivers there exist a wide variety of flora and fauna contributing to the water and vegetation texture measures. Due to the infrastructure development and urbanization there exist a lot of urban areas. Also, some barren land exists at the study site. So, these texture measures are considered as objects or classes into which the whole area is classified. Fig. 3. shows the google earth image of Alwar city which clearly shows the multiple land cover features of that area.

Fig. 3. Google Earth Image of Alwar City

B. *Dataset*

Here 7-band, multi-resolution, multi-spectral, and multi-sensor remotely sensed images of district Alwar, Rajasthan is taken with dimensions 472*546 pixels. The dataset was made available by DTRL Lab, DRDO, Delhi for research purpose. The dataset also contains the original false-color composite image of the study area which is used as a visual input image to be classified. With the help of expert knowledge, radiometric indices and Erdas Imagine software, excel files containing spectral reflectance for pure-barren, pure-vegetation, pure-rocky, pure-urban and pure-water were generated. These classes are considered as objects and contribute to object-based feature extraction for rule-based supervised classification.

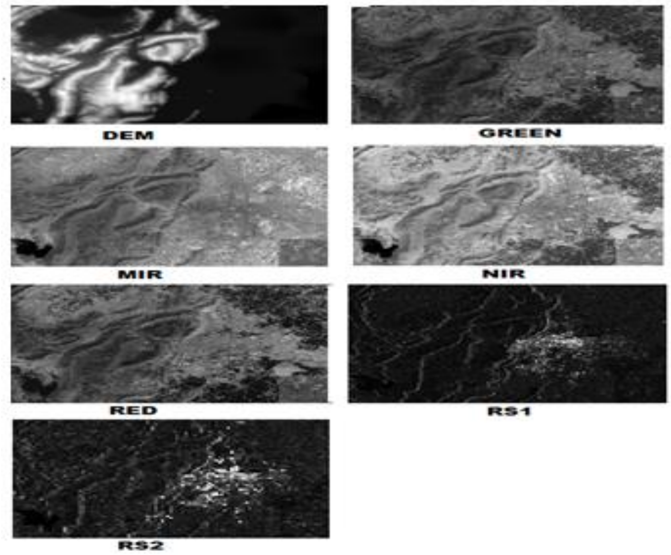

Fig. 4. 7-band images of Alwar city

Fig. 4. shows the 7-band images and Fig. 5. shows the original false-color composite image used for classification. Table I. displays name of different band and satellite sensor from which they acquired.

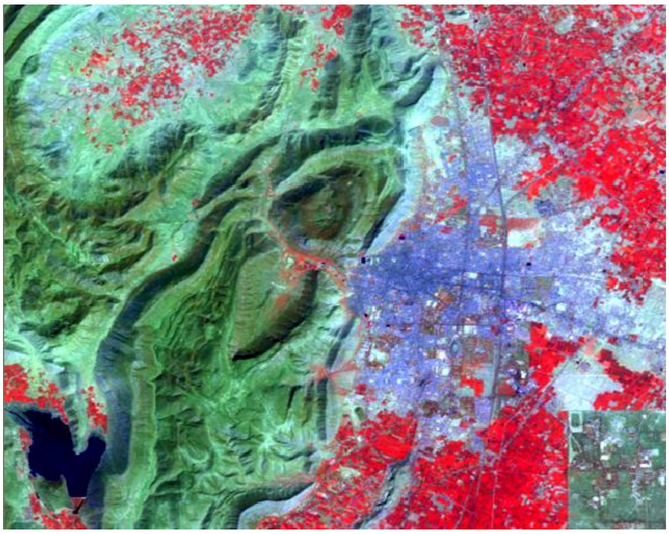

Fig. 5. False-color composite image of Alwar city

Table I: 7 bands and satellite from which they acquired

S.No	Band Name	Satellite
a.	Red	Liss-III, Resourcesat 1
b.	Green	Liss-III/, Resourcesat 1
c.	Near-Infrared	Liss-III, Resourcesat 1
d.	Middle Infrared	Liss-III, Resourcesat 1
e.	Lower Incidence, C Band	Radarsat-1
f.	Higher Incidence, C Band	Radarsat-1
g.	Digital elevation model (DEM) (Res:25M)	

V. METHODS

Fig. 6. Describes the flow of methodology. From the given band images, processed data have been prepared and after segmentation image objects are generated.

A. *Feature Extraction and Selection*

Features are directly calculated according to the requirement of the algorithm. For dimensionality reduction mean of the training set has been calculated and distance matrices are generated for every class by computing Euclidian distance of band images with mean values of training set. It reduces the redundancy that leads to comparatively low computation time. Some features are considered directly and some indirectly. In this work, Correlation, homogeneity, density, standard deviation and mean values of objects and bands have been considered. Homogeneity considered in terms of minimum distance and density in terms of size.

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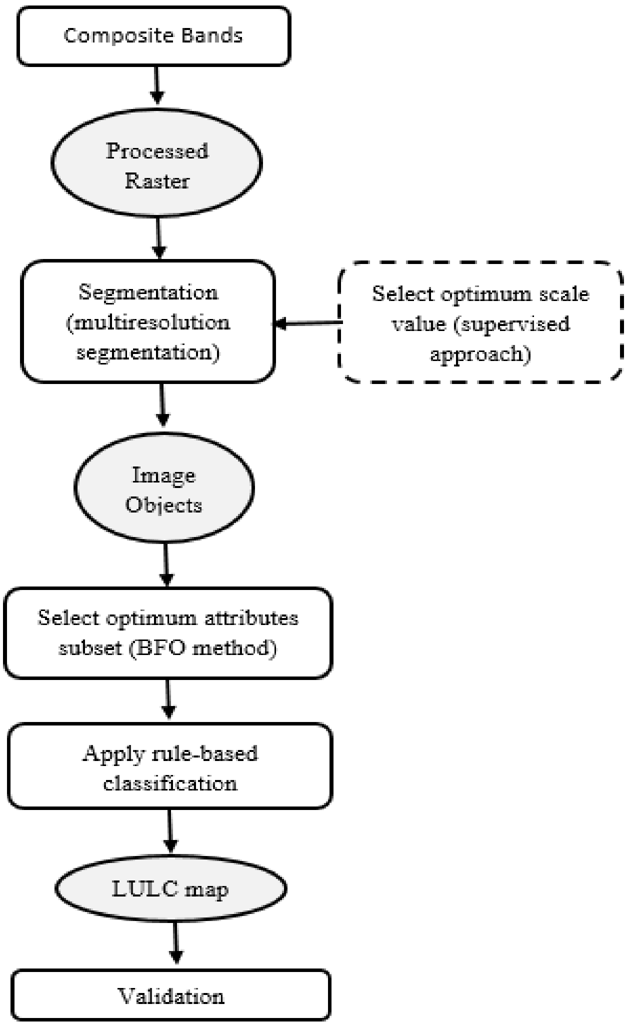

Fig. 6. Methodology for SAR image classification with BFO and OBIA

B. *Rule-Based Classification Using BFOA*

Bacterial foraging optimization algorithm comes under the branch of the nature-inspired algorithm. Proposed by Kevin Passino in 2002, it is based on the nature of E.coli bacteria which could sense chemical substances in its living area and move towards it. This behavior is known as chemotaxis nature of bacteria. The algorithm works in three steps.

1) Chemotaxis: where the cost of bacteria is considered with respect to others and the movement of bacteria has been decided.

2) Reproduction: Fittest bacteria go to next generation and rest are discarded.

3) Elimination and dispersal: new bacteria are inserted with lower probability and old are discarded.

$$fitness = \begin{cases} if\ B > Jlast\ then\ (a-x)^2 + b(y-x^2)^2 \\ else\ if\ B < Jlast\ then\ Jlast \\ else\ B = Jlast \qquad No\ change \end{cases} \qquad (1)$$

Equation 1 shows the fitness function of bacteria. Decrease in cost function represents favorable environment, while increase in cost function represents unfavorable environment. Fig. 6. shows the iterative steps for bacterial foraging algorithm. The algorithm continues execution until the best solution reached. The fitness function checks the health or fitness of bacteria and eliminates the unhealthy group of bacteria. In every iteration, the current best observation is

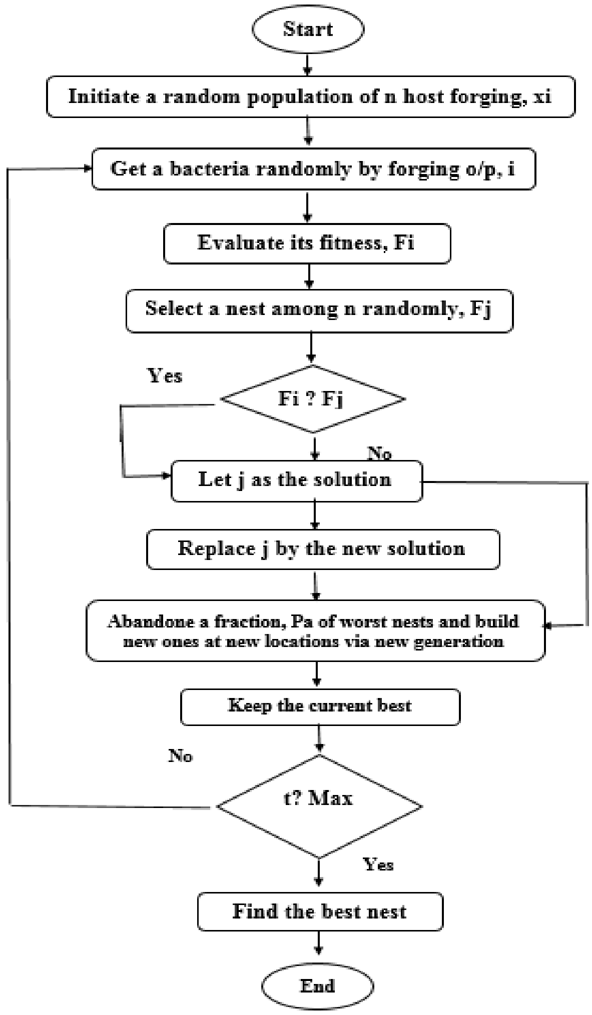

Fig. 7. Steps showing BFOA

saved and after completion of all iterations, the best observation is selected.

VI. RESULTS AND DISCUSSIONS

Fig. 8. shows the final reconstructed classified image of Alwar city where red represents water, yellow represents rocky, light blue represents barren, dark blue represents urban and green represents vegetation area (Fig. 9.). The overall work has been implemented in MATLAB R2018a. From this LULC map, all the classes can be easily observed and located.

To validate the result an error matrix has been generated by taking the random samples points from the reference data which is considered as the ground truth and the predicted values. Table. II show the error matrix. According to this out of total 40 barren pixels, 38 are predicted as barren whereas 1 is misclassified as rocky and 1 as urban. Same can be seen in other classes. The overall accuracy is coming as 97.43 % and Kappa value is calculated by using kappa function which is coming as 0.96. Hence, improvement can be observed in results as compared to the previous studies.

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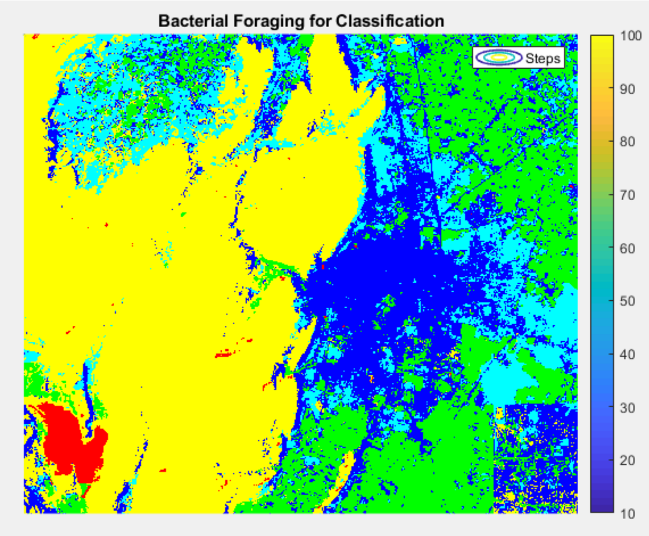

Fig. 8. Classified output image

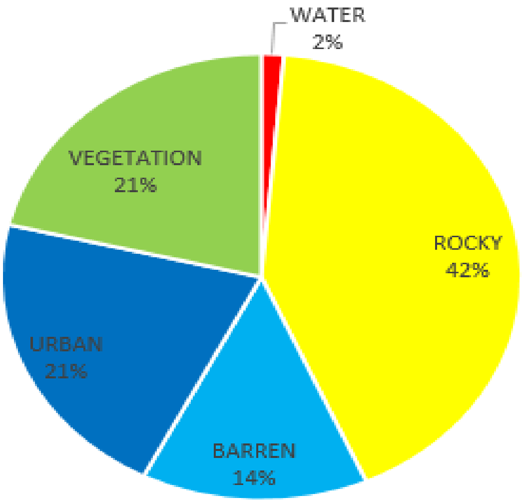

Fig. 9. Class distribution chart

Table- II: Error Matrix

		Actual Values					
Predicted Values		Barren	Rocky	Urban	Veg	Water	Total
	Barren	38	1	2	1	0	42
	Rocky	1	165	1	0	0	167
	Urban	1	1	38	0	0	40
	Veg	0	1	1	168	0	170
	Water	0	1	1	0	46	48
	Total	40	169	43	169	46	467

- Kappa coefficient is the ratio of chance agreement and actual agreement out of total values. It can be calculated by the equation 2 where OA is overall accuracy and AC is agreement by chance.

$$K = \frac{OA - AC}{1 - AC} \qquad (2)$$

- Overall Accuracy is the ratio of total correctly classified pixels out of total number of pixels.
- Producer's accuracy is the ratio of total misclassified pixels out of total actual number of pixels in each class subtracted by 1.
- User's accuracy is the ratio of total misclassified pixels out of total predicted number of pixels in each class subtracted by 1.

Table III shows the overall results.

Table III: Accuracy Parameters

Classes	User's Accuracy (UA) %	Producer's Accuracy (PA) %
Barren	90.47	95
Rocky	98.8	97.6
Urban	95	88.3
Veg	98.8	99.4
Water	95.8	100
Overall Accuracy (OA) = 97.43%		
Kappa Coefficient (K) = 0.096		

VII. CONCLUSION AND FUTURE SCOPE

Overall it can be seen that nature-inspired algorithms with OBIA for very large high-resolution satellite images provide better results as compared to previous methods. BFO with rule-based classification needs training data in the form of objects from the same dataset. Because of which results may variate for other datasets. Hence the approach can be extended to unsupervised image classification where the number of classes is not known. The land is an innate resource

and is continuously changing due to various reasons like natural hazards, developments, atmosphere change so there is always a requirement of efficient geographical information system leads to the good scope of study in this area. Especially in urban area development. As due to the fast-growing population the city's boundaries are expanding at a very fast rate. So other artificial intelligence algorithms can be applied for further analysis of the work

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