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Original Article

Comparison of Pixel-based and Object-based Image Analysis for LULC Classification of Satellite Images

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Abstract *- The analysis of the Land Use and the Land cover changes plays an important role in infrastructure management. Pixel-based classification methods are simple and intuitive and achieve good accuracy but are prone to misclassifications. This happens because the context information is not taken into consideration. In this work, an object-based image classification technique (mean shift segmentation) is implemented for the LULC classification of the Dandeli Forest area. This method groups the pixels together based on the contextual and spectral information. Further, the classification scale is also varied to arrive at an optimum segmentation scale. It is found that the accuracy initially improves when the segmentation scale is reduced (finer scale). However, after a certain point, the accuracy of the classification goes on to decrease. It is also pointed out that the scale of segmentation used here and the optimum results obtained thereof depend on the geographic area under consideration. The area under consideration has imbalanced classes, and hence, the accuracy of the algorithm depends on the scale of segmentation. The scale of segmentation depends on the parameters Spatial Radius and Range Radius. Results obtained indicate that the optimal accuracy of 91.57% is obtained when the Spatial Radius = 5 and the Range Radius = 15, below and above which the accuracy tapers off.*

Keywords *- Mean shift segmentation, Context-based classification, Forest mapping, Spectral angle mapping, LULC classification.*

1. Introduction

Land Use and Land Cover (LULC) classification of forests is a crucial process that involves categorizing and mapping different land cover types and land use within forested areas. LULC classification is critical for understanding and conserving biodiversity, as different species may be associated with specific forest types (Tripathi et al., 2019). Effective forest management requires accurate data on the extent and composition of forest types. LULC classification helps forest managers make informed decisions about harvesting, reforestation, and protection efforts (Roy et al., 2022). Urban development and infrastructure projects often encroach upon forested areas. LULC data can inform land-use planning to balance development needs with forest conservation. Forests play a role in regulating water resources. Understanding forest cover and land use can help manage watersheds, protect water quality, and prevent erosion and runoff. An environmental impact assessment is typically required before embarking on any major development project in or near forested areas. LULC data provides essential assessment information (Shimrah et al., 2022). Governments and environmental organizations use LULC data to formulate and implement policies related to forest conservation, sustainable forest management, and land-use regulations. To carry out LULC classification of forests, remote sensing technologies, satellite imagery, GIS (Geographic Information Systems), and ground-based surveys are often used. Machine Learning classification algorithms have been traditionally used for the LULC classification (Balha et al., 2021). The most commonly implemented algorithms are pixel-based (Srivastava et al., 2022). Each pixel is classified depending on the reflectance values obtained from the satellite sensors in these cases.

These methods are easy to implement and fast and give appreciable results in cases where the geographic area is homogenous in nature. Pixel-based classification techniques are also preferred where the shape of individual classes is not a matter of concern. However, in the case of heterogeneous classes, these methods may give erroneous results due to misclassification of the pixels (Tran et al., 2014). Object-based classification techniques consider not only the spectral information but also the spatial context and relationships between neighbouring pixels. This contextual information helps better differentiate land cover types (Tiwari et al., 2021). Object-based classification is well-suited for scenarios where land cover classes are mixed or have irregular shapes and where spatial patterns and context play a significant role in classification. It is commonly used in urban planning, forestry, and detailed land cover mapping. It effectively reduces the effects of noise, improves classification accuracy in complex landscapes, and addresses issues related to edge effects and mixed pixels (Parida & Manda, 2020).

2. Literature Survey

A literature survey is carried out in three phases for the present research work. In the first phase, the individual pixel-based classifiers and their relative pros and cons are explored. In the second phase, the parameters of these classifiers, which may improve the classification accuracy, are studied. In the third phase, methods to overcome the drawbacks of pixel-based classifiers are surveyed. These include hybrid approaches, Deep Learning (DL) approaches and context-based classification approaches. A detailed survey of the Resources at LISS-III and Landsat-8 imagery (Venkateswarlu et al., 2014) shows that the Landsat-8 imagery is more suitable for the LULC classification of the present geographic study area.

Themistocleous and Hadjimitsis (2008) emphasized the importance of atmospheric corrections, especially when the classified images are used for temporal comparison. A comparison of different techniques for atmospheric corrections (Ilori et al., 2019) shows that the DOS-1 method gives the best results when the cloud cover is less than 10%. Further, methods for radiometric calibration of the Landsat-8 imagery were given by Barsi et al. (2019). A comparison of the Random Forest (RF), Support Vector Machine (SVM), and k-Nearest Neighbour(kNN) algorithms for LULC classification (Noi & Kappas, 2017) shows that the classification accuracy is a function of the training sample size.

A tuned SVM is shown to achieve a maximum classification accuracy of 94% compared to the Maximum Likelihood (ML) and the Minimum Distance (MD) algorithms (Ghayour et al., 2021). In yet another study (Oo et al., 2022), it is shown that RF achieves a maximum classification accuracy compared to SVM and CART. Ouma et al., (2022) have shown that SVM proved better accuracy for the LULC classification in Urban areas. The comparison was made with respect to RF, CART, and GTB. SVM was found to perform better in both urban and rural areas (Rahman et al., 2020).

The variation of the classification accuracy with respect to the parameters previous studies shows an optimal value of the parameters that achieves maximum classification accuracy. Non-parametric classifiers with parameter tuning were shown to have maximum accuracy compared to the parametric classifiers (Verma et al., 2020). A detailed review of the ML and DL algorithms and their statistical analysis and comparison is given by Digra et al., 2022. Deep learning algorithms are found to perform better than all the above-said algorithms (Jozdani et al., 2019). Again, in this case, the area under study was urban. Fuzzy object-based deep learning methods achieved better accuracy than RF, SVM, and CART in the LULC classification of the lake basin (Feizizadeh et al., 2021).

A Convolutional Neural Network (CNN) statistical analysis found it to perform better than the traditional ML algorithms (Carranza-García et al., 2019). A hybrid classification approach involving the ML and decision methods was shown to have better classification accuracy in the Sawantwadi taluk area (Kantakumar, & Neelamsetti, 2015). A hybrid method using ML and clustering in the arid region of Rajasthan was done by Kumar et al. (2020), and it was shown to perform satisfactorily.

The above survey indicates that the classification accuracy of any pixel-based classifier depends on the features used, the algorithm and their parameter tuning, training data size and the class imbalance. The problem with all the pixel-based classifiers is that they consider only the spectral information while ignoring the spatial information. Even with parameter tuning, the pixel-based classifiers cannot perform better. However, if the spatial (context) information is considered, the classification accuracy can improve.

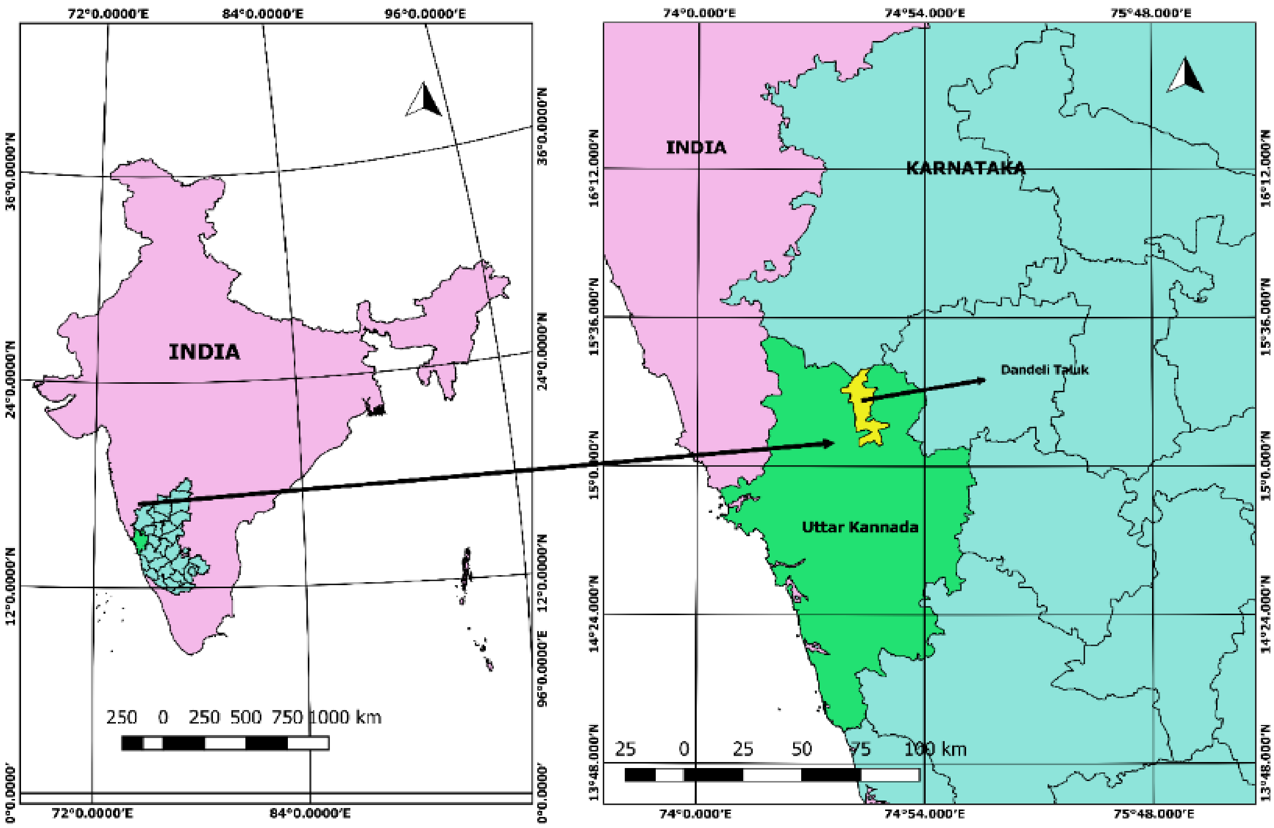
The area under consideration is a heterogeneous forest area with the predominant forest class. So, it can be considered a relatively homogenous area for all intents and purposes. Here, we suggest a hypothesis that classification accuracy can be better if groups of pixels are considered objects rather than individual pixels. Taking into consideration the context information (in this case, the proximity and the spectral signature information) may improve the classification accuracy compared to the pixel-based approaches.

3. Study Area

The study area is the Dandeli Forest, a part of the Western Ghats (India) and is well known for its rich biodiversity. The river Kali runs through the forest. It is also a tourist hotspot, with many resorts coming up in the forest area and surrounding the river. Figure 1 shows the study area with respect to the Indian State of Karnataka. The satellite Imagery is obtained from LANDSAT-8, the details of which are given in Table 1.

Table 1. Details of the Satellite Image (LANDSAT-8)

Product Type	L1
Date of Acquisition	16th October 2023
Cloud Cover	Less than 10%
Spatial Resolution	30m
Number of Bands	11
Source	Glovis
Map Projection	WGS84/43N
Type of File	Geotiff



Source: Map courtesy: https://surveyofindia.gov.in/

Fig. 1 Study area

4. Methodology

The methodology adopted to carry out the research work is shown in Figure 2. The acquired image has a cloud cover of less than 10%, so no preprocessing for cloud coverage removal is required.

Instead, the image must be corrected for atmospheric effects, which is done using the DOS-1 algorithm. The process used for the same is standard and is available on the website (https://www.usgs.gov/landsat-missions/landsat-collection-2-level-1-data).

Mean shift filtering is a nonparametric technique used in image processing and computer vision for various tasks, including image denoising, image segmentation, and object tracking. It is a method that can be used to locate the modes or peaks in a density function. It is particularly useful for tasks where you want to identify regions of interest in an image or group similar pixels together. The salient features of the mean shift segmentation are given below.

4.1. Mode Seeking

Mean shift filtering is a mode-seeking algorithm. A “mode” in this context represents a cluster or region in the feature space (e.g., colour space for an image) where data points are densely concentrated.

4.2. Kernel Density Estimation

The algorithm is based on kernel density estimation. It estimates the probability density function of the data points in the feature space, and the modes correspond to the local maxima in this density function.

Mean Shift Segmentation works as follows:

- Data Representation: Each pixel in an image is typically represented as a point in a feature space, defined by its colour and/or spatial attributes.
- Window or Kernel: Mean shift operates with a sliding window or kernel that moves iteratively over the data points. This kernel defines a search region in the feature space. The spatial search region, in this work, is implemented in the form of *Spatial Radius*. The Euclidean distance of the spectral signatures is considered in the parameter *Range Radius*.
- Mode Shifting: At each iteration, the kernel calculates the mean of the data points within its current window. This mean represents the “mean shift” from the current position.
- Updating Position: The centre of the kernel is then shifted to this mean position.
- Iterative Process: The process is repeated until convergence, where the kernel stops shifting and stays at a position corresponding to a mode.

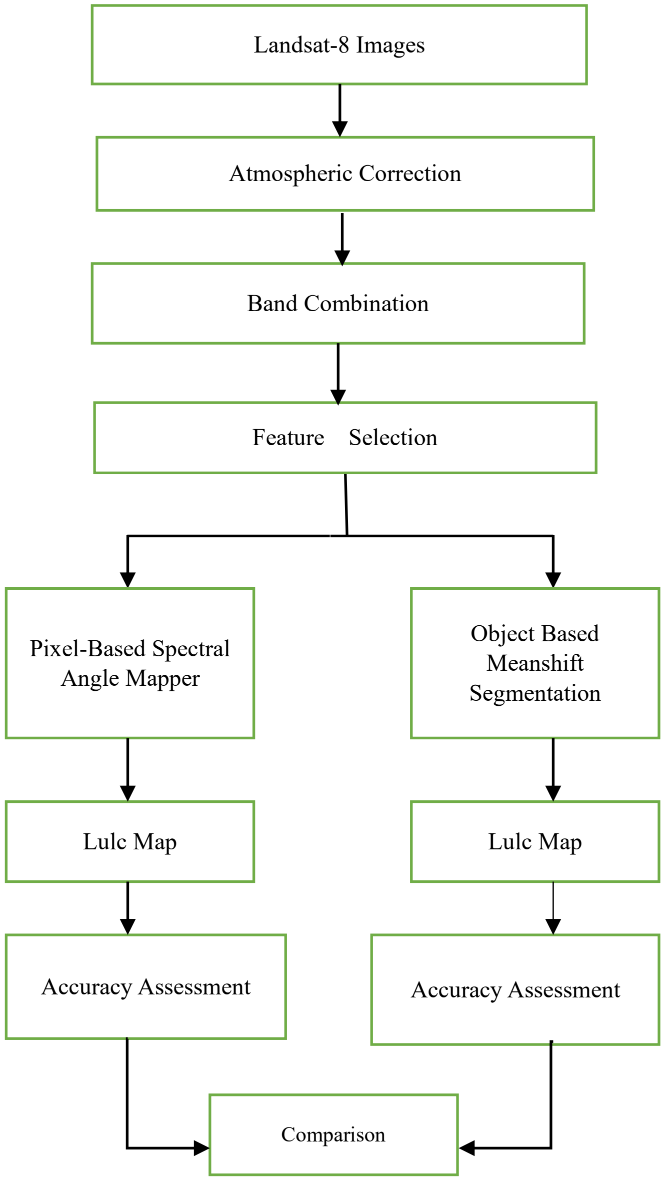


Fig. 2 Methodology for the proposed work

Mean shift segmentation considers both spatial and feature information to group similar data points together. In the case of satellite images, the features are the spectral signatures that are distinct for each land cover class.

4.3. Spatial Radius

The spatial radius determines the spatial neighbourhood around each data point or pixel that is considered when calculating the mean shift vector. The mean shift vector is used to shift a data point towards the mode (the centre) of its neighbouring data points with similar spectral signatures and spatial characteristics. The spatial radius defines how far the algorithm should search for similar data points regarding their spatial proximity. A larger spatial radius will consider a broader area around each data point, potentially leading to larger and smoother regions in the segmentation result. In comparison, a smaller spatial radius will lead to smaller, more detailed regions. The choice of an appropriate spatial radius depends on the specific image and the desired segmentation results. It is often combined with the spectral signature radius, which determines the range for considering similarity in colour space. Adjusting these two parameters is important to control the trade-off between preserving fine details and achieving smoother, more coarse-grained segmentation results.

4.4. Range Radius

It determines the range in feature space (spectral signature space) within which the algorithm considers data points similar. A smaller range radius restricts the colour similarity to a narrow range, leading to fine-grained segmentation where only very similar colours are grouped together. On the other hand, a larger range radius allows for a broader range of colours to be considered similar, resulting in more extensive regions in the segmentation. For comparison, this method is compared with the Spectral Angle Mapper (SAM), which is implemented as a pixel-based classifier. It is employed to classify or compare the spectral signatures of different objects or materials in a scene based on the angles between their spectral vectors in a high-dimensional space.

The brief working of the mapper is given below.

4.4.1. Spectral Signatures

Each pixel in a hyperspectral image has a spectral signature, which represents the reflectance or radiance of the material at various wavelengths. This information is typically represented as a vector in a high-dimensional space, with each dimension corresponding to a different wavelength band.

4.4.2. Reference Spectra

To use SAM, you need one or more reference spectra representing the materials or classes you want to identify. These reference spectra are also represented as vectors in the same spectral space.

4.4.3. Calculation

SAM calculates the spectral angle (θ) between the spectral signature of a pixel and the reference spectra. The spectral angle is determined using the dot product of the two vectors and can be expressed in Equation 1.

$$\theta = arccos\left(\frac{A \cdot B}{\|A\| * \|B\|}\right) \qquad (1)$$

4.5. Classification

The spectral angle is compared to a threshold value, and the pixel is classified based on this comparison. If θ is less than the threshold, the pixel is classified as the material represented by the reference spectrum B. If θ is greater than the threshold, the pixel may be classified as a different material or left unclassified.

5. Results and Discussion

Three distinct classes are chosen for the classification, namely, Forest, Water and Built-up areas. The work is implemented using QGIS 3.10 and Python. The algorithms are run on a system having Intel(R) Core (TM) i5-8250U CPU @ 1.60GHz 1.80 GHz and 16GB RAM. Figure 3 shows the variation of Overall Accuracy (OA) with Spatial Radius and Range Radius. It is seen that the OA increases with the increase in the spatial Radius initially, but after the value of 5, OA goes on decreasing. This result is applicable even when the Range Radius is changed. Three different values of range radii are used here: 10, 12 and 15. It is found that the maximum OA of 91.5% is achieved when the Spatial Radius is 5, and the Range Radius is 15. Also, the following observations are made from the graph in Figure 3.

For the Range Radius of 10, the increase in OA with the increase in Spatial Radius is rather drastic. But when the Range Radius increases to 15, the OA increase with Spatial Radius is gradual. It indicates that, in essence, a higher Range Radius gives a higher OA, but increasing it further does not contribute much to the increase in OA. Hence, a Range Radius of 15 and a Spatial Radius of 5 are considered optimal values, which give a maximum OA of 91.5%.

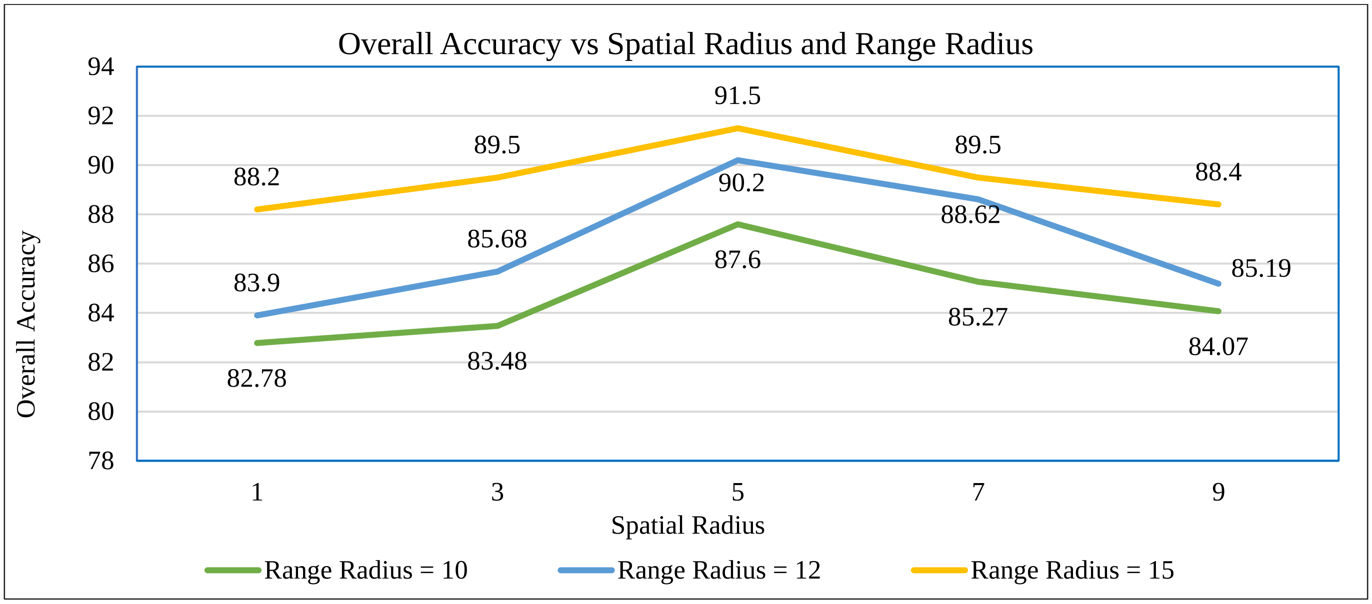


Fig. 3 Variation of overall accuracy with the range radius and spatial radius

Figure 4a shows the result (LULC map of the Dandeli Forest Region) using the pixel-based Spectral Angle Mapper Algorithm. Figure 4b shows the LULC map using the object-based mean shift algorithm (*Spatial Radius = 5, Range Radius = 15)*.

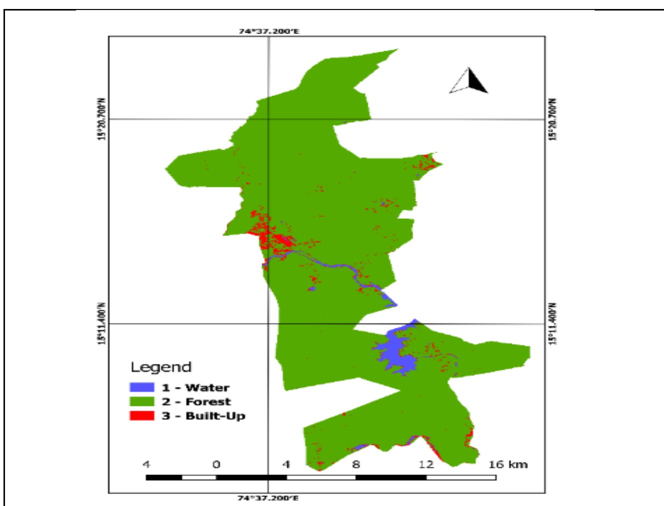


Fig. 4a LULC Map using Spectral Angle Mapper

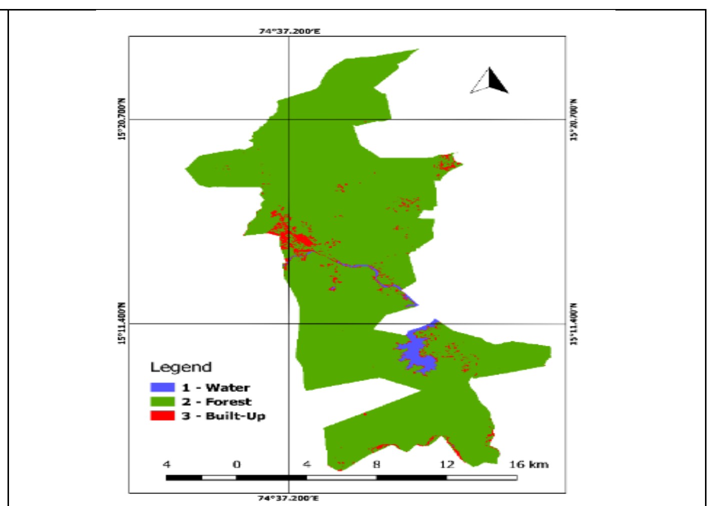


Fig. 4b LULC Map using Mean Shift Segmentation

Pixel-Based Spectral Angle Mapper	Patch-Based Mean Shift Segmentation

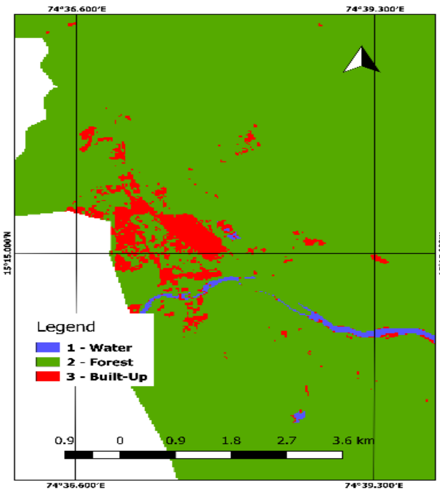
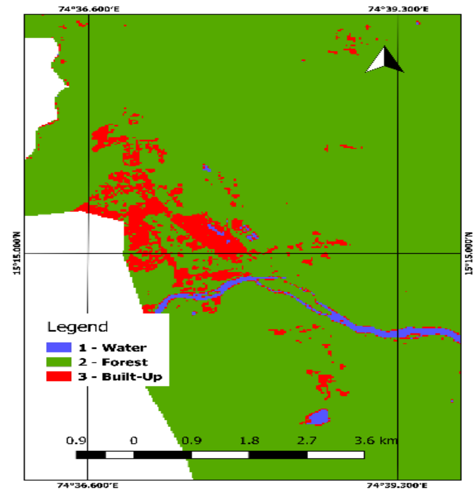

	

Fig. 5(a) ROI-1	**Fig. 5(b) ROI-1**

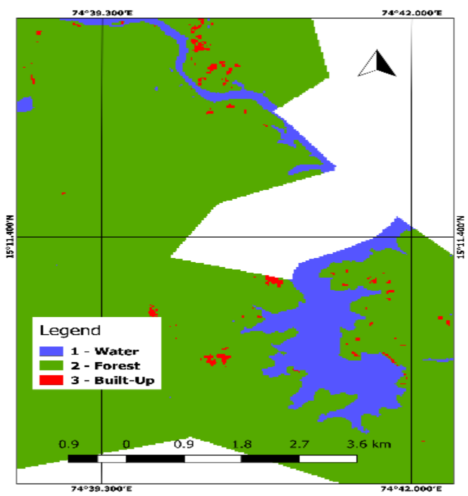
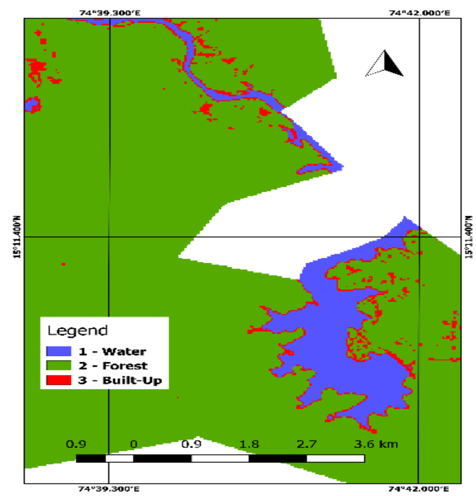

	

Fig. 5(c) ROI-2	**Fig. 5(d) ROI-2**

Fig. 5 Region of interest using pixel based spectral angle mapper and patch based mena shift segmentation

To get better clarity about the results obtained, the LULC maps have been zoomed to two Regions of Interest (ROIs), as shown in Figure 5a – Figure 5d. The first ROI is a part of the river around which built-up areas are surrounded by forest. The second ROI is a major portion of the river surrounded by forests and settlements. Since the geographic area under consideration has imbalanced classes, only OA may not be enough of an evaluation measure. OA is a measure of the classifiers' performance. It may or may not depict the ground realities. Hence, as additional performance metrics, User and Producer Accuracies and Omission and Commission Errors are also calculated here. These four metrics are based on the confusion matrix created as an output of the classifiers. These four metrics are shown in Table 2. PA is the accuracy from the viewpoint of the mapmaker. This metric measures the ability of a model to correctly identify all relevant instances in a dataset. A complementary measure for the same is the Omission Error (OE), calculated as 1-PA. OE measures the number of pixels that belong to the actual class but fail to be classified into that class. UA is from the viewpoint of the map user. A high user accuracy indicates that the model is precise in its positive predictions. A complementary measure is Commission Error (CE), calculated as 1-UA. It measures the number of pixels that belong to another class but are classified to this class. Both PA and UA should be considered in conjunction with each other, and the classifiers should aim to achieve a balance between them. Table 2 shows a fine balance is achieved between the UA and the PA (both have nearly the same values) in this work. Comparing with the results obtained by [26], it is found that overall accuracy shows a considerable improvement from 82% to 85%, which indicates the usability of the algorithm for the LULC analysis. The main reason for these better results is using the mean shift segmentation method, which operates iteratively.

Table 2. Evaluation metric values for the SAM and the mean shift method

	SAM	Mean Shift Segmentation
User Accuracy	86.02	91.77
Producer Accuracy	85.93	91.73
Overall Accuracy	85.64	91.57
Omission Error	14.07	8.27
Commission Error	13.98	8.23
Kappa	0.82	0.90

6. Conclusion

The working hypothesis of this work is that the classification accuracy can be improved if the context of the pixels is also considered for the classification process. An object-based Mean Shift Segmentation is implemented in this work to prove this hypothesis. It is then compared with a pixel-based Spectral Angle Mapper. The results indicate that the object-based Mean Shift Segmentation gives a better accuracy of 91.57% compared to the pixel-based Spectral Angle Mapper (85.64%). This is because the pixels are considered objects, and the spectral context of the pixels is also considered for the classification. The advantage of using a Mean Shift Segmentation algorithm is that it is non-parametric in nature and, hence, does not make any assumptions about the image statistics. It is important to note that the results obtained are for a heterogenous forest area where the forest class is predominant. So, it can be considered a relatively homogenous area for all intents and purposes.

The same results may not be applicable in a heterogeneous area (urban areas), where further parameter tuning may be required to achieve optimum results. As a future work, the classification can be extended to deep learning methods if the training data and the time are not a constraint. As a future work, the mean shift segmentation method can be combined with any other image processing method to improve the accuracy of the prediction.

Declaration

All authors have read, understood, and have complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors.

Availability of data and material

Freely downloadable from the USGS/glovis website

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