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Research Article

Land use land cover change detection in the lower Bhavani basin, Tamil Nadu, using geospatial techniques

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Abstract
Land use land cover (LULC) change detection is essential for sustainable development, planning and management. This study was an attempt to evaluate the LULC change in the lower bhavani basin from 2014 to 2019, using Landsat 8 data integrating Google Earth Engine (GEE) as a web-based platform and Geographic Information System. The CART and Random Forest classifiers in GEE were used for performing supervised classification. The classified map accuracy was assessed using high resolution imagery and evaluated using a confusion matrix implemented in GEE. Five major LULC classes, viz., agriculture, built up, current fallow, forest and waterbody, were identified, and the dominant land use in the study area was agriculture and current fallow, followed by dominant land use of forest. During the study period (2014–2019) the change in built-up area 7.37% in 2019 and 5.45% in 2014, was noted due to urban sprawl. GEE showed significant versatility and proved to be an effective platform for LULC detection.

Keywords: Google Earth Engine, GIS, Land use land cover, Landsat, Remote sensing

INTRODUCTION

Land cover denotes the cover that exists over land's surface, such as vegetation, water bodies, man-made buildings, or soil. The way people use the biophysical or biological features of land is referred to as land use, or the multifarious ways through which humans utilize land with the motive of change and sustenance is referred to as land use. This constitutes a clear relationship between land cover and human activity in their surroundings. Land use and land cover data are needed for various facets of land resource management and policy formulation, observing and modelling land use and ecological transformation, and establishing a foundation for land use statistics at all levels (Jansen and Di Gregorio, 2004). In a global context, the necessity for the development of repeatable, efficient, and accurate monitoring of land cover change is paramount to the successful management of our planet's natural resources (Campbell *et al*., 2015)

Owing to its consecutive data acquisition competencies, time savings and lower cost compared to traditional methods, and suitability of format for performing computer operations, remote sensing data are widely and efficiently used in land-use and landcover classification (Brahabhatt al., 2000; Alaguraja *et al*., 2010; Sinha *et al*., 2013). Repetitive satellite imagery is valuable for visual evaluation of the changing natural resource characteristics at a certain period and location and quantitative examination of land-cover changes (Tekle and Hedlund, 2000).

GIS provides an environment for analysing digital data that is important for detecting changes, modelling future changes and data transmission to plan efficient management. Satellite remote sensing offers vital information for mapping and analysing the planet's surface. The increased availability of satellites, as well as the improvement in image resolutions, are allowing people to effectively acquire as well evaluate huge timeseries information, however at extra time and processing expenses. Remote sensing data handling has shifted in the previous decade from conventional computers with hardware and remote sensing software into cloud-based systems like GEE that enable people to instantly acquire, and analyse huge geographic data (preprocessed) via comprehensible web-based platforms and sophisticated program code, which can handle big data processing rapidly in contrast to the traditional remote sensing processes (Wang *et al*., 2020).

Google Earth Engine is a cloud-based geospatial analytic application that allows people to handle tremendously vast volumes of data and their storage, processing, and analysis in a highly effective manner (Gorelick *et al*., 2017). In this sense, GEE allows users to specify different methods for combining input data allowing for the creation of light, cloud-free, multitemporal composite datasets with ease (Griffiths *et al*., 2013; Hermosilla *et al*., 2018).

GEE is a multipetabyte cloud-based platform for planetary-scale geospatial analysis that provides parallel computation and data catalogue services. The available sets of data are in a readily usable format and comprise everything, including the total Landsat archive of the United States Geological Survey, the Sentinel dataset, numerous climate datasets, global land cover data, and more. It also features a large library of functions, including masking, logical operators, sampling data, and so on, that may be used to conduct a variety of operations. GEE additionally allows users to leverage Python and the JavaScript Application Programming Interface to implement extra logic. Google Earth Engine is employed in a number of LULC-based studies due to its vast capabilities (Gorelick *et al*., 2017).

Recent machine learning (ML) classifiers have outperformed classic maximum likelihood classifiers and do not require any assumptions about data distribution (Ghimire *et al*., 2012). Nonparametric machine learning classifiers such as Classification and Regression Trees (CART), Support Vector Machine (SVM), and Random Forest (RF) have been shown to deliver exceptionally accurate results from RS imagery (Foody, 2002; Nery *et al*., 2016). Classification and regression trees are basic binary decision tree classifiers that use a predefined threshold (Mather and Tso, 2001), whereas RF is an ensemble classifier that uses many CART-like trees. Because it performs better than other common classifiers, RF is one of the favoured classifiers for LULC classification (Gislason *et al*., 20016; Jin *et al*., 2018).

The aim of this study was to assess the LULC change in the lower Bhavani basin, Tamil Nadu, from 2014 to 2019, integrating Google Earth Engine (GEE) and GIS.

MATERIALS AND METHODS

Study area

The Lower Bhavani basin is located in Tamil Naidu and includes sections of the Erode, Coimbatore, and Tirupur districts. The basin's overall geographical area is 2402 km^2, with latitudes ranging from 11° 15′ and 11° 45′ north and longitudes ranging from 77° 0′ and 77° 40′ east (Fig. 1). The ground elevation ranges between 154 and 1669 metres in terms of mean sea level. The basin's regional slope is to the southeast (Anandakumar *et al*., 2008). The climate in the area is semiarid, the annual average rainfall varies from 575.55 mm to 840.64 mm and the temperature of the area varies from a maximum of 40 degrees Celsius to a minimum of 22 degrees Celsius (Anand and Karunanidhi, 2020).

Datasets

Landsat 8

This study used Landsat 8 data that are freely available in the public repository of GEE. The calibrated top-of-atmosphere (TOA) reflectance dataset contained 11 bands, including two thermal bands.

Training data

The five dominant land use land cover classes in the lower bhavani basin were considered. The GEE interface (Fig. 2) was used to identify a total of 220 points for various classes to assess the usability and reliability of the whole approach.

Methodology

Without downloading the data to the local machine, the remotely sensed imagery was analysed by means of indetail code executed in the code editor .We can quickly access, filter, and analyse enormous amounts of data for a vast area in this way. Aside from quick processing, another major feature that is driving GEE popularity is the availability of various packages with a variety of algorithms that make remote sensing tools more accessible. The general workflow of the methodology is depicted in Fig. 3.

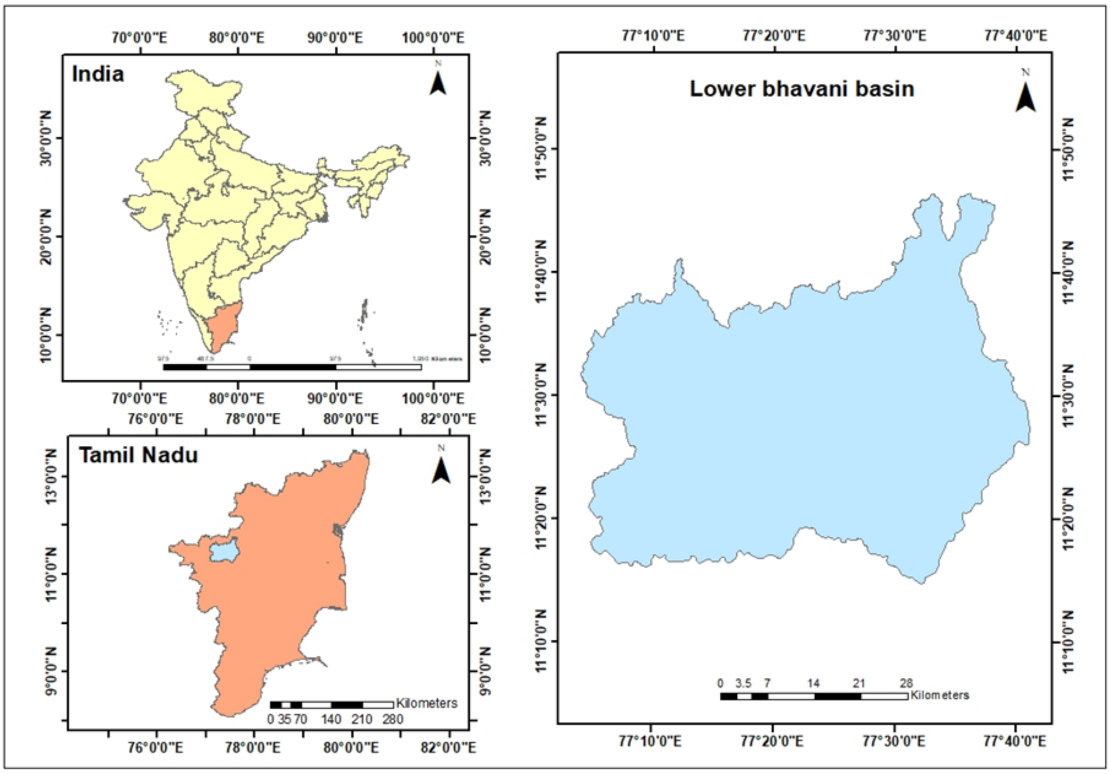

Fig.1. *Showing the lower Bhavani river basin*

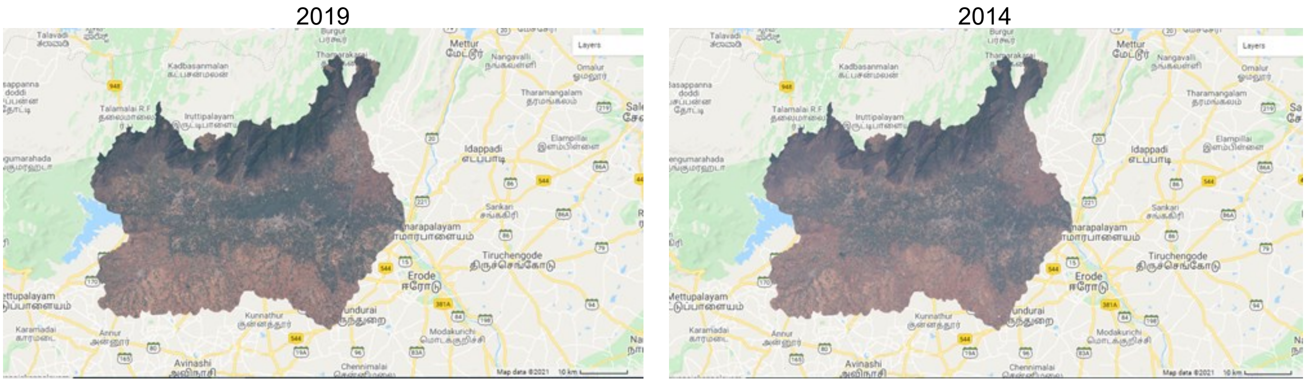

Fig. 2. *GEE interface displaying Landsat 8 image of lower Bhavani basin*

Composite image

The formation of the base dataset is an important stage in any LULC classification. The compilation of this dataset for the Landsat 8 data in this application begins with a filter (by region and the period) and cloud-mask (maximum 5%) image collection in GEE. This selection process produced the composite image for the study area.

Land-cover classification scheme

Five LULC classes were selected for change detection: agriculture, built up, current fallow, forest and water-body (Table 1).

LULC Classification

The classifiers are trained using the training points in supervised classification. The CART and RF classifiers were used in GEE. To perform the LULC classification, the code required the following inputs to conduct the LULC classification:

The area of interest

Feature Collection: which included overall training data that have been coded to match to LULC classes;

Dataset: Earlier generated in the "Dataset composition" step.

Integers beginning with 0 were used for class labels. The GEE interface made it simple to enter training data by adding as many feature sets as the needed LULC classes.

LULC change detection

A change detection approach was employed to analyse the changes. Several change detection approaches, such as post-classification change matrix, image differ-

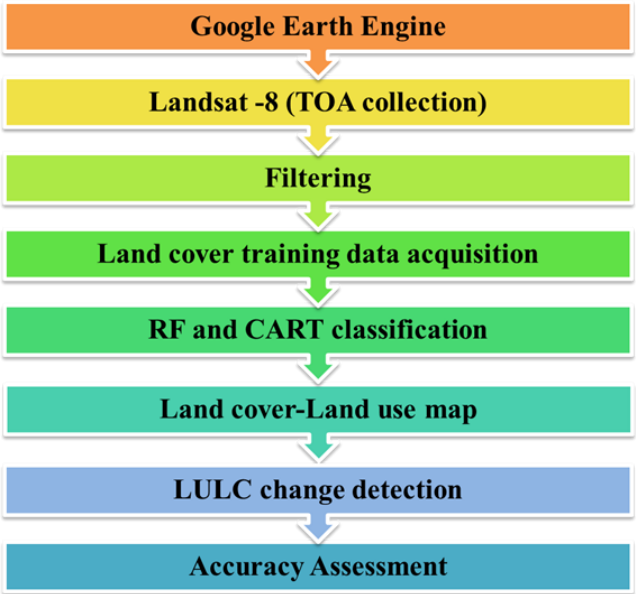

Fig. 3. *General workflow followed for LULC change detection*

encing, and principal component analysis (PCA), have been developed in recent years (Lu *et al*., 2004). The change- matrix displays vital information regarding the geographical distribution of LULC change (Shalaby *et al*., 2007). A change matrix depicting land cover changes in the lower Bhavani basin from 2014 to 2019 was generated from classified imagery.

Table 1. LULC used for classification

LULC type	Description
Agriculture	Crop fields
Built-up	Residential, commercial, industrial, transportation, roads, exposed rocks
Current Fallow	Current fallow lands in agricultural area
Forest	Diverse forest area
Water bodies	Open water,lakes/ponds, reservoirs/tanks,River

Accuracy assessment

The accuracy of LULC classifications was assessed in this work by means of a confusion- matrix developed in Google Earth Engine that statistically compares land use land cover associated with the validation points with the output classifications. The total accuracy of the process was calculated using the confusion-matrix.

RESULTS AND DISCUSSION

The natural reasons and the significant changes over the earth's surface for a long time interval have led to the process of land use land cover change analysis. Land cover changes over the different time intervals are recognized. Steps involved in the analysis of land use land cover change are acquisition of satellite images, image pre-processing, land use land cover change classification, post-classification, accuracy assessment, and change analysis.

LULC status

For the LULC classification, the selected CART and RF classifiers were trained using the training data from the feature collection's "LULC" attribute. The entered code implements the LULC classifications using the classifiers in the Google Earth Engine. The original composite dataset and training data were used to classify the data. The number of trees in the RF classifier was set to 50 in the interface. The output was exported from GEE interface in tif file format and was evaluated in an ArcGIS environment. These steps were used to evaluate the LULC classes for 2014 and 2019 and then computed the LULC change from 2014 to 2019.

Multitemporal LULC covering five major classes: agriculture, builtup, current fallow, forest and waterbody of 2014 and 2019 are shown in Fig. 4 and Fig. 5, respectively. The mountainous portions were clearly covered with forest and plantations, while the plain areas were covered by cropland, builtup, fallowland, and waterbodies. Table 2 shows the spatial distribution pattern of LULC as determined by supervised classification in GEE.

Table 2. LULC distribution in Lower Bhavani basin

LULC Class	2014		2019	
	Area (ha)	Area (%)	Area (ha)	Area (%)
Agriculture	78055.41	32.45	85644.03	35.60
Builtup	13110.59	5.45	17730.18	7.37
Current Fallow	85060.68	35.36	72342.96	30.07
Forest	63349.31	26.34	63830.48	26.54
Waterbody	968.41	0.40	996.77	0.41
Grand Total	240544.41	100.00	240544.41	100.00

Table 3. Confusion Matrix of classified image of 2019

LULC Class 2019	Forest	Waterbody	Agriculture	Builtup	Current Fallow	30% of training data
Forest	**20**	0	6	0	1	27
Waterbody	1	**9**	0	0	0	10
Agriculture	2	0	**18**	0	0	20
Builtup	0	0	0	**9**	1	10
Current Fallow	0	0	1	0	**11**	12
Total	23	9	25	9	13	79

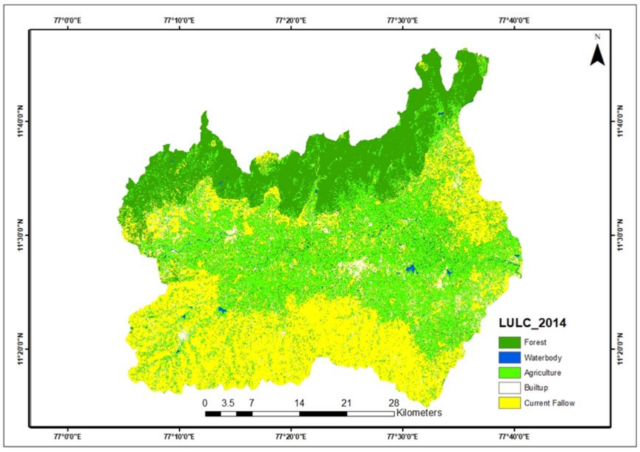

Fig. 4. *LULC map of lower Bhavani basin during 2014*

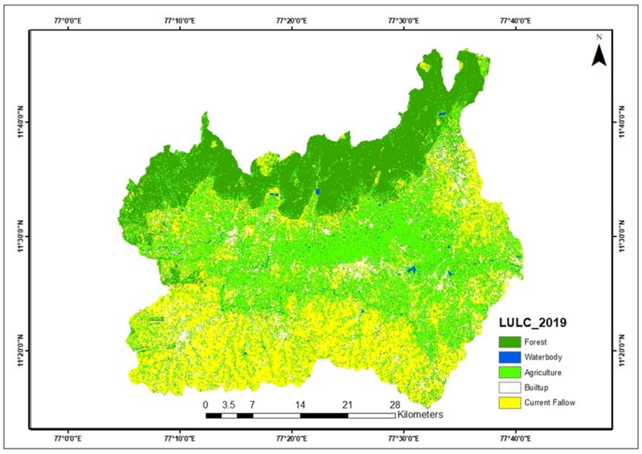

Fig. 5. *LULC map of the lower Bhavani basin during 2019*

According to classified maps, the area occupied by different classes in 2014 was agriculture 32.45%, builtup was 5.45%, current fallow covered 35.36%, forest covered 26.34% and waterbody occupied approximately 0.40% area respectively. During the year 2019 agricultural area was 35.60%. Builtup and current fallow covered 7.37% and 30.07%, respectively, while forest covered 26.54%. The area covered by water bodies was 0.41% (996.77 ha) (Table 2).

Accuracy assessment

Accuracy assessment is an important feature of land-cover and land-use mapping, not only as a guide to map quality and reliability but also in understanding thematic uncertainty and its likely implications to the end-user (Czaplewski, 2003). Accuracy assessment was performed using 30% of training data in each class, and a confusion matrix was generated (Table 3). The classification accuracy was determined to be 85% from the classified image of 2019. According to (Anderson, 1976), the minimum accuracy value for reliable land cover classification is 85 %. On the other hand, accuracy levels are accepted by users may not be acceptable to other users for a certain task (Geremew, 2013).

LULC change from 2014 to 2019

Land use and land cover change detection based on remote sensing images have been widely applied in research for LUCC, natural resource management and environment monitoring & protection (Zhang *et al*., 2014).

The LULC change matrix from 2014 to 2019 is represented in Fig 6. The representation of the same classes from and to the same class demonstrates that the LULC categories have not changed over time.

For this period, changes were observed from fallow land to agricultural land. Approximately 4% (10243.87 ha) of agricultural land was converted to current fallow while 7% (16014.84 ha) of the area changed from current fallow to agricultural land in 2019. The area under the current fallow in 2014 was converted to a builtup area (8460.70 ha) in 2019 due to urban sprawl. The findings were similar to those (Tewabe and Fentahun, 2020), who reported that bushland had decreased while buitup areas and agricultural land had increased due to the increment of population growth and high demand for agricultural production. It can be observed that there is no change from other classes to waterbodies. Mohamed Ali *et al*. ((2020)) also reported that the water bodies had not changed considerably in comparison to other LULC types. The results obtained from the LULC change matrix (Fig. 6) showed no significant land cover changes in the lower Bhavani basin throughout the research period of 2019.

Conclusion

Using Landsat-8 data for the years 2014 and 2019, this study assessed and tracked changes in the LULC pattern in Tamil Nadu's Lower Bhavani basin. The results revealed that the major land use in the lower Bhavani basin was agriculture and current fallow. The next dom-

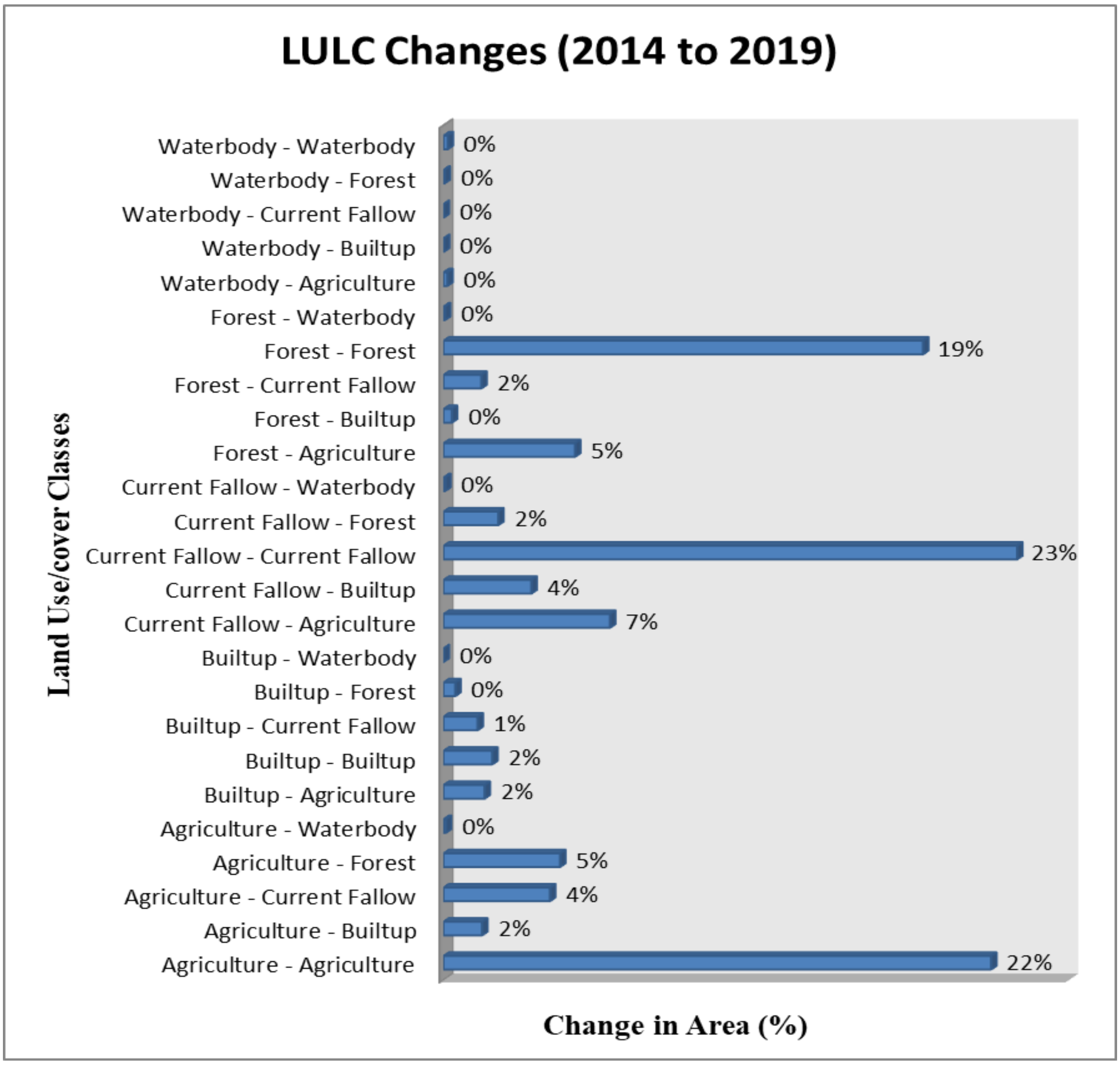

Fig.6. Land use and land cover change in the lower Bhavani basin from 2014 to 2019

inant land use was the forest, recorded as 26.54% in 2019 due to agroforestry practices. During the study period (2014–2019), there was no change in waterbodies. The change in builtup area, 7.37% in 2019 versus 5.45% in 2014, was noted due to urban sprawl. GEE owing to its cloud architecture, userfriendly, and effective and sophisticated programming language, demonstrated remarkable versatility and adaptability. Machine learning classifiers have recently been used to generate extremely accurate classification results among the various image classification approaches available. Various factors influence the accuracy of these classifiers, and knowing these characteristics can assist in improving classification results. Sensible accuracy was obtained from this approach in the study area.

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Conflict of interest

The authors declare that they have no conflict of interest.

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