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REVIEW ARTICLE

Survey on Land Use/Land Cover (LU/LC) change analysis in remote sensing and GIS environment: Techniques and Challenges

Sam Navin MohanRajan[1] · Agilandeeswari Loganathan[1] · Prabukumar Manoharan[1]

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Abstract

The surface of the earth is rapidly changing every day due to certain natural reasons and other impacts by society. Over the last few decades, the hottest topics in the field of remote sensing and GIS (geographic information system) environments have evolved from observing the nature of the earth. Owing to the enlargement of several worldwide modifications related to the nature of the earth, land use/land cover (LU/LC) change is considered as the matter of utmost importance in the natural atmosphere, and it has also become an interesting area to be studied by the researchers. As there is a lack of review articles in the land use/land cover change analysis process, we presented a comprehensive review which may help the researchers to proceed further. This paper deals with the most frequent methods used by researchers on various processes like pre-processing, classification, and prediction of time series satellite images for analyzing the LU/LC changes using satellite images. The generic flow of the LU/LC change analysis process and the challenges faced during each process by the researchers are discussed. Varied resolutions of the environmental image captured by remote sensing satellites for analyzing the LU/LC changes are discussed. Various LU/LC classes depending on change in the earth's surface are also studied and the constraint used in each application is stated. The importance of this review lies in the motivation for future researchers to work on the LU/LC change analysis problem effectively.

Keywords Remote sensing · Geographic information system · Classification and prediction · Land use/land cover change

Introduction

The significance of timely and precise information relating to the nature and scope of land possessions and changes over time is increasing rapidly, particularly in metropolitan areas. Inspecting the Earth from space is crucial for understanding the influence of man's actions on natural resources over different time intervals. The information from the remote sensing satellites in mapping the earth's features and infrastructures has become dynamic. Map-to-map comparisons and image-to-image comparisons are observed in the variations caused by the factors of the LU/LC change process. Land use and land cover are the terms with different degrees of significance in the field of scientific remote sensing. Natural and biological landscapes such as forests, marshlands, grasslands, water lands, and urbanized and built areas denote the land cover area detected from the surface of the earth. The events that take place in the land represent the current use of the properties such as built-up institutions, shopping centers, parks, and reservoirs are described as land use categories (Fonji and Taff 2014). When the land cover of a certain place or locality has been changed or converted from one type to another, the problem of LU/LC change is detected, for instance, the change of forest area to either infertile land, barren land, or agricultural land. Two or more satellite images taken on different time intervals were compared on the subject of performance of the LU/LC change analysis process. Remote sensing plays an important role in the study of LU/LC changes. Remote sensing image classification is considered an essential practice in processing an image, and hence it is used in the extraction of valuable information by classifying the spectral signs of land cover nature for natural resource management (Panigrahi et al. 2017).

Remote sensing is also regarded as an essential cause of thematic maps, depicting land cover as it affords a map-like representation of the specific surface of the earth that is

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✉ Agilandeeswari Loganathan
agila.l@vit.ac.in

[1] School of Information and Technology, Vellore Institute of Technology, Vellore, India

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spatially constant and extremely reliable, as well as accessible at a range of spatial and temporal measures. Thematic presentation or mapping from remotely detected or sensed images is naturally based on image classification which is attained by computer-aided or visual analysis. The main use of image classification is the labeling of the pixels in the images captured with meaningful information of the real world for enhanced and advantageous information extraction. Thematic maps holding information such as cadastral information, vegetation, and the land cover type could be obtained through the classification of satellite images (Usman 2013). Several remote sensing image classification approaches have been used for LU/LC mapping. It includes the commonly used supervised and unsupervised methods. The unsupervised methods are K-means, ISODATA (Iterative Self-Organizing Data Analysis) clustering, Fuzzy C-means clustering, and self-organizing map (SOM) neural network method. Some commonly used supervised methods are maximum likelihood classifier (MLC), k-nearest neighbor (kNN), Mahalanobis distance, Parallelepiped, minimum distance classifier, support vector machines (SVM), and Random Forest Classifiers (RFC) (Li et al. 2014). LU/LC change predictions through the use of remotely detected images have engrossed massive consideration among researchers. Various prediction methods are considered for predicting the future LU/LC change and they are as follows: multi-layer perceptron, linear regression model, cellular automata, Markov chain, regression tree, and artificial neural network method (Bounouh et al. 2017).

From the broad analysis, we observed many researchers describe the problem of LU/LC change analysis for different regions across the world in the field of remote sensing. Some of the research articles are summarized and explained as follows: Zagros forest preservation plan was made for the protection of forest-covered regions in Iran against destruction. A study of the LU/LC change analysis process for a different time interval between 1992 and 2016 was made by using the Landsat images for the Zagros forest region. Atmospheric and geometric corrections were made for the removal of errors seen in the Landsat images. The supervised maximum likelihood algorithm was used for classifying the images into different classes like the forest, agriculture, rangeland, and built-up areas. Post-processing was done to enhance the image for attaining good classification accuracy. Suitability map was extracted using a Markov chain model. The LCM (Land Change Modeler) using a multi-layer perceptron (MLP) neural network helped in calibrating the dependent and the independent variables for predicting the future LU/LC changes in the year 2024 (Heidarlou et al. 2019).

The spatial and temporal pattern of LU/LC change was observed in the forest-covered area of Ningxia Hui Autonomous Region (NHAR), China, from 1991 to 2015. Cloud shadows were removed from the Landsat images and the landscape brightness effects on the DEM (digital elevation model) data were reduced using the topographic correction method. The maximum likelihood classification map was used for further post-processing and LU/LC change analysis process (Restrepo et al. 2017).

Changes in the Savannah River Basin for four-time intervals during the period 1999–2005, 1999–2015, 2005–2009, and 2009–2015 were analyzed for determination of LU/LC change, using geospatial Landsat and Google Earth Engine images. The LU/LC change analysis was processed using NDVI (Normalized Difference Vegetation Index) which helped during the analysis of the deforestation and reforestation rate of change. Random Forest–Supervised Classification provided flexibility for classifying the geospatial image. Google Earth Engine (GEE) geospatial software was launched by Google in December 2010. Forty-year multitemporal data were available in the GEE platform which helped the researchers in the analysis of the changes that happened on the Earth's surface. GEE mainly acts as the reference data for the classified satellite images during the time of accuracy assessment (Zurqani et al. 2018). Machine learning methods like Classification and Regression Tree (CART), Random Forest (RF), and multivariate adaptive regression spline (MARS) were applied and compared for determining the LU/LC change for the region of Shirgah, located in the north of Iran. Pre-classification and post-classification phase was performed on Landsat satellite images for attaining good accuracy during the time interval of 1991, 2001, and 2011. The association between the dependent and the explanatory variables is analyzed for calibrating the future LU/LC changes (Ahmadlou et al. 2018).

The Random Forest, k-nearest neighbor (k-NN), and support vector machine (SVM) non-parametric classifiers were in the classification of the Sentinel-2 satellite data for the region of the Red River Delta (RRD), Vietnam. The performance of machine learning methods is compared and analyzed. Google Earth images were used as the training datasets during the process of accuracy assessment. The results revealed that the high overall accuracy by support vector machine followed by Random Forest and k-nearest neighbor (Thanh Noi and Kappas 2018). Many researchers have worked on the LU/LC change prediction problem for different regions across the world. The hybrid model of cellular automata and Markov chain has been broadly used for LU/LC prediction in the built-up area, forest-covered area, watershed area, mountainous region, and desert region (Gashaw et al. 2017, Liping et al. 2018, Singh et al. 2015, Karimi et al. 2018, Etemadi et al. 2018, Halmy et al. 2015, Yagoub and Bizreh 2014, Yirsaw et al. 2017).

Using the hybrid classification methods provides good accuracy during the LU/LC classification process. The unsupervised ISODATA clustering method with the pixel-based supervised maximum likelihood classification method was used for classifying the Landsat imageries for the region of Andassa watershed, Blue Nile Basin, Ethiopia. The LU/LC changes were analyzed and calculated from 1985 to 2015. Cellular automata with Markov model is used to predict the LU/LC condition for the year 2030 and 2045 (Gashaw et al. 2017). Various prediction models like the Markov chain, cellular automata, artificial neural network, linear regression, logistic regression, GEOMOD, CLUE (Conversion of Land Use and Its Effects), and Land Change Modeler (LCM) were used for predicting the LU/LC change that occurred in a specific area for a different time interval (Nwaogu et al. 2017).

Motivation

From the above study, we infer that none of the existing literature reviews on LU/LC presents the complete review on land use/land cover change analysis process. They focused only on a specific stage, i.e., either LU/LC classification (Li M et al. 2014 Phiri and Morgenroth 2017) or LU/LC prediction (Nwaogu et al. 2017, Bounouh et al. 2017). Hence, it motivates us to write a review article that covers the whole stages of LU/LC analysis for the benefits of the new researchers in this field.

Objective

The main objective of this paper is listed as follows:

i. The utmost purpose of this review paper is to provide a road map for the researchers who are interested to work on the land use/land cover change analysis to predict the future land cover.
ii. This paper presents a comprehensive review of detailed techniques and benefits in various stages of the land use/land cover change analysis process that starts from the image acquisition stage to the prediction and validation stage.
iii. This paper provides a generic flow and the possible framework of the LU/LC change analysis process.
iv. The challenges in each stage of LU/LC change analysis have been identified and briefed which might guide future researchers to work effortlessly on the LU/LC change prediction problem.

The observations of many researchers have helped us to model the generic flow of the LU/LC change process, which is shown in Fig. 1. The procedure for LU/LC change analysis includes image acquisition, pre-processing, LU/LC classification, post-classification, change detection, modeling the dependent and independent variables, LU/LC change prediction, and validation.

Organization of the paper

The rest of the paper provides detailed information and is organized as follows: The "Satellite image acquisition" section describes the datasets and their sources. The "Image processing software types and its key features" section explains the software tools used for processing an image. The "Image pre-processing techniques" section explains the image pre-processing techniques. The "LU/LC classification methods" section illustrates a few LU/LC classification methods, the "Post-classification and LU/LC change analysis" section describes the use of post-classification and change detection or dependent variables, the "LU/LC classes and its factors" section explains the different LU/LC classes and their corresponding factors or independent variables, and the "LU/LC prediction models" section informs the few environmental models used for predicting the future LU/LC changes. In the "Commonly used metrics" section, the commonly used metrics are presented, the "Conceptual framework" section depicts the conceptual framework of the study, the "Discussions" section provides the discussion, the "Challenges" section presents the challenges faced during LU/LC change analysis, and the "Conclusions" section enlightens the conclusions of the study.

Satellite image acquisition

The selection of a suitable dataset is the most significant process in the LU/LC change analysis. The image was collected through aerial photographs, satellite imageries, ancillary data, Google maps, forest department, land resource management, and urban planners. The datasets from different time intervals require careful collection for further processing in remote sensing environment. From various studies, we observed that there were many datasets used by the researchers in the analysis of the LU/LC change. Some of them are shown in Table 1.

Image processing software types and its key features

In the precise study of remote sensing, we identified the different geospatial software tools used by the researchers for various stages such as pre-processing, classifying, analyzing, and predicting the LU/LC changes using the multispectral satellite images. Some of them are described in Table 2 and are as follows: ENVI, ArcGIS, IDRISI, ERDAS Imagine, Quantum GIS, and Google Earth.

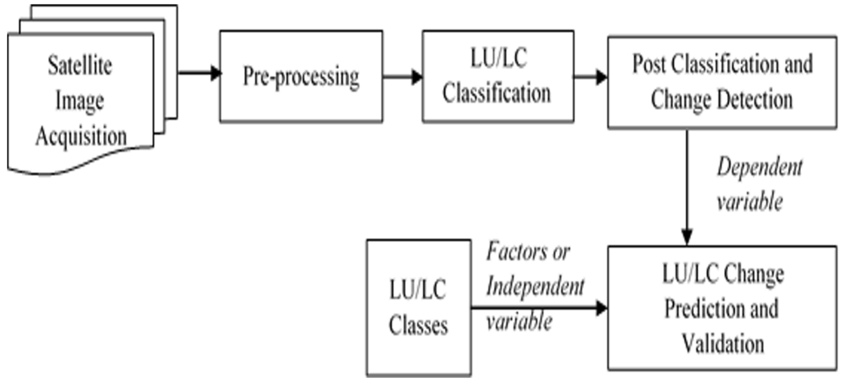


Fig. 1 Generic flow of LU/LC change process

Image pre-processing techniques

The image pre-processing techniques are used for improving the quality and visibility of the satellite images. It is considered as an initial stage where the image enhancement, geometric, radiometric, atmospheric, and topographic corrections are made to improve the quality of the satellite image. Table 3 presents a few image pre-processing techniques depending upon the image position, visibility, and quality in every application.

LU/LC classification methods

LU/LC classification is the method of labeling the pixels in the pre-processed satellite image for obtaining the classified images. Every pixel is considered as a unique entity and assigned to a particular class through pixel-based classification. Object-based classification is the collection of information from a group of related pixels, i.e., it grabs the pixels into graphical shapes, sizes, and other spatial properties. The normally distributed data is assumed under parametric classifiers. The non-parametric classifiers do not consider the classification of statistical parameters or normal assumptions. Fuzzy methodology and spectral mixture analysis are considered as effective methods for sub-pixel-based image classification as they help in sorting out the land cover types in the particular region (Phiri and Morgenroth 2017). Supervised, unsupervised, and fuzzy methods are commonly used for categorizing the remotely sensed images (Yagoub and Bizreh 2014, Pande et al. 2018). MoreovBanerjee and Buddhiraju 2015er, semi-supervised techniques were also used for performing the LU/LC classification (Yan Y et al. 2017, , Maulik and Chakraborty 2013). In this study, a few LU/LC classification algorithms are described. They are shown in Table 4. The maximum likelihood classification, Random Forest Classifier, k-nearest neighbor, support vector machine classifiers, Iterative Self-Organizing Data Analysis Technique, CART (classification and regression trees), K-means clustering, artificial neural network model, multivariate adaptive regression splines method, Fuzzy C-means (FCM) clustering, minimum distance, Mahalanobis distance, Parallelepiped, spectral angular mapper classification, graph-based semi-supervised model, self-trained models semi-supervised classification model, semi-supervised transductive SVM (TSVM), and semi-supervised co-training model are some frequently used methods for classifying the satellite image. The classification method such as ANN made its imprint not only on classification but also in a prediction process.

Post-classification and LU/LC change analysis

Post-classification is an improvement process, which improves the quality of the classified LU/LC map through the removal of noise and misclassification errors. This process helps in the enhancement of the overall accuracy by removing the single and scattered pixels present in the LU/LC classified image. Post-classification processing assists in solving the misclassification error that occurs due to substantial spectral confusion between the LU/LC classes, (i.e., confusion between the agricultural land and the barren land). This process holds the advantage of reclassifying the pixels that are misclassified (Fonji and Taff 2014, Heidarlou et al. 2019, Restrepo et al. 2017, Birhane et al. 2019, Hernández-Guzmán et al. 2019, Bakr and Afifi 2019, Li et al. 2018, Ahmadlou et al. 2018, Zhu and Woodcock 2014, Pande et al. 2018, John et al. 2019, Adhikari et al. 2017, Alkaradaghi et al. 2018, Ganasri and Dwarakish 2015, Asubonteng et al. 2018, Mohamed and Elmahdy 2018, Nadoushan et.al 2012, Ashaolu et al. 2019, Mirkatouli et al. 2015, Pathiranage et al. 2018). We observed that the performance of the post-classification is considered as a significant process in the LU/LC change analysis for the data relating to the time series. Geospatial tools like ENVI and ArcGIS are mainly used for performing the post-classification analysis. From this observation, we infer that the post-classification process is one of the important steps required for the analysis of the LU/LC change. The concept of LU/LC classes is explained in the "LU/LC classes and its factors" section.

The LU/LC change analysis process will be incomplete without the accuracy assessment for the LU/LC classified image (Fonji and Taff 2014, Usman 2013, Li et al. 2014, Yang et al. 2018, Restrepo et al. 2017, El Jazouli et al. 2019, Birhane et al. 2019, Hernández-Guzmán et al. 2019, Bagan et al. 2018, Bakr and Afifi 2019, Hu and Yu Dong 2018, Li et al. 2018, Kabisch et al. 2019, Zurqani et al. 2018, Ahmadlou et al. 2018, Thanh Noi and Kappas 2018, Ce et al. 2019, Gashaw et al.

Table 1 Datasets and its source

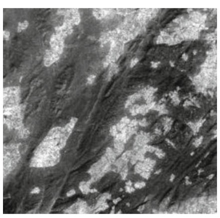
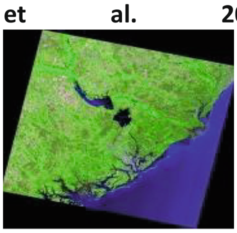
Dataset	Instrument	Data Source	Benefits
LISS-III (Linear Imaging Self-Scanning System - III) **(Pande et al. 2018, Mallupattu and Reddy 2013, Adhikari et al. 2017, Firoozynejad and Torahi 2017, Murtaza and Romshoo 2014, Vibhute et al. 2013, Ganasri and Dwarakish 2015, Nadoushan et.al 2012)** 	Resourcesat1/ Resourcesat-2	Bhuvan Indian Geo-Platform of ISRO (www.bhuvan.com)	It helps in analyzing the agricultural harvest monitoring, water resource consumption, forest mapping, and rural/urban infrastructure expansion.
Landsat 8 (**Heidarlou et al. 2019, Restrepo et al. 2017, El Jazouli et al. 2019, Birhane et al. 2019, Hernández-Guzmán et al. 2019, Bakr and Afifi 2019, Hu and Yu Dong 2018, Li et al. 2018, Kabisch et al. 2019, Zurqani et al. 2018, Gashaw et al. 2017, Liping et al. 2018, Karimi et al. 2018, Etemadi et al. 2018, John et al. 2019, Taufik et al. 2019, Alkaradaghi et al. 2018, Firoozynejad and Torahi 2017, Shaharum et al. 2018, Nery et al. 2019, Asubonteng et al. 2018, Mohamed and Elmahdy 2018, Nurwanda et al. 2016, Ashaolu et al. 2019**) 	Operational Land Imager (OLI) and the Thermal Infrared (TI) Sensor	USGS (https://earthexplorer.usgs.gov/)	It helps in analyzing different kinds of LU/LC changes like deforestation, agriculture development, the evolution of built-up areas, and loss of wetlands.

Table 1 (continued)

Landsat 7 **(Li et al. 2014, Heidarlou et al. 2019, Yang et al. 2018, El Jazouli et al. 2019, Birhane et al. 2019, Hernández-Guzmán et al. 2019, Bakr and Afifi 2019, Li et al. 2018, Kabisch et al. 2019, Ahmadlou et al. 2018, Gashaw et al. 2017, Singh et al. 2015, Zhu and Woodcock 2014, Sisodia et al. 2014, Yagoub and Bizreh 2014, Pande et al. 2018, John et al. 2019, Saputra and Lee 2019, Nery et al. 2019, Mohamed and Elmahdy 2018, Wolfe et al. 2013, Nurwanda et al. 2016, Das et al. 2013, Tsai and Chen 2008, Nwaogu et al. 2017, Kusuma 2013, Ahmadlou et al. 2015, Ashaolu et al. 2019, Mirkatouli et al. 2015, Pathiranage et al. 2018)** 	Enhanced Thematic Mapper (ETM+) Sensor	USGS (https://earthexplorer.usgs.gov/)	It helps in analyzing different kinds of LU/LC changes like deforestation, agriculture development, the evolution of built-up areas, and loss of wetlands.
Landsat 4 & Landsat 5 **(Fonji and Taff 2014, , Heidarlou et al. 2019, Yang et al. 2018, Restrepo et al. 2017, Birhane et al. 2019, Hernández-Guzmán et al. 2019, Bagan et al. 2018, Bakr and Afifi 2019, Hu and Yu Dong 2018, Kabisch et al. 2019, Zurqani et al. 2018, Ahmadlou et al. 2018, Gashaw et al. 2017, Liping et al. 2018, Singh et al. 2015, Karimi et al. 2018, Etemadi et al. 2018, Halmy et al. 2015, Zhu and Woodcock 2014, Yagoub and Bizreh 2014, Yirsaw et al. 2017, John et al. 2019, Adhikari et al. 2017, Alkaradaghi et al. 2018, Kumar et al. 2014, Nery et al. 2019, Asubonteng et al. 2018, Wolfe et al. 2013, H-p et al. 2013, Nurwanda et al. 2016, Das et al. 2013, Nwaogu et al. 2017, Regmi et al. 2014, Han et al. 2015, Baboo and Devi 2011, Ashaolu et al. 2019, Abbas et al. 2017, Mirkatouli et al. 2015, Pathiranage et al. 2018)**	Thematic Mapper (TM)	USGS (https://earthexplorer.usgs.gov/)	It helps in analyzing different kinds of LU/LC changes like deforestation, agriculture development, the evolution of built-up areas, and loss of wetlands.

Table 1 (continued)

			
Sentinel 2 **(El Jazouli et al. 2019, Kabisch et al. 2019, Thanh Noi and Kappas 2018, Priyadarshini et al. 2018)** 	Sentinel 2A, Sentinel 2B	Sentinels Scientific Data Hub (https://scihub.copernicus.eu) USGS (https://earthexplorer.usgs.gov/)	It helps to map LU/LC changes by monitoring the core areas like the forest, green lands, and water bodies.
DEM (Digital Elevation Model) **(Fonji and Taff 2014, Heidarlou et al. 2019, Yang et al. 2018, Restrepo et al. 2017, Birhane et al. 2019, Bakr and Afifi 2019, Zurqani et al. 2018, Gashaw et al. 2017, Liping et al. 2018, Singh et al. 2015, Karimi et al. 2018, Halmy et al. 2015, Yagoub and Bizreh 2014, Pande et al. 2018, Adhikari et al. 2017, Kumar et al. 2014, Saputra and Lee 2019, Nery et al. 2019, Wolfe et al. 2013, H-p et al. 2013, Regmi et al. 2014, Han et al. 2015, Nadoushan et.al 2012, Ashaolu et al. 2019, Pathiranage et al. 2018)** 	(Space Shuttle Radar Topography Mission (SRTM) and ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) Global Digital Elevation Model	USGS (https://earthexplorer.usgs.gov/) Bhuvan Indian Geo-Platform of ISRO (www.bhuvan.com)	Used to determine the terrain features like elevation, slope, and aspect.
MODIS (Moderate Resolution Imaging Spectroradiometer) **(Panigrahi et al. 2017, Li et al. 2018, Wolfe et al. 2013)** 	NASA Terra Satellite	Earth data (http://earthdata.nasa.gov/) USGS (http://earthexplorer.usgs.gov/)	It helps to analyze the changes happened in different types of land resources.

Table 1 (continued)

REIS (Rapid Eye Earth Imaging System) **(Kabisch et al. 2019)** 	Rapid Eye Satellite Sensors (5m) i.e. Five constellation satellites -TACHYS (RAPID), MATI (EYE), CHOMA (EARTH), CHOROS (SPACE), TROCHIA (ORBIT)	ESA EARTH ONLINE (https://earth.esa.int)	Rapid Eye constellation Images provides the geospatial information about the areas that include agriculture, forest and vegetation areas, etc.
Quick Bird **(Usman 2013, HongLei et al. 2013, Mohamed and Elmahdy 2018, Achmad et al. 2015)** 	BGIS-2000 (Ball Global Imaging System 2000)	Digital Globe (www.digitalglobe.com)	Quick Bird satellite image gives a clear view of built-up areas and other infrastructures.

2017, Liping et al. 2018, Singh et al. 2015, Karimi et al. 2018, Etemadi et al. 2018, Halmy et al. 2015, Zhu and Woodcock 2014, Phiri and Morgenroth 2017, Sisodia et al. 2014, Yagoub and Bizreh 2014, Pande et al. 2018, Yirsaw et al. 2017, Mallupattu and Reddy 2013, John et al. 2019, Adhikari et al. 2017, Alkaradaghi et al. 2018, Hemasinghe et al. 2018, Kumar et al. 2014, Firoozynejad and Torahi 2017, Shaharum et al. 2018, Murtaza and Romshoo 2014, Saputra and Lee 2019, Nery et al. 2019, HongLei et al. 2013, Taufik et al. 2019, Vibhute et al. 2013 Ganasri and Dwarakish 2015, Asubonteng et al. 2018, Khan et al. 2018, Priyadarshini et al. 2018, Mohamed and Elmahdy 2018, Nurwanda et al. 2016, Nwaogu et al. 2017, Regmi et al. 2014, Han et al. 2015, Kusuma 2013, Ahmadlou et al. 2015, Nadoushan et.al 2012, Ashaolu et al. 2019, Achmad et al. 2015, Abbas et al. 2017, Pathiranage et al. 2018). The performance of the classification method is evaluated, and then the accuracy and kappa value of the LU/LC classified image will be calculated. We observed the Google Earth Engine geospatial tool, topographic maps, and other field survey data that provide the reference data during the process of accuracy assessment. The reference data is usually compared with the classified data during the process of accuracy assessment through an error matrix. The metrics used for calculating the accuracy assessment and kappa statistics are shown in Eqs. (3) and (4).

The LU/LC classified image will be processed for validating the change analysis for different time intervals over a particular region. LU/LC change analysis is done for the determination of the changes that occurred in some specific areas and for helping in making useful decisions relating to the protection of an environment. The percentage and rate of change are calculated for identifying the magnitude of changes that occurred between different time intervals (Fonji and Taff 2014, Birhane et al. 2019, Bakr and Afifi 2019, Gashaw et al. 2017, Liping et al. 2018, Singh et al. 2015, Karimi et al. 2018, Etemadi et al. 2018, Halmy et al. 2015, Yagoub and Bizreh 2014, Yirsaw et al. 2017, Alkaradaghi et al. 2018, Saputra and Lee 2019, Asubonteng et al. 2018, Mohamed and Elmahdy 2018, Regmi et al. 2014, Nadoushan et.al 2012, Ashaolu et al. 2019, Mirkatouli et al. 2015, Pathiranage et al. 2018). The change cover map over a different time interval for a particular region is considered as the dependent variable for calibrating the prediction method. The metrics for demonstrating the magnitude of changes is shown in Eqs. (5) and (6). We observed many researchers across the world still work on the LU/LC change analysis problem since it is considered as a matter of grief concern in the remote sensing and GIS environment.

Table 2 Software types

Software	Source	Key Features	Benefits
ENVI (Environment for Visualizing Images) (Heidarlou et al. 2019, Restrepo et al. 2017, El Jazouli et al. 2019, Bagan et al. 2018, Bakr and Afifi 2019, Li et al. 2018, Liping et al. 2018, Karimi et al. 2018, Etemadi et al. 2018, Phiri and Morgenroth 2017, Yagoub and Bizreh 2014, Alkaradaghi et al. 2018, Firoozynejad and Torahi 2017, Shaharum et al. 2018, HongLei et al. 2013, Taufik et al. 2019, Vibhute et al. 2013, Asubonteng et al. 2018, Priyadarshini et al. 2018, Nwaogu et al. 2017, Abbas et al. 2017)	Harris Geospatial Solutions (www.harrisgeospatial.com)	Anomaly detection, geometric correction, feature extraction, image sharpening, radiometric correction, topographic modelling, image sharpening, mosaicking, spatiotemporal analysis, supervised and unsupervised classification, post-classification, accuracy assessment, and change detection.	Multispectral and Hyperion satellite data are processed efficiently.
ArcGIS (Fonji and Taff 2014, Restrepo et al. 2017, El Jazouli et al. 2019, Birhane et al. 2019, Li et al. 2018, Thanh Noi and Kappas 2018, Ce et al. 2019, Gashaw et al. 2017, Liping et al. 2018, Karimi et al. 2018, Phiri and Morgenroth 2017, Yagoub and Bizreh 2014, Pande et al. 2018, Yirsaw et al. 2017, Mallupattu and Reddy 2013, John et al. 2019, Adhikari et al. 2017, Hemasinghe et al. 2018, Kumar et al. 2014, Firoozynejad and Torahi 2017, Saputra and Lee 2019, Vibhute et al. 2013, Ganasri and Dwarakish 2015, Nurwanda et al. 2016, Das et al. 2013, Nwaogu et al. 2017, Regmi et al. 2014, Han et al. 2015, Kusuma 2013, Nadoushan et.al 2012, Ashaolu et al. 2019, Achmad et al. 2015, Pathiranage et al. 2018)	ESRI (Environmental Systems Research Institute) (http://www.esri.com/software/arcgis)	Geo-referencing, panchromatic sharpening, mosaicking, spatiotemporal analysis, supervised and unsupervised classification, post-classification, accuracy assessment, and identifying the area of LU/LC change for a different time interval.	Multispectral and hyperspectral satellite data are processed efficiently.
IDRISI (Heidarlou et al. 2019, El Jazouli et al. 2019, Hernández-Guzmán et al. 2019, Gashaw et al. 2017, Liping et al. 2018, Singh et al. 2015, Karimi et al. 2018, Etemadi et al. 2018, Halmy et al. 2015, Yagoub and Bizreh 2014, John et al. 2019, Kumar et al. 2014, Nurwanda et al. 2016, Nwaogu et al. 2017, Regmi et al. 2014Nadoushan et.al 2012, Achmad et al. 2015)	Clark Labs (clarklabs.org)	Image restoration, enhancement, segmentation, transformation, image classification (machine learning supervised and unsupervised classifiers), accuracy assessment, distance measures, prediction methods, simulation models (Land Change Modeler, Earth Trends Modeler, Climatic Change Adaptation Modeler, and Ecosystem Services Modeler)	IDRISI helps to process the multispectral data and it provides the special services for processing the hyperspectral data.
ERDAS IMAGINE (Earth Resources Data Analysis System) (Fonji and Taff 2014, Gashaw et al. 2017, Singh et al. 2015, Phiri and Morgenroth 2017, Sisodia et al. 2014, Pande et al. 2018, Yirsaw et al. 2017, Mallupattu and Reddy 2013, John et al. 2019, Adhikari et al. 2017, Kumar et al. 2014, Nurwanda et al. 2016, Das et al. 2013, Regmi et al. 2014, Han et al. 2015, Baboo and Devi 2011, Ashaolu et al. 2019)	Hexagon Geospatial (www.hexagongeospatial.com)	Radiometric correction, pan sharpening, geometric calibration, supervised, unsupervised and sub-pixel based classification, change detection, and terrain feature analysis.	Multispectral and hyperspectral satellite data are processed efficiently.
QGIS (Quantum GIS) (El Jazouli et al. 2019, Kabisch et al. 2019, Saputra and Lee 2019, Ashaolu et al. 2019)	QGIS Developers Team (qgis.org/en/site)	Image clipping, pre-processing, post-processing, classification, distance measures, Topographic Position Index, prediction modules, and Terrain Ruggedness Index Analysis.	Multispectral and hyperspectral satellite data are processed efficiently.
Google Earth (Fonji and Taff 2014, Heidarlou et al. 2019, Restrepo et al. 2017, Birhane et al. 2019, Hu and Yu Dong 2018, Li et al. 2018, Zurqani et al. 2018, Thanh Noi and Kappas 2018, Gashaw et al. 2017, Liping et al. 2018, Karimi et al. 2018, Etemadi et al. 2018, Zhu and Woodcock 2014, Yagoub and Bizreh 2014, Yirsaw et al. 2017, Shaharum et al. 2018, Ganasri and Dwarakish 2015, Asubonteng et al. 2018, Regmi et al. 2014, Han et al. 2015, Gorelick et al. 2017, Ashaolu et al. 2019, Pathiranage et al. 2018)	Google (earth.google.com)	Band manipulation, edge detection, image clipping and registration, terrain operations, resampling, metadata properties, area measurements, and spatial filtering.	Google Earth provides the multi-temporal time series data and it helps during the process of accuracy assessment.

LU/LC classes and its factors

The LU/LC classified classes include areas like built-up area, agricultural land, forest area, vegetation land, water bodies, wasteland, mountain area, and desert area. We collected the LU/LC information of India in the year 2015 to 2016 from Bhuvan-Thematic Services of the National Remote Sensing Centre (NRSC), Indian Space Research Organization (ISRO), for getting a good understanding of LU/LC classes. The LU/LC classified classes in India, for the year 2015 to 2016, are shown in Fig. 2. The total geographical area for India in the year 2015 to 2016 is shown along with the statistics of each area in Fig. 3. This LU/LC information of India will help the researchers to understand how each pixel was classified and labeled.

Based on the development of land transformation in a specific area, the suitability map provides the information needed for the specific LU/LC classes. For instance, forest suitability maps provide information on the different species of trees grown in a specific location of the forest-covered region. The suitability of areas is mapped with the consideration of weighted factors like slope, elevation, and distance from the forest edge, road, water bodies, wasteland, grassland, agricultural land, and settlements (Gashaw et al. 2017, Singh et al. 2015, Yagoub and Bizreh 2014, John et al. 2019, Regmi et al. 2014, Ahmadlou et al. 2015, Nadoushan et.al 2012, Achmad et al. 2015, Mirkatouli et al. 2015).

Table 5 helps in understanding the few LU/LC classes and their factors. Among the numerous independent variables, elevation, slope, and aspect have a major impact on LU/LC proliferation mostly in the forest-covered area.

Statistical tests were conducted for finding the association between the dependent variable (LU/LC change map) and the independent variables (slope, elevation, and distance from the river, forest edge, barren land, built-up area, and agriculture area). The Cramer's V coefficient test is widely used by the researchers for enabling observation of the association between the dependent and independent variables. The

Table 3 Pre-processing techniques

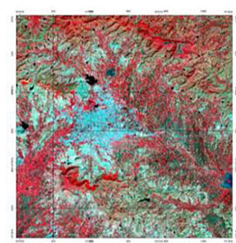
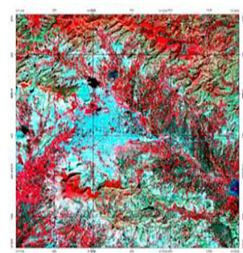
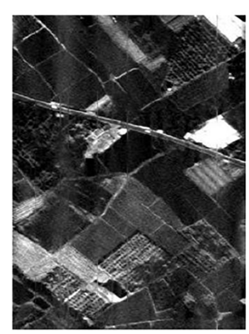
Pre-processing techniques	**Explanation**	**Commonly used task**	**Before correction**	**After correction**
Image Enhancement **(Birhane et al. 2019, Zurqani et al. 2018, Karimi et al. 2018, Phiri and Morgenroth 2017, Sisodia et al. 2014, Mallupattu and Reddy 2013, Taufik et al. 2019, Vibhute et al. 2013, Priyadarshini et al. 2018, Rehman and Hussain 2018, Nadoushan et.al 2012, Ashaolu et al. 2019, Abbas et al. 2017)**	To remove the noise and for sharpening the satellite image. It also helps in increasing the contrast of the satellite image.	Fourier Domain Transformation, Principal Component Analysis, Linear Discriminant Analysis, Mosaiking, Image Filtering, and Pan Sharpening.	 **(Vibhute et al. 2013)**	 **(Vibhute et al. 2013)**
Radiometric Correction **(El Jazouli et al. 2019, Birhane et al. 2019, Gashaw et al. 2017, Liping et al. 2018, Etemadi et al. 2018, Phiri and Morgenroth 2017, Firoozynejad and Torahi 2017, Shaharum et al. 2018, Nery et al. 2019, Vibhute et al. 2013, Asubonteng et al. 2018, Das et al. 2013, Tsai and Chen 2008, Baboo and Devi 2011)**	Radiometric calibration is performed to correct the sensor errors like periodic line stripping and noise. It mainly helps in improving image fidelity.	Image De-striping, LookUp Table (LUT) Strech, Rescaling, and Point Spread Convolution method.	 **(Tsai and Chen 2008)**	 **(Tsai and Chen 2008)**

Table 3 (continued)

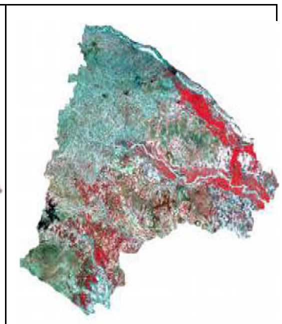
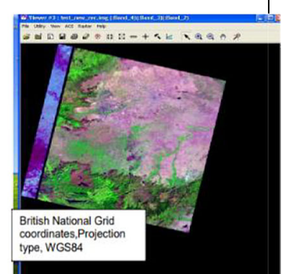
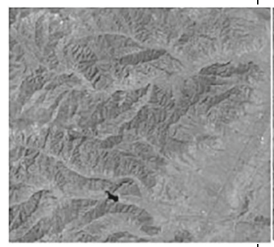
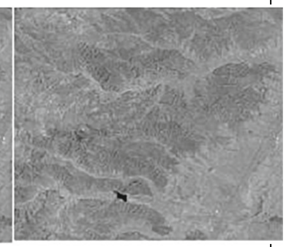
Atmospheric Correction **(Heidarlou et al. 2019, Yang et al. 2018, Restrepo et al. 2017, Birhane et al. 2019, Bagan et al. 2018, Kabisch et al. 2019, Zurqani et al. 2018, Thanh Noi and Kappas 2018, Liping et al. 2018, Zhu and Woodcock 2014, Phiri and Morgenroth 2017, Yirsaw et al. 2017, John et al. 2019, Alkaradaghi et al. 2018, Firoozynejad and Torahi 2017, Shaharum et al. 2018, HongLei et al. 2013, Asubonteng et al. 2018, Das et al. 2013, Baboo and Devi 2011, Mirkatouli et al. 2015)**	Atmospheric correction helps to remove the atmospheric effects in the satellite image to produce the cloud-free images.	QUick Atmospheric Correction (QUAC), Dark Object Subtraction (DOS) Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLASSH) atmospheric correction, Tasseled Cap Transformation, and F Mask method.	 **(Das et al. 2013)**	 **(Das et al. 2013)**
Geometric Correction **(Fonji and Taff 2014, Heidarlou et al. 2019, El Jazouli et al. 2019, Bakr and Afifi 2019, Gashaw et al. 2017, Liping et al. 2018, Singh et al. 2015, Karimi et al. 2018, Etemadi et al. 2018, Phiri and Morgenroth 2017, Sisodia et al. 2014, Pande et al. 2018, Yirsaw et al. 2017, Mallupattu and Reddy 2013, John et al. 2019, Adhikari et al. 2017, Alkaradaghi et al. 2018, Firoozynejad and Torahi 2017, Vibhute et al. 2013, Ganasri and Dwarakish 2015, Asubonteng et al. 2018, Wolfe et al. 2013, Das et al. 2013, Nadoushan et.al**	Geometric correction is the process of aligning an earthly data to the known coordinate system so that it can be observed and analyzed with other remotely sensed datasets.	Geo-referencing, Orthorectification, Resampling, Image Registration, and ASCII Coordinate Conversion.	 **(Baboo and Devi 2011)**	 **(Baboo and Devi 2011)**

Table 3 (continued)

2012, Baboo and Devi 2011, Achmad et al. 2015)				
Topographic Correction **(Restrepo et al. 2017, Liping et al. 2018, Karimi et al. 2018, Phiri and Morgenroth 2017, John et al. 2019, Alkaradaghi et al. 2018, Firoozynejad and Torahi 2017, H-p et al. 2013, Baboo and Devi 2011, Mirkatouli et al. 2015)**	Topographic Correction helps in reducing the effect of terrain radiance in the satellite image.	Topographic Normalise, Surface Difference, Level slicing, and Route Intervisibility.	 **(H-p et al. 2013)**	 **(H-p et al. 2013)**

Cramer's V coefficient value always lies between zero (no association between the variables) and one (complete association between the variables). These independent variables are considered as the key factors in analyzing the future LU/LC changes (Heidarlou et al. 2019, Kumar et al. 2014).

LU/LC prediction models

Different environmental models are used by the researchers for forecasting future LU/LC changes. It is necessary for every researcher to work on LU/LC change prediction problem considering the provision of the predicted results to the land resource management and to urban planners to help them in taking suitable actions for protecting the land cover environment. Table 6 shows a few of the environmental models for the LU/LC change prediction process. Markov chain-cellular automata hybrid model, logistic regression model, Land Change Modeler, GEOMOD, and CLUE (Conversion of Land Use and Its Effects) model were used for LU/LC change prediction. By using the IDRISI software, the VALIDATE module is to validate the predicted data with the reference data and the CROSSTAB module is used for performing the cross-tabulation between the predicted and the actual LU/LC map (Liping et al. 2018).

THE Markov chain (MC) model is used for analyzing the time-based changing landscapes among the LU/LC classes based on the transition probabilities (Bounouh et al. 2017, Heidarlou et al. 2019, El Jazouli et al. 2019, Hernández-Guzmán et al. 2019, Gashaw et al. 2017, Liping et al. 2018, Singh et al. 2015, Karimi et al. 2018, Etemadi et al. 2018, Halmy et al. 2015, Yagoub and Bizreh 2014 Yirsaw et al. 2017, John et al. 2019, Nwaogu et al. 2017, Regmi et al. 2014, Han et al. 2015, Nadoushan et.al 2012, Achmad et al. 2015, Mirkatouli et al. 2015). Cellular automata (CA) model is used to simulate the spatial changing landscapes among the LU/LC classes in the remote sensing environment (Bounouh et al. 2017, El Jazouli et al. 2019, Hernández-Guzmán et al. 2019, Gashaw et al. 2017, Liping et al. 2018, Singh et al. 2015, Karimi et al. 2018, Etemadi et al. 2018, Halmy et al. 2015, Yagoub and Bizreh 2014, Yirsaw et al. 2017, Saputra and Lee 2019, Nwaogu et al. 2017, Regmi et al. 2014, Nadoushan et.al 2012). We observed most of the researchers have used the hybrid model for predicting the LU/LC change for the particular area. One of the frequently used hybrid models for predicting the LU/LC change is the Markov chain and cellular automata model. SLEUTH (slope, land use, exclusion, urban, transportation, and hill shade) is a process of cellular automata model applied in the process of LU/LC change analysis to simulate and predict the status of the urban growth (Pathiranage et al. 2018). The QGIS software includes MOLUSCE (Modules for Land Use Change Evaluation) simulated plugin which provides a different set of algorithms like ANN, logistic regression model, WoE (weight of evidence), and multi-criteria evaluation (Saputra and Lee 2019, Ashaolu et al. 2019).

Commonly used metrics

We identified the most commonly used metrics for analyzing the satellite images and they are listed as follows: NDVI, NDWI, confusion matrix (used to equate the classified image with the reference image), the kappa coefficient, and overall accuracy. The percentage of change and rate of change is calculated for determining the number of changes experienced between a certain time interval.

Table 4 LU/LC classification methods

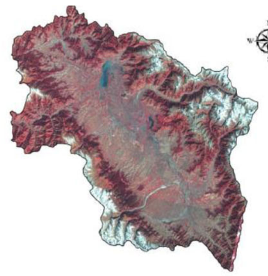
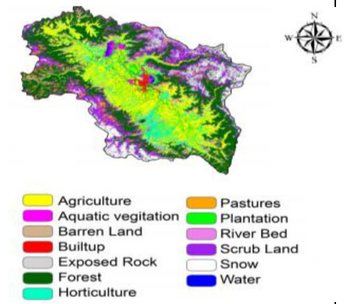
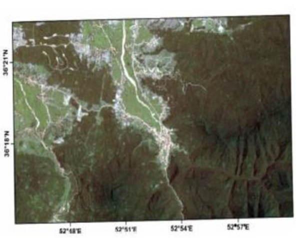
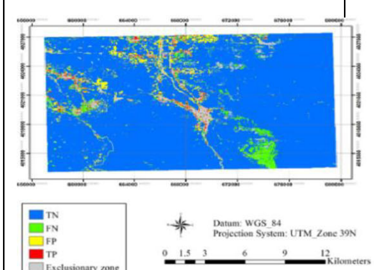
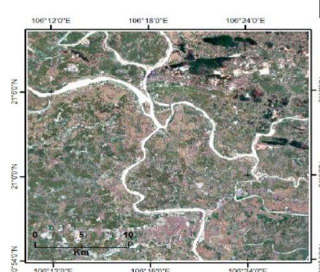
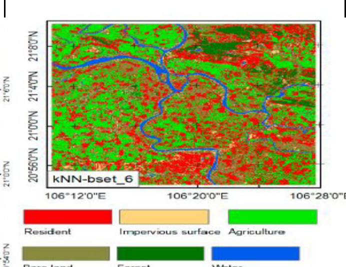
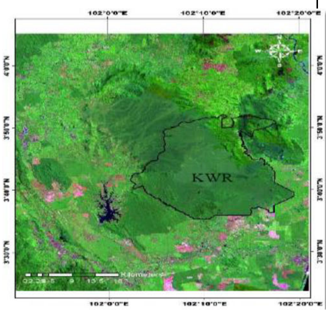
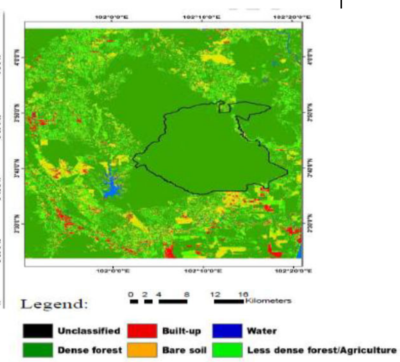
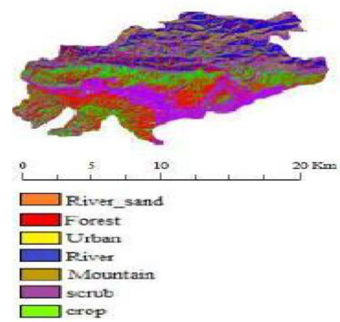
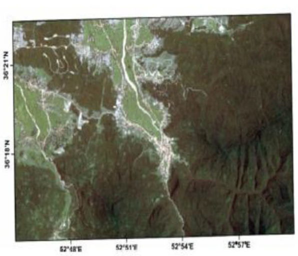
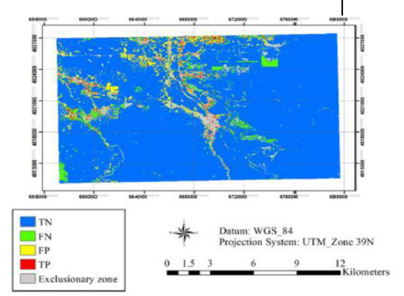
Method	General Explanation	Before Classification	After Classification
Maximum Likelihood Classification (Supervised Classifier) **(Fonji and Taff 2014, Li et al. 2014, Heidarlou et al. 2019, Restrepo et al. 2017, El Jazouli et al. 2019, Birhane et al. 2019, Bagan et al. 2018, Bakr and Afifi 2019, Li et al. 2018, Gashaw et al. 2017, Liping et al. 2018, Karimi et al. 2018, Etemadi et al. 2018, Sisodia et al. 2014, Pande et al. 2018, Yirsaw et al. 2017, Mallupattu and Reddy 2013, John et al. 2019, Adhikari et al. 2017, Alkaradaghi et al. 2018, Kumar et al. 2014, Firoozynejad and Torahi 2017, Murtaza and Romshoo 2014, Vibhute et al. 2013, Ganasri and Dwarakish 2015, Asubonteng et al. 2018, Priyadarshini et al. 2018, Nurwanda et al. 2016, Das et al. 2013, Ashaolu et al. 2019, Achmad et al. 2015, Pathiranage et al. 2018)**	Maximum Likelihood algorithm estimates the probability distributions for the LU/LC classes.	 **(Murtaza and Romshoo 2014)**	 **(Murtaza and Romshoo 2014)**
Random Forest Classifier (Supervised Classifier) **(Li et al. 2014, Yang et al. 2018, Zurqani et al. 2018, Ahmadlou et al. 2018, Thanh Noi and Kappas 2018, Halmy et al. 2015, Zhu and Woodcock 2014, Nery et al. 2019)**	The random forest method is based on the decision tree classifiers. It is used for improving the predictive accuracy for LU/LC classification and controls the over-fitting of data.	 **(Ahmadlou et al. 2018)**	 **(Ahmadlou et al. 2018)**
k-Nearest Neighbor (kNN) (Supervised Classifier) **(Li et al. 2014, Thanh Noi and Kappas 2018)**	k-Nearest Neighbor is measured by the distance function and finds the nearest LU/LC class by classifying it.		

Table 4 (continued)

	.	(Thanh Noi and Kappas 2018)	(Thanh Noi and Kappas 2018)
Support Vector Machine (SVM) classifiers (Supervised Classifier) **(Li et al. 2014, Thanh Noi and Kappas 2018, Firoozynejad and Torahi 2017, Shaharum et al. 2018, Nery et al. 2019, Priyadarshini et al. 2018, Abbas et al. 2017)**	This method is memory efficient and shows sensible results of classified LU/LC classes even when there are fewer amounts of training data.	 (Shaharum et al. 2018)	 (Shaharum et al. 2018)
Iterative Self-Organizing Data Analysis Technique (ISODATA) (Unsupervised Classifier) **(Li et al. 2014, Gashaw et al. 2017, Yagoub and Bizreh 2014, Adhikari et al. 2017, Nery et al. 2019, Taufik et al. 2019, Asubonteng et al. 2018, Priyadarshini et al. 2018)**	This method is used to compute the minimum distance of each satellite data point to a definite cluster.	 (Priyadarshini et al. 2018)	 (Priyadarshini et al. 2018)
CART (Classification and Regression Trees) (Supervised Classifier) **(Hu and Yu Dong 2018, Zurqani et al. 2018, Ahmadlou et al. 2018, Nery et al. 2019)**	This method is used for classification as well as for the regression calculation problems.	 (Ahmadlou et al. 2018)	 (Ahmadlou et al. 2018)

NDVI

The probability of having lower or higher vegetation is identified by the NDVI values (Yang et al. 2018, Hu and Yu Dong 2018, Kabisch et al. 2019, Zurqani et al. 2018, Etemadi et al. 2018, Nery et al. 2019, Taufik et al. 2019, Das et al. 2013, Kusuma 2013). So the higher vegetation cover is recognized by the higher NDVI value and lower vegetation cover is recognized by the lower NDVI value. The values of NDVI are between the ranges of − 1 to + 1.

$$\mathrm{NDVI} = \frac{(NIR - RED)}{(NIR + RED)} \quad (1)$$

where NIR represents the Near-Infrared Band and RED represents the Red Band.

Table 4 (continued)

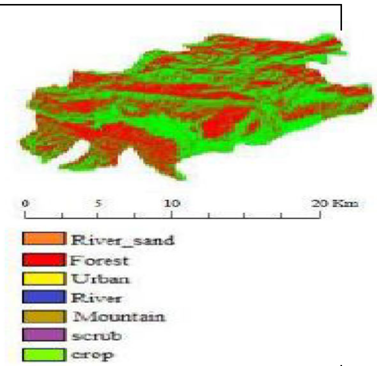
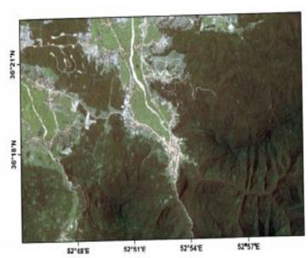
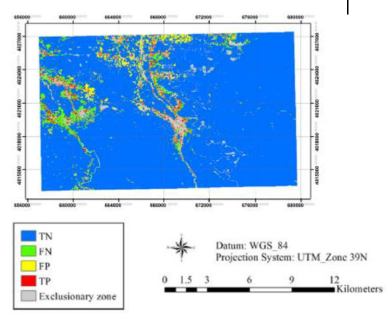
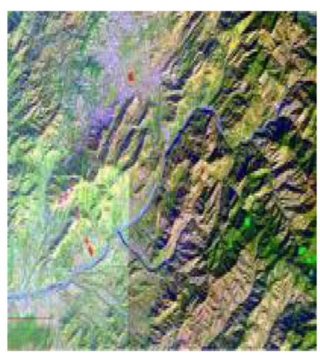
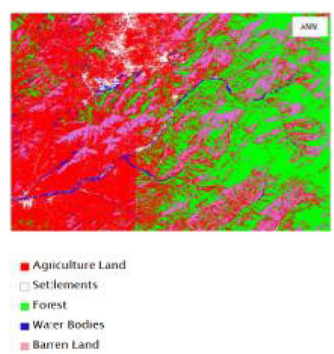
K-means classification (Unsupervised Classifier) **(Usman 2013, Li et al. 2014, Hernández-Guzmán et al. 2019, Taufik et al. 2019, Priyadarshini et al. 2018)**	This method separates the given image into different clusters of pixels based on specific requirements. Similar image objects are kept in one group and dissimilar image objects in a different group.	 **(Priyadarshini et al. 2018)**	 **(Priyadarshini et al. 2018)**
Multivariate Adaptive Regression Splines (MARS) (Supervised Classifier) **(Ahmadlou et al. 2018, Ahmadlou et al. 2015)**	This model is applied to the LU/LC classification and prediction problems. The main purpose is to calculate the continuous dependent variables from the set of independent variables.	 **(Ahmadlou et al. 2018)**	 **(Ahmadlou et al. 2018)**
Artificial Neural Network (ANN) (Either Supervised or Unsupervised) **(Li et al. 2014, Bounouh et al. 2017, Heidarlou et al. 2019, Bagan et al. 2018, Li et al. 2018, Ce et al. 2019, John et al. 2019, Saputra and Lee 2019, Nwaogu et al. 2017, Kusuma 2013, Ahmadlou et al. 2015, Nadoushan et.al 2012, Abbas et al. 2017)**	It also used for classifying the satellite image for the LU/LC change problems. ANN is considered as the time series LU/LC classification problem of predicting the future status of the land.	 **(Abbas et al. 2017)**	 **(Abbas et al. 2017)**

Table 4 (continued)

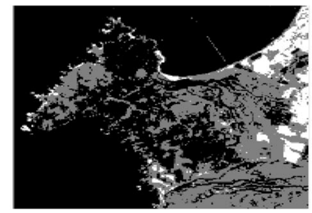
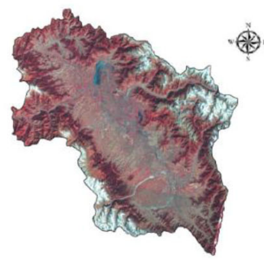
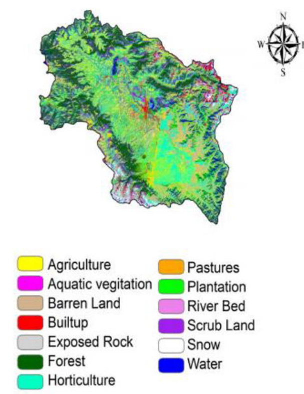
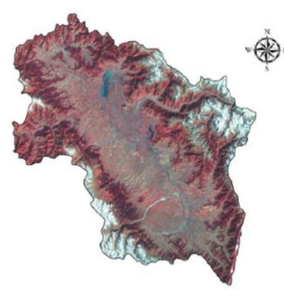
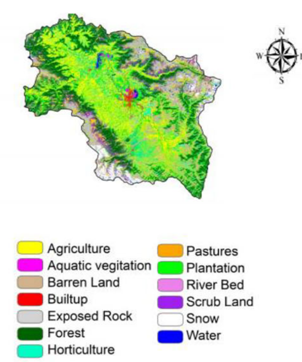
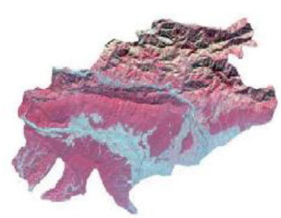
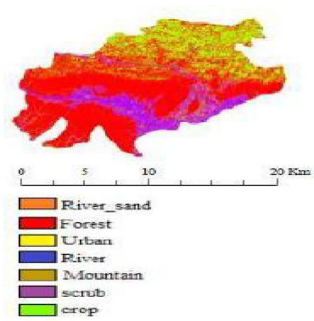
Fuzzy C Means (FCM) (Unsupervised Classifier) **(HongLei et al. 2013, Taufik et al. 2019, Khan et al. 2018, Rehman and Hussain 2018)**	FCM method is used to segment the satellite images into different clusters. The objective function helps in minimizing the dissimilarities within the cluster.	 **(Rehman and Hussain 2018)**	 **(Rehman and Hussain 2018)**
Minimum Distance (Supervised Classifier) **(Murtaza and Romshoo 2014, Vibhute et al. 2013, Ganasri and Dwarakish 2015, Priyadarshini et al. 2018)**	This method classifies the unknown satellite data by measuring the distance between satellite data points with their centroids.	 **(Murtaza and Romshoo 2014)**	 **(Murtaza and Romshoo 2014)**
Mahalanobis Distance (Supervised Classifier) **(Murtaza and Romshoo 2014, Vibhute et al. 2013)**	This method is used to find the distance between the two data points in the multivariate space.	 **(Murtaza and Romshoo 2014)**	 **(Murtaza and Romshoo 2014)**
Parallelepiped (Supervised Classifier) **(Vibhute et al. 2013, Ganasri and Dwarakish 2015, Priyadarshini et al. 2018)**	This method defines the standard deviation threshold from the mean of every class.	 **(Priyadarshini et al. 2018)**	 **(Priyadarshini et al. 2018)**

Table 4 (continued)

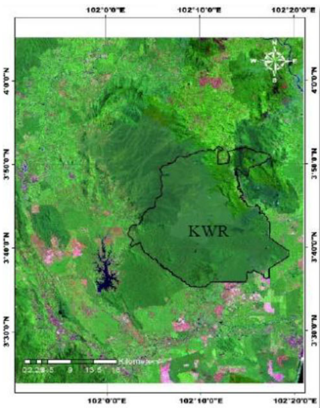
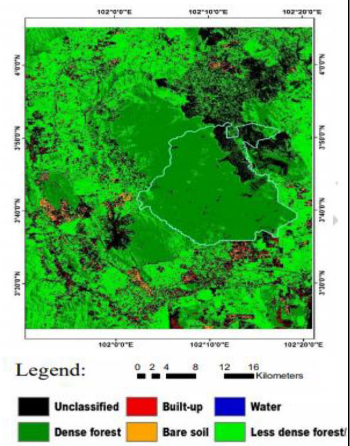
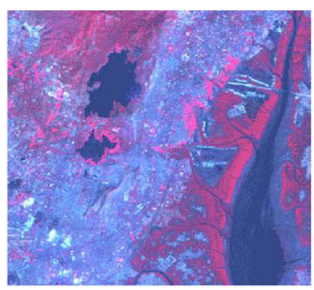
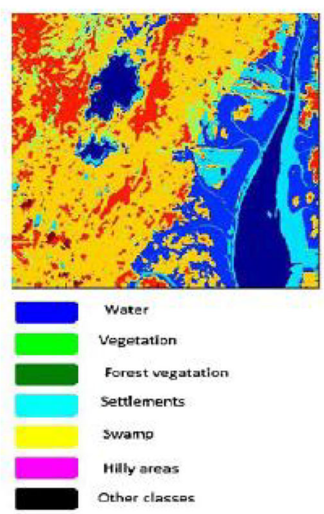
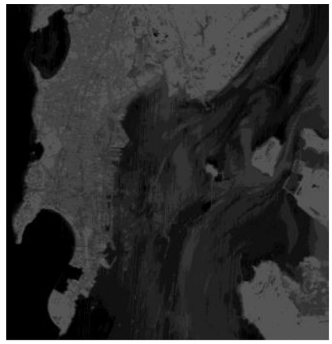
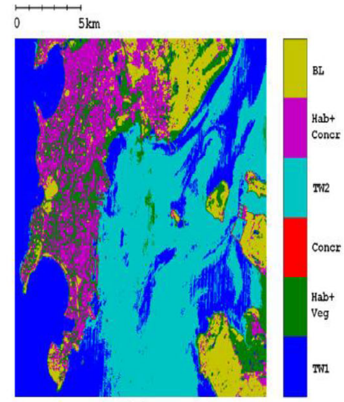
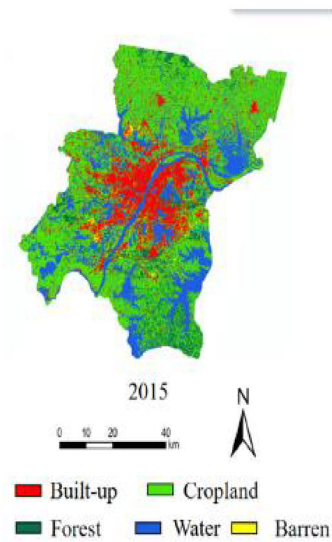
Spectral Angle Mapper (SAM) Classification (Supervised Classifier) **(Shaharum et al. 2018, Mohamed and Elmahdy 2018)**	This method is a process of the spectral classification where the n-D angle is used to match the satellite data pixels to the reference spectra.	 **(Shaharum et al. 2018)**	 **(Shaharum et al. 2018)**
Graph-Based model (Semi-Supervised) **(Yan Y et al. 2017, Aydav and Minz 2017, Sawant and Prabukumar 2017)**	This method constructs the graph by connecting similar data points in the image.	 **(Yan Y et al. 2017)**	 **(Yan Y et al. 2017)**
Self-Trained Models (Semi-Supervised) **(Banerjee and Buddhiraju 2015, Maulik and Chakraborty 2011, Liu et al. 2013, Aydav and Minz 2017, Sawant and Prabukumar 2017)**	This method is a wrapper method that provides the label to the unlabeled data through a hybrid classification technique.	 **(Banerjee and Buddhiraju 2015)**	 **(Banerjee and Buddhiraju 2015)**

Table 4 (continued)

Transductive SVM (TSVM) (Semi-Supervised) **(Chakraborty and Maulik 2011, Aydav and Minz 2017, Sawant and Prabukumar 2017, Maulik and Chakraborty 2013)**	This method used to treat the margins of the partially labeled data to find the labels of unlabeled data.	 **(Chakraborty and Maulik 2011, Maulik and Chakraborty 2013**)	 **(Maulik and Chakraborty 2013**)
Semi-Supervised Co-training model **(Aydav and Minz 2017, Sawant and Prabukumar 2017, Hu et al. 2018)**	This method is used when the unlabelled data is larger than the labeled data.	 **(Hu et al. 2018)**	 **(Hu et al. 2018)**

NDWI

The probability of having lower or higher water content is identified by the NDWI (Normalized Difference Water Index) values (Hu and Yu Dong 2018, Zurqani et al. 2018, Taufik et al. 2019). So the higher water content is recognized by the higher NDWI value and lower water content is recognized by the lower NDWI value. The values of NDWI are between the ranges of − 1 to + 1.

$$\mathrm{NDWI} = \frac{(NIR-SWIR)}{(\mathrm{NIR}+SWIR)} \tag{2}$$

where NIR represents the Near-Infrared Band and SWIR represents the Short Wave Infrared Band.

Confusion matrix, accuracy assessment, and kappa coefficient

Accuracy assessment is an indispensable and decisive measure in the remotely sensed image classification for detecting the LU/LC change. The reference images are compared with the classified images employing the confusion matrix. Table 7 shows the illustration of the confusion matrix.

The confidence of the classified images largely depends on accuracy assessment. The analysis of various studies shows the computation of the overall accuracy as the basic need and the kappa coefficient for testing the correctness of the classification process.

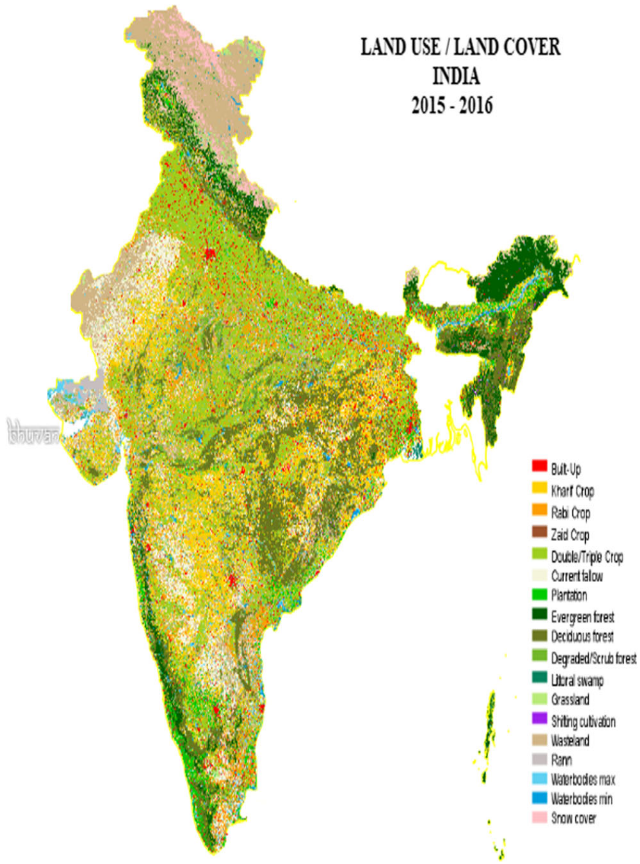


Fig. 2 LU/LC map information India (2015–2016)

$$\text{Overall Accuracy} = \left(\frac{\text{TP} + \text{TN}}{\text{N}}\right) \times 100 \tag{3}$$

$$\text{KS} = \frac{N\sum_{i=1}^{r} x_{ii} \sum_{i=1}^{r} \left(x_{i+} {*} x_{+i} \right)}{N^{2-} \sum_{i=1}^{r} \left(x_{i+} {*} x_{+i} \right)} \tag{4}$$

where KS represents kappa statistics; N signifies the matrix total observations; r signifies the number of rows in the confusion matrix; x_{ii} denotes row i and column i observations; x_{i+} denotes row i observations; x_{+i} represents column i observations.

Rate and percentage of change

For demonstrating the magnitude of the LU/LC change for the different time intervals in a modest way, the rate of change and the percentage of change are calculated.

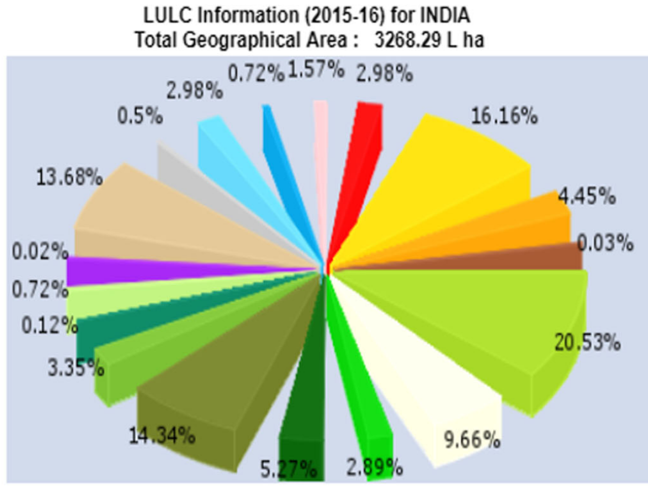
$$POC = \left(\frac{T_2 - T_1}{T_1}\right) \times 100 \tag{5}$$

$$ROC\left({}^{ha}/_{yr}\right) = \frac{T_1 - T_2}{T_i} \tag{6}$$

where POC represents the percentage of change; ROC represents the rate of change; T_1 represents the area (ha) of LU/LC for the time interval 1; T_2 represents the area (ha) of LU/LC for the time interval 2; T_i represents the time interval between the T_1 and T_2 in years (yr).

Conceptual framework

The utmost purpose of this review paper is to provide a conceptual framework for the comprehensive land use/land cover change analysis process and it is shown in Fig. 4. The first step in LU/LC change is to understand the problem carefully through a different survey in the field of remote sensing around the world. Many researchers had analyzed and proposed different algorithms for analyzing the LU/LC change problem. Moreover, to deal with the identified problem, certain research challenges and difficulties should be known. The research questions can be formulated to define the objectives precisely. Our research work of LU/LC change analysis in the field of remote sensing begins with selecting the study area *(*Javadi Hills, India*)*. The Javadi Hills covered with the forest-covered region will be interesting to perform the LU/LC change analysis. The satellite images *(*LISS-III*)* will be collected and analyzed for further process. The multispectral bands in LISS-III satellite images have a good resolution for LU/LC mapping. Other data includes field survey data, aerial images, open government data (OGA), and licensed data. The image preprocessing will be performed after the process of image acquisition. Based on the satellite image, the preprocessing techniques like geometric, radiometric, atmospheric, and topographic corrections will be performed. Many researchers had used different classification algorithms for their study area. With high-performance systems, we will prefer the deep learning methods, as it will lead to the new direction of research. The classified results will be validated by calculating the accuracy and kappa statistics. Post-classification will be performed to check the misclassification errors that occurred in the LU/LC classified map. The rate and percentage of LU/LC change will be calculated for the identified datasets over different time intervals. The dependent (LU/LC change cover map) and the independent (slope, elevation, aspect, distance from forest edge, climatic data, and population density) variables associated with our study area (Javadi Hills) will be modeled and processed for



LULC Class	Area (L ha)	LULC Class	Area (L ha)
Built-up	97.32	Kharif Crop	528.31
Rabi Crop	145.53	Zaid Crop	1.08
Double/Triple Crop	671.11	Current Fallow	315.78
Plantation	94.44	Evergreen Forest	172.33
Deciduous Forest	468.74	Degraded/Scrub Forest	109.55
Littoral Swamp	3.94	Grassland	23.68
Shifting Cultivation	0.67	Wasteland	447.11
Rann	16.34	Waterbodies max	97.39
Waterbodies min	23.6	Snow Cover	51.37
Total			3268.29

Fig. 3 Statistics of LU/LC classes of India (2015–2016)

predicting the future LU/LC map. The new prediction method will be proposed for analyzing future LU/LC change. The results are validated and processed finally. The predicted LU/LC change results will assist the government officials, urban planners, and forest department to take actions in the protection of the LU/LC environment.

Discussions

The natural reasons and the significant changes over the earth's surface for a long time interval have led to the process of LU/LC change analysis. In a remote sensing and GIS environment, several images from different satellites have been deliberated as the important data source where numerous kinds of land cover changes like deforestation, expansion of agricultural land, increase in urban growth, and loss of wetlands over the different time interval is recognized. Steps involved in the analysis of LU/LC change are, acquisition of satellite images, image pre-processing, LU/LC classification, post-classification, accuracy assessment, change analysis, validating dependent and independent variables, and LU/LC change prediction. The different datasets and their sources have been discussed and defined in this paper. The commonly used software programs for processing the different satellite images have also been discussed in this study. Among them, ENVI, ArcGIS, ERDAS Imagine, and IDRISI are frequently used by researchers. Image pre-processing is considered the most important stage, and therefore it should be performed before the LU/LC change analysis process. A few image pre-processing techniques used by researchers help in correcting the atmospheric, radiometric, geometric, and topographic errors in the satellite image. Pre-processing of satellite images should be processed carefully since it is the initial process following data collection. The LU/LC classification is the strongly focused part in remote sensing environment. Different classification algorithms were used by researchers for classifying the pre-processed satellite image into different classes. We observed that the hybrid classification algorithms provide good accuracy for the pre-processed satellite image. The process of post-classification should be carefully made for removing the misclassification errors in the LU/LC classification map. The Google Earth Engine is the widely used geospatial software for analyzing and obtaining the reference data during the process of accuracy assessment. The classified LU/LC map is analyzed

Table 5 LU/LC classes and its factors

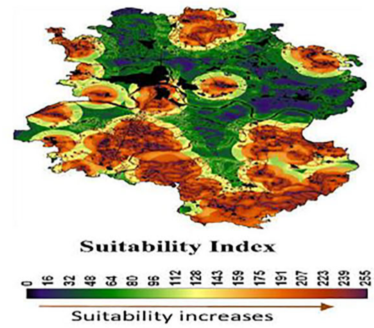
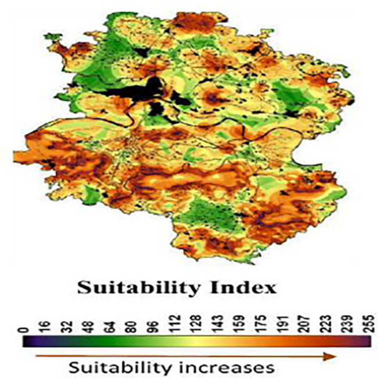
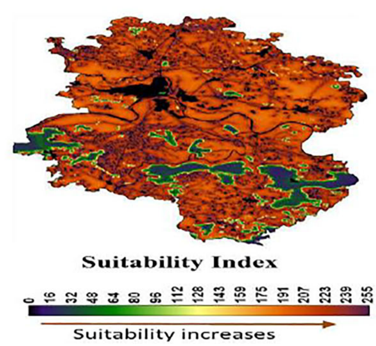
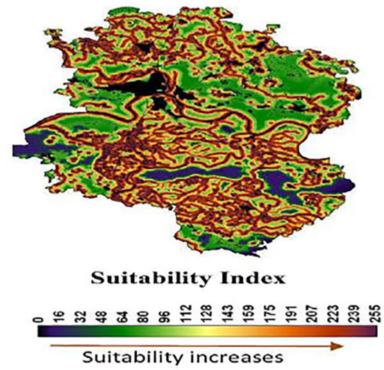
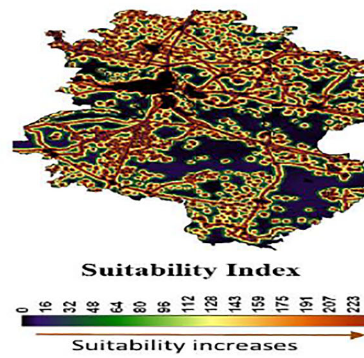
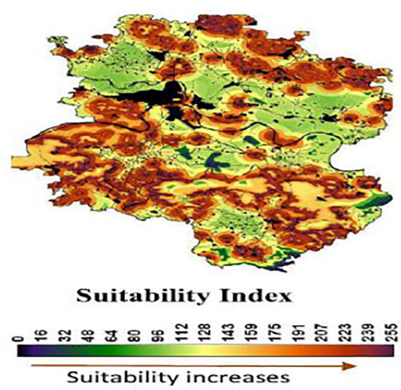
S.No	LU/LC Classes	General Explanation	Factors or Independent Variables	Suitability Map
1	Farmland	Areas include agricultural and cultivated farmlands.	Soil erosion, slope, elevation, and aspect.	 Suitability to Cultivated Land **(Singh et al. 2015)**
2	Forest Land	Areas covered with different species of trees.	Slope, elevation, aspect, Temperature, and Distance from the edge of the forest.	 Suitability to Forest **(Singh et al. 2015)**
3	Grassland	Areas include the green land, croplands with vegetation, and pasture regions.	Proximate to the recognized vegetated land, elevation, and slope.	 Suitability to Crop Land **(Singh et al. 2015)**

Table 5 (continued)

4	Water Bodies	Coastal areas that include rivers, lakes, ponds, and seaside covers.	Distance to the river, elevation, slope, aspect, rainfall or runoff factor, soil erosion factor, cover factor, and topographic factor.	 Suitability to Water Bodies **(Singh et al. 2015)**
5	Built-up Land	The area includes residential, industrial, transport, and developed constructional lands.	Distance from built-up areas, Settlements, slope, elevation, and aspect.	 Suitability to Built-up Land **(Singh et al. 2015)**
6	Waste Land	The area includes Barren Land and Scrub Land.	Distance to the road, and the barren land, elevation, slope, and aspect.	 Suitability to Waste Land **(Singh et al. 2015)**

by calculating the area of change that happened for different time intervals. Dependent (LU/LC map) and independent variables (slope, elevation, and distance variables) are the important factors in predicting the LU/LC change. Hence, most of the researchers tend to prefer an effective hybrid prediction method for monitoring and predicting the land cover changes for certain time series in a particular region. Among the performance metrics, the accuracy assessment and kappa statistics were considered as the efficient and required metrics for every LU/LC classification and prediction problem to validate the performance of the results.

Challenges

This paper provides a few research challenges faced during every stage of the LU/LC change analysis process. The challenges are summarized as:

- Acquisition: During the image acquisition process, extracting the region of interest from the study area through datum coordinates from the suitable satellite system is a challenging task for researchers.
- Pre-processing: During satellite image pre-processing, geo-referencing the unknown coordinates of

Table 6 Environmental models used for LU/LC prediction

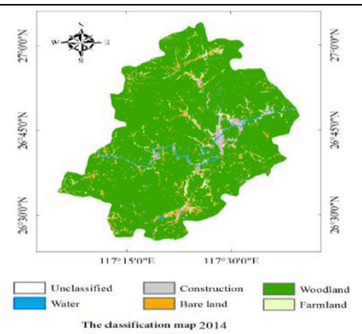
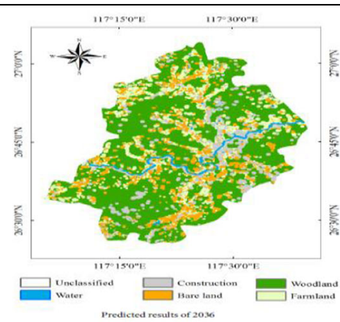
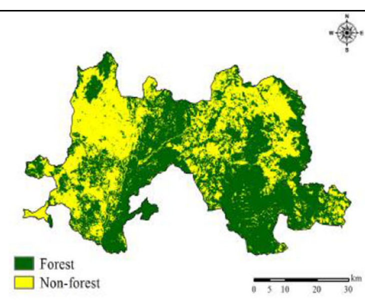
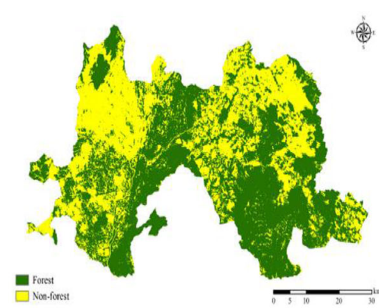
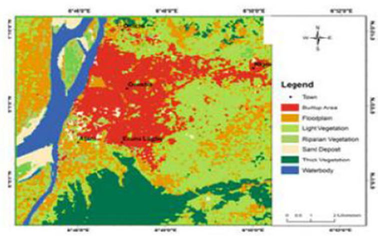
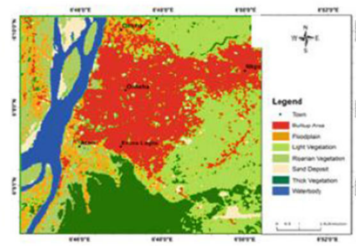
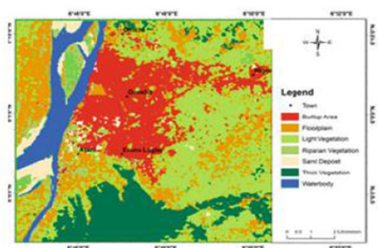
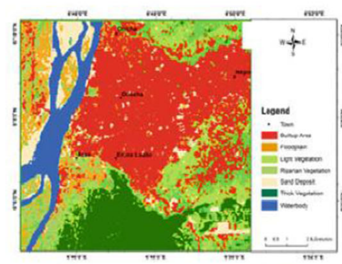
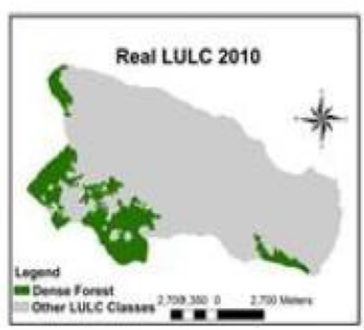
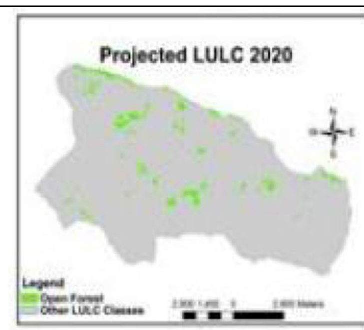
Prediction Models	General Explanation	Actual/ Classified Image	Predicted Image
Markov Chain (MC) - Cellular Automata (CA) (Hybrid model) **(Bounouh et al. 2017, El Jazouli et al. 2019, Hernández-Guzmán et al. 2019, Gashaw et al. 2017, Liping et al. 2018, Singh et al. 2015, Karimi et al. 2018, Etemadi et al. 2018, Halmy et al. 2015, Yagoub and Bizreh 2014, Yirsaw et al. 2017, Nwaogu et al. 2017, Regmi et al. 2014, Nadoushan et.al 2012)**	The time-based and spatial changing landscapes among the LU/LC classes based on transition probabilities.	 **(Liping et al. 2018)**	 **(Liping et al. 2018)**
Logistic Regression Model **(Bounouh et al. 2017, John et al. 2019, Alkaradaghi et al. 2018, Hemasinghe et al. 2018, Nurwanda et al. 2016, Nwaogu et al. 2017, Han et al. 2015, Achmad et al. 2015)**	Logistic Regression is the predictive analysis model used when the corresponding dependent variables are binary.	 Actual Classified LU/LC Map Of 2010 **(Kumar et al. 2014)**	 Prediction of Logistic Regression Model for 2010 **(Kumar et al. 2014)**

Table 6 (continued)

Land Change Modeler (LCM) **(Heidarlou et al. 2019, Etemadi et al. 2018, John et al. 2019, Nwaogu et al. 2017, Achmad et al. 2015)**	Land Change Modeller is a tool that helps in calibrating the relationships between dependent and the explanatory variables to simulate future LU/LC change.	 Current LULC as at 2015 **(Nwaogu et al. 2017)**	 LCM prediction output for 2035 **(Nwaogu et al. 2017)**
CLUE (Conversion of Land Use and Its Effects) model **(Bounouh et al. 2017, Nwaogu et al. 2017, Han et al. 2015)**	CLUE model is a tool to examine the LU/LC change processes spatial pattern in the field of remote sensing and to predict future LU/LC changes in the particular region.	 Current LULC as at 2015 **(Nwaogu et al. 2017)**	 CLUE prediction output for 2035 **(Nwaogu et al. 2017)**
GEOMOD **(Nwaogu et al. 2017, Regmi et al. 2014, Nadoushan et.al 2012)**	GEOMOD is a grid-based LU/LC change analysis modeling tool that helps in analyzing the increase or decrease in the LU/LC category over a definite time interval.	 **(Regmi et al. 2014)**	 **(Regmi et al. 2014)**

the ground truth image with the referenced satellite image for a particular region remains the challenge.

- LU/LC classification: During the LU/LC classification process, the provision of accurate training datasets through the ground survey remains a challenge.
- Post-classification: Post classification assessment for checking the misclassification errors in the classified image remains a challenge.
- LU/LC change prediction: During the LU/LC change prediction process, calibration of the exact independent and dependent variables with the prediction model remains a challenge.

Table 7 Confusion matrix

Classified data	Reference data	
	Positive	Negative
Positive	True positive (TP)	False negative (FN)
Negative	False positive (FP)	True negative (TN)

- Validation: Accurate prediction for future LU/LC change in different application areas remains a challenge.

The challenges focused in this paper could be a fertile source for future researchers to do their work actively in LU/LC remote sensing environment.

Conclusions

This paper evidently presents the generic flow of the LU/LC change analysis process and also provides a detailed discussion on techniques and the challenges faced during each stage of the LU/LC process. The importance of finding the future LU/LC change today employing prediction methods is in the provision of judgments to the land resource management. Moreover, this information will help the government officials, namely, urban planners and forest department, to take necessary actions over the protection of a LU/LC environment.

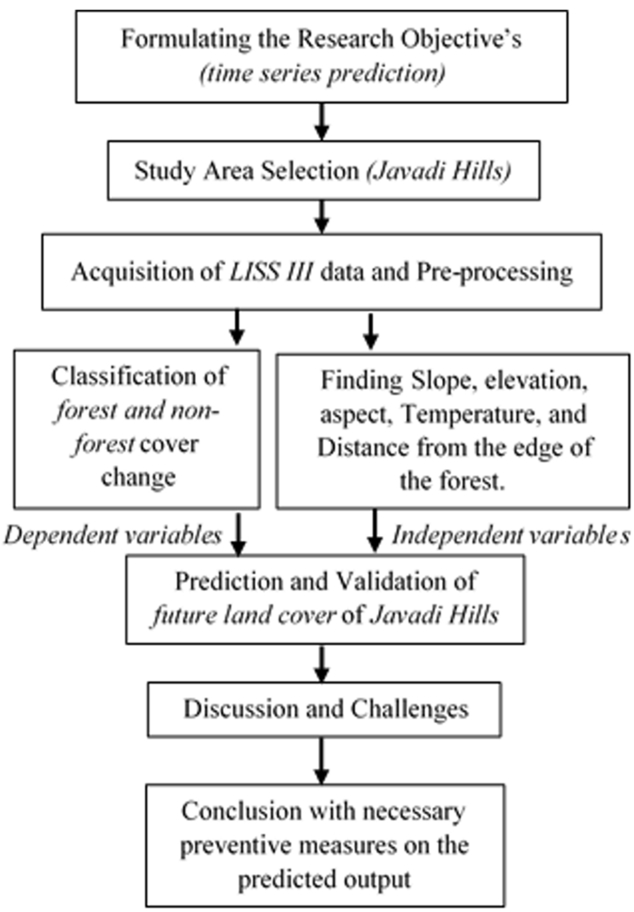


Fig. 4 Conceptual framework

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