Environmental Science and Pollution Research (2022) 29:86349–86361
https://doi.org/10.1007/s11356-022-18707-z

RESEARCH ON SUSTAINABLE DEVELOPMENTS FOR ENVIRONMENT MANAGEMENT

Land use/land cover changes of Noyyal watershed in Coimbatore district, India, mapped using remote sensing techniques

Sapna Kinattinkara[1] · Thangavelu Arumugam[2] · Shanthi Kuppusamy[1] · Manoj Krishna[2]

Received: 18 May 2021 / Accepted: 12 January 2022 / Published online: 4 February 2022

Abstract

The present study undertakes to produce the land use/land cover map and to explore the change detection analysis of Noyyal watershed, Coimbatore, for a time period of 18 years. Based on the remote sensing and geographical information system for monitoring the temporal variations of land use/land cover, multi-temporal Landsat satellite 30-m spatial resolution images of Landsat 4/5 MSS and TM (1999), Landsat 7 ETM + (2008), and Landsat 8 Operational Land Imager (OLI) were obtained from the USGS website. The satellite images were geocoded into the universal transverse mercator (UTM) coordinate system zone 43 N. The unsupervised classification method was done by using an iterative self-organizing data analysis algorithm to compare the images and to classify the images into various land cover categories. Kappa statistics were used to assess the validation of the present study. The analysis suggests the total forest covered in 1999 was 22.69% and that of 2008 was 24.04% and reduced to 6.09%, in 2017. The agricultural land of 17.8% is reduced to 3.11% in 2008 and 0.86% in 2017. The settlements increased from 15.59 to 24.21% in 2008 and 27.14% in 2017. Increase in deforestation leads to increase in barren land. In 1999, the percentage of barren land was 17.2%; in 2008, it was 13.19%, and 50.93% in 2017. The overall accuracy estimation of the study is 73.19% and Kappa coefficient is 0.72. This study has proven a substantial strength of agreement for the map of 2017 from the result of validation rating criteria of Kappa statistics.

Keywords LULC · Watershed · Deforestation · Coimbatore · Unsupervised classification · Kappa statistics

Introduction

Land cover studies (LULC) has been considered an important exploratory issue because it can cause environmental changes to a greater extent (Xiao et al. 2006; Fayaz Ahmad et al. 2015; Shafiq et al. 2017). LULC data can be used for better management of natural resources (Iqbal and Khan 2014; Lin et al. 2015; Kantakumar and Neelamsetti 2015): increasing population and development activities, putting pressure on the country's natural resources, and changing land use (Islam et al. 2016). LULC of rural watersheds has a great influence on water quality and stream characteristics (Paul and Meyer 2001; Tong and Chen 2002). The effects of climate and land use changes on watershed rely upon the degree and perspective of land use (Martin Katherine et al. 2017). The LULC plays a significant role in the relationships between man and environment (Regmi et al. 2017). In LULC detection studies, land use affects the land cover; the changes in LULC do not have a potential impact on the degradation of the land cover (Rawat and Kumar 2015). Several investigations on LULC showed that metropolitan populace development rates have amplified the rates of alteration of forest and built-up land in developing nations in everywhere in the world (Klosterman 2008; Zhang et al. 2010; Barsimantov and Navia Antezana 2012; Chen et al. 2013).

The catchment processes and biochemical cycles are affected by the degradation of forest and prompt soil degradation and water scarcity both in the district areas, such as, quickly influenced, affected by deforestation, and also far-away areas. The problems and after effects caused by LULCC are many (Saadat et al. 2011). For the better understanding of relationships and interactions between human

Responsible Editor: Philippe Garrigues

✉ Thangavelu Arumugam
thangavelgis@gmail.com

[1] Department of Environmental Science, PSG College of Arts and Science, Coimbatore, Tamil Nadu 641014, India

[2] Department of Environmental Studies, Kannur University, Mangattuparamba Campus, Mangattuparamba, Kerala 670567, India

and natural occurrence, timely and accurate change detection of earth surface features is very important and it is useful for management of resources. To quantitatively investigate the alterations of land cover classes in change detection, it involves the application of multi-temporal data sets (Afify 2011).

Numerous investigators have evaluated the issue of precise examining of LULC change in different conditions (Singh1989). Musa and Odera (2015) have been performed Landsat ETM + data sets for years 1984, 1993, 2002, and 2013 to calculate land use cover change's effects on agricultural land of Kenya. Wanhui et al. (2011) have been investigated six Landsat images; one image is Landsat Multi-Spectral Scanner (MSS) for the year 1977, and the rest of it is Thematic Mapper (TM) 1988, 1992, 1996, 2001, and 2007 used to process many LULC classes like forests and wetlands have changed to human settlements in Daqing City, China.

For LULCC detection, numerous strategies have created and applied of remotely sensed data (Shalaby and Tateishi 2007). LULC study mainly depends on satellite remote sensing techniques to extract multitemporal data (Lu et al. 2004). To monitor the gradual change of the LULC, geospatial techniques have been used, and this plays an important role in the conservation of natural resources, observation and assessment of the quality of the watershed, and also in study of the hydrological response and flow system of water sources. (Ayele et al. 2018). Accurate and ideal data on huge LULC spatially dispersed areas were collected using geographic information systems (GIS) and remote sensing (RS). Effective techniques for investigating land use and classification problems are RS and GIS (Zhu and Woodcock. 2014). To identify and map land use categories, today, remote sensing satellites are widely used (Virghileanu and Mihai 2016).

There are several approaches to classifying remotely sensed data, such as unsupervised and supervised classification techniques. An algorithm is chosen that will take a remotely sensed data set and find a pre-determined number of statistical clusters in multispectral space in unsupervised classification. Unsupervised classification cannot be applied without knowing the earlier information of the land cover in the study area, because these clusters are not always equivalent to actual classes of land cover (Guzha et al. 2018). In the case, supervised classification of earlier information of the land cover in the study area is needed. The algorithm would then be able to be applied to the whole image once trained, and overall classification image is achieved (Thangavelu et al. 2021).

The pixels with common properties are grouped without user, providing sample classes are used in the unsupervised classification (Butt et al. 2015). In a software analysis of the image, the PC utilizes different methods to choose which pixels are connected and bunches them into classes. The desired number of output classes and a selection of the algorithm can be desired by the user (Hassan et al. 2017). The user should have a familiar knowledge of the study area because pixel grouping depends on common properties created and must be identified with real feature on the land, for example, such as water bodies, settlements, and agricultural area.

Accuracy of the image classification has a vital role because remote-sensed data are regularly utilized for planning and creating environmental models that are utilized for the board and dynamic purposes. Accuracy assessment can be done qualitatively or quantitatively to determine the quality of information acquired from remotely sensed data. A fast differentiation to observe if the remotely sensed map seems alike and match up to what is exactly on the real land is carried out qualitatively. To identify and quantify error, quantitative assessments are used (Rwanga and Ndambuki 2017; Roy and Inamdar 2019; Mishra et al. 2020). The error matrix and kappa coefficient have become an arising rule for evaluation of image classification accuracy. The error matrix was a vital element of this research and has been used in a variety of land change studies.

The LULC changes are vast number of situations for local, regional, and global level indicated in watershed management. So, a LULC change plays a most important character in the study, and the analysis generates changes in different situations is universal. The different data were used, and there have been more changes necessary for giving a critical contribution to decision-making in future planning and management of watershed. The main aim of this investigation is to make LULC maps of the study region to assess the nature and degree of land use/land cover changes of past 18 years, and also to examine whether the LULC changes are gradual or not, and to validate the study by accuracy assessment to discover how well the classification system was attempted.

Materials and methodology

Study area

Coimbatore is the third most significant urban area and placed in the western piece of Tamil Nadu state, close by line of Kerala state. The study area of Noyyal watershed is starting from Vellingiri hills in the Western Ghats of Coimbatore district and is a seasonal river. Entering the Cauvery River at Noyyal village, the watershed flows through the districts of Coimbatore, Tiruppur, Erode, and Karur. The amount of waste released into waterways is extremely high in the study area due to population growth, urbanization, and industrialization. It approximately lies between 10° 56′ 20″ to 11° 19′ 12″ Northern latitude, and 76° 41′ 28″ to

77° 56′ 48″ Eastern longitude. The maximum of every 3 km people depend on watershed for irrigation, drinking, and other activities, and it flows over a distance of 175 km. The overall catchment area of the river is 2, 58,834 ha. The minimum temperature is ranging between 17.3 and 24.4° C, and maximum temperature is 29.1 to 36.6° C. There are five soil types in the investigation area like red soil, gray soil, alluvial soil, colluvial soil, and forest soil (Soil Survey and Land Use Organization, 2002). Figure 1 shows the study area map.

Methods

Image processing

The digital elevation model from the prism sensor with a spatial resolution of 30 m was downloaded from ALOS (Advanced land observation satellite; http://www.eorc.jaxa.jp/ALOS/en/guide/contact.htm). The map is opened in the ArcMap v10.5 software and then the shape file of the study area is overlaid which is then exploited to extract the elevation of the study region. Landsat 7 Enhanced Thematic Mapper Plus (ETM+) of 1999, Landsat 4/5 Multispectral Scanner (MSS)/Thematic Mapper (TM) of 2008, and Landsat 8 Operational Landsat imagery (OLI) of 2017 were used for this study. Based on the remote sensing (RS) and geographical information system (GIS) techniques, we were using the software's like ERDAS 10.2 and ArcGIS 10.5 for processing the image. United States Geological Survey (USGS) website (https://earthexplorer.usgs.gov/) is an open-source website where all the Landsat images of this study is downloaded. The satellite images were geocoded into the universal transverse mercator (UTM) coordinate system zone 43 N, and Google Earth was also used for ground truthing. The satellite data that were obtained from Landsat sensors has an 18 years of temporal extent and substantial spectral resolution.

Data interpretation

Land cover classification

The Landsat 7 (ETM +), Landsat 4/5 (MSS/TM) of 2008, and Landsat 8 (OLI) were layers stacked in ERDAS software. In this study, unsupervised classification was carried out by using ERDAS software. Iterative Self- Organizing Data Analysis Technique (ISODATA) is the algorithm used to perform unsupervised classification for LULC. The user inputs number of clusters required and confidence

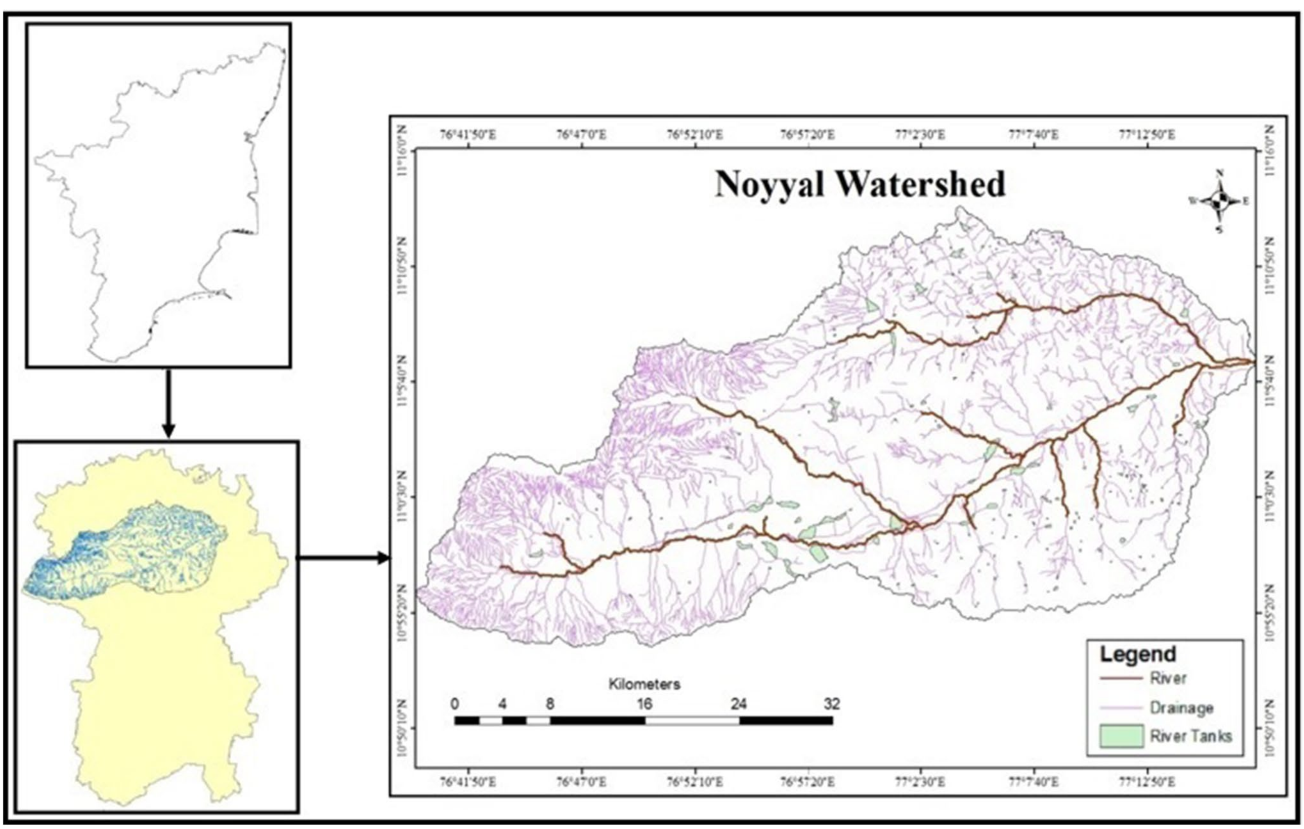

Fig. 1 Study area map of Noyyal watershed in Coimbatore district

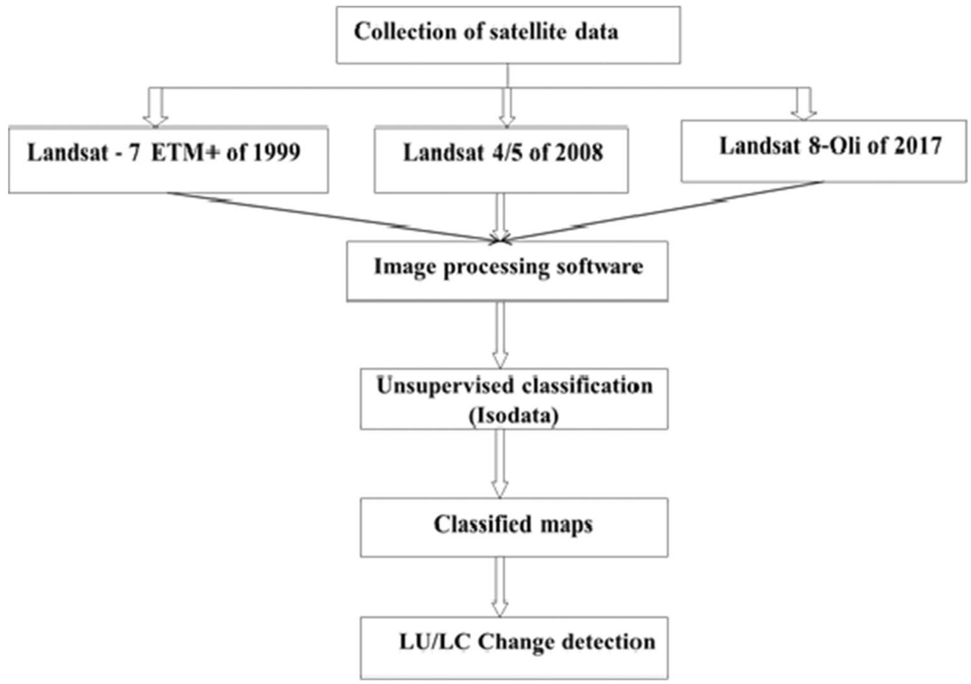

Fig. 2 Flow chart of unsupervised classification of change detection

threshold in the algorithm. The software creates clustered iteratively, which denotes that each one new iteration the clusters turn into more advanced, and once the confidence level is attained, iteration will be stopped. After the clusters are built, select the land cover classes such as water bodies, agricultural land, and forest, then each cluster is allotted for suitable class. The image of the cluster can be finalized into a layer which shows each land cover class with a different color once all clusters have been allocated to a class. LULC categories, for example, water bodies, barren, rocky, evergreen forest, deciduous forest, sandy land, agricultural land, barren land, settlements, and shifting cultivation were identified and classified for the years 1999, 2008, and 2017 as in Fig. 2.

Field survey and accuracy assessment

Along with the remote sensing work, field work was also performed to verify the ground of the area using the Global Positioning System (GPS). Field collection or field verification is the ideal method for baseline data collection. GPS is used to discover predefined reference locations. After data collection, a geospatial analysis was performed using ArcMap to compare the results of the two. The accuracy was detected by calculating the data extraction error matrix. The error matrix consists of an $n \times n$ part, where n is the number of classes in the data. The column containing the reference data indicates that the data is determined to be true. The rows are made up of mapping layers generated from the plan layers generated from remote sensing data. The error matrix is allocated to determine a range of precision measurements from the data. In this study, overall accuracy is used to measure thematic accuracy.

The overall accuracy is normally communicated as a percent, with 100% precision being an ideal classification where all reference sites were classified effectively (Zhu and Woodcock, 2014; Mishra et al. 2020). The elements present diagonal in the error matrix were the elements classified correctly. For calculating the overall accuracy, the number of correctly classified sites of water bodies, barren rocky, evergreen forest, deciduous forest, sandy land, agricultural land, barren land, settlements, and shifting cultivation is added and then it is divided by the total number of reference sites. In this investigation, Kappa statistical analysis was also done. The kappa analysis is utilized to control just those occurrences that may have been effectively grouped by some coincidence. This can be determined utilizing both the observed (total) accuracy and the random accuracy. Kappa statistics were calculated by using the following formula (1)

$$\text{Kappa coefficient} = (n * \Sigma Xii) - \Sigma(Xi+ * X+i)n^2 - \Sigma(Xi+ * X+i) \quad (1)$$

where

Σ	across all rows in matrix
Xii	diagonal
$Xi+$	total marginal row (row i)
$X+i$	total marginal column (column i)

n # of observations

Result and discussion

Land use/land cover (LULC) map for the years 1999, 2008, and 2017 were created (Figs. 3, 4 and 5). LULC categories such as water bodies, barren rocky, evergreen forest, deciduous forest, sandy land, agricultural land, barren land, settlements, and shifting cultivation were identified and classified for the years 1999, 2008, and 2017. LULC detection during 1999, 2008, and 2017 was shown in Table 1. Change detection during 1999, 2008, and 2017 is given in Fig. 6. The settlements were increased from 15.59 to 27.14% due to the increase in population. This value showed that extreme land cover change in the build-up area applies an extreme power for non-built-up surfaces, particularly agricultural lands. Advancement of the fast-building destinations of private units, business and modern units, street organizations, road networks and pavements, and relaxation units all joined together prompted the continuous development of built-up surfaces in the various corners of the city. Compared to 1999, the agricultural land, deciduous forest, and evergreen forest were decreased in 2017.

The urban development influences the environment, whichever positively or negatively. The negative effect on the environment is always due to unchecked urban development. Both developing and developed countries have parallel environmental problems related to urban development. The rapid activities like construction of buildings, associated road and pavement construction, and parking areas for the city plane increase as regular basis because of metropolitan settlements. The change from the natural landscape to a metropolitan territory is a lasting and irreversible interaction, which alters land's original state. Once urban land development increases, it will cause valuable habitat loss. The important environmental effects of urbanization are deforestation and habitat loss.

Water bodies

The water body group contains surface waters like lakes, ponds, drains, and canals. The total area covered by water

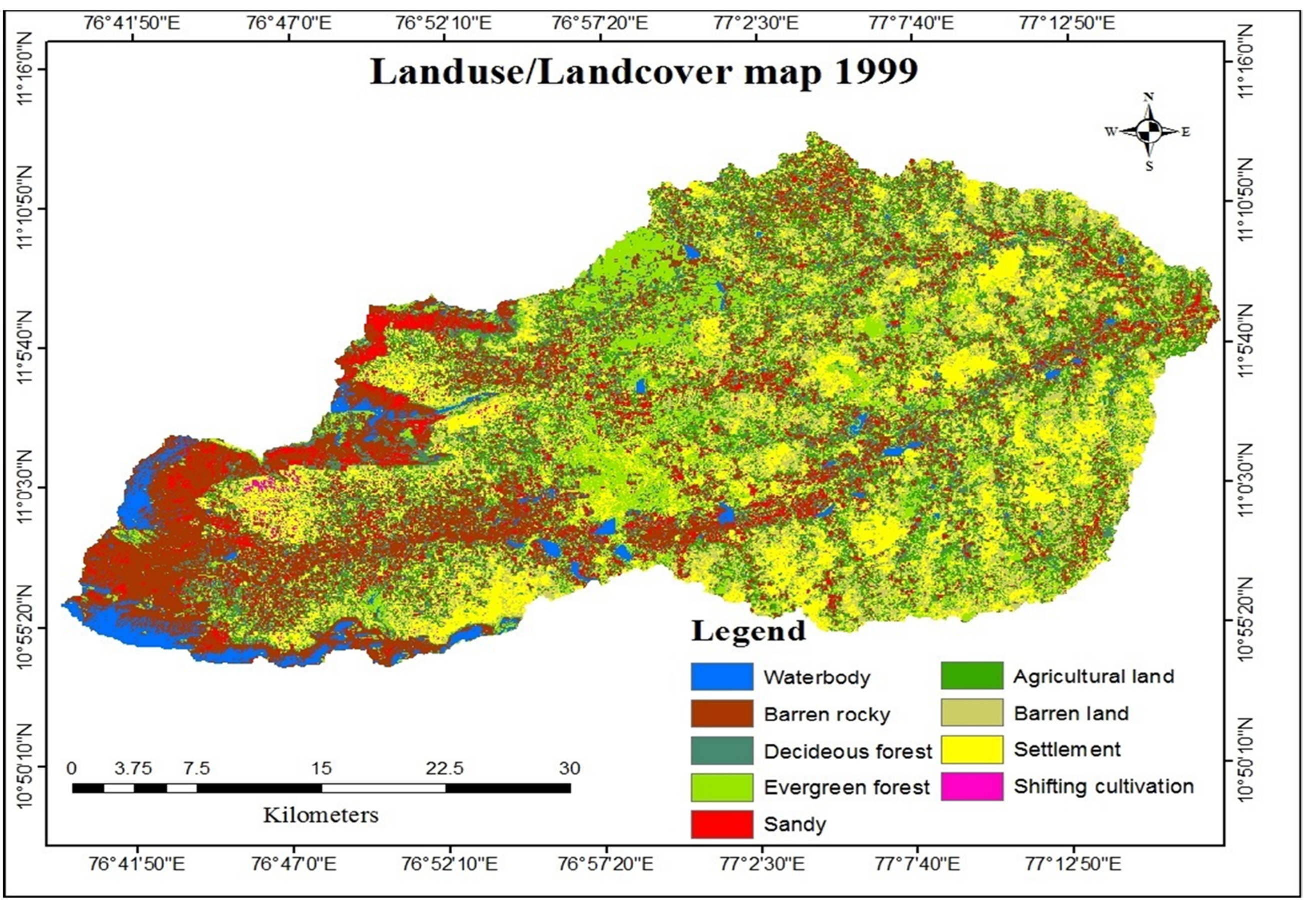

Fig. 3 Land use/land cover map of 1999

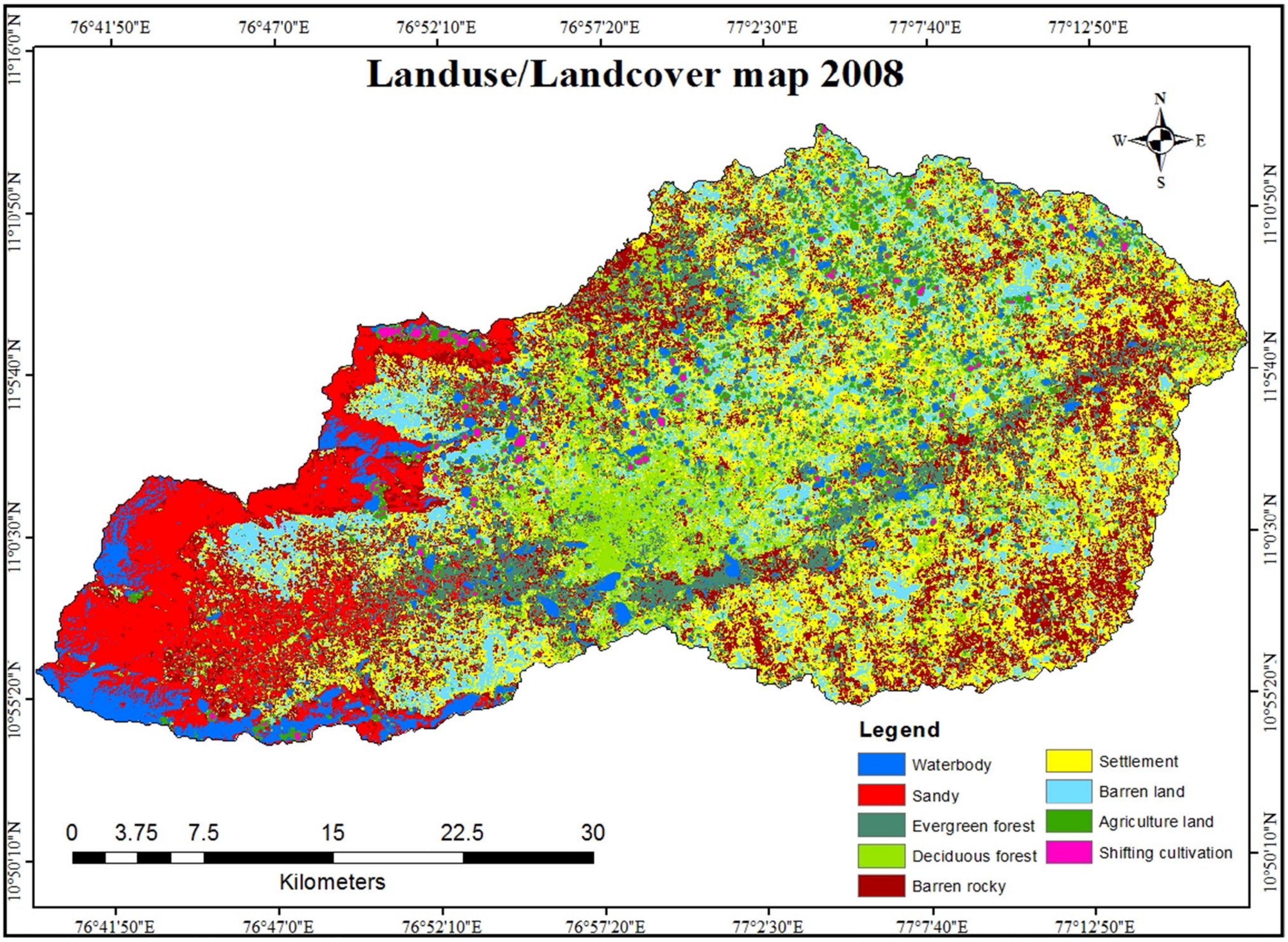

Fig. 4 Land use/land cover map of 2008

bodies in 1999 was 51.99 square kilometers (sq.km). This comprises 3.43% of the total area. Due to the adequate drought faced by people, most of the people are now aware of water conservation and artificial rain water harvesting methods; the water bodies increased from the last 18 years. An area of 79.44 sq.km was covered with water bodies in 2008, which comprises 5.25% of the total area. There is a seasonal lake in Perur and Pachapalayam, and it was overflowed in 2008, and almost all the water bodies were overflowing in the year of 2008 due to heavy rainfall.

Compared to 2017, the area covered by water bodies in 2008 was high. Perur, Singanallur, Periyakulam, Ukkadam, Sulur, Narasampathi, Kurichikulam, Krishnampathy, Selvampathy, and Kumaraswami lakes are the main water bodies in the study area. In 2017, 73.70 sq.km of the area was covered with water bodies, which comprises 4.87% of the total area. Some of the small water bodies located at Karugampalayam, Kulathur, Thenmanallur, and Thoppampattipirivu were disappeared in 2017, due to less rainfall. The study carried out to compare LULC of 1990 and 2000 showed that the percentage of water body was decreased only 1%. Due to the adequate awareness programs among people, schools and colleges, and artificial water storages, such as swimming pools, created in luxury villas and apartments, the percentage of water bodies increased from 3.43 to 4.87%. The rate of change of water bodies was observed as 21.71 sq.km.

Barren rocky

It is a bare uncovered land without vegetation, and the rough texture with thin soil, sand, and rocks. Barren rocky land in 1999 was 195.63 sq.km that is 12.92% of the total area and that of 2008 was 157.03 sq.km that is 10.38% of the total area. Chinnakodangipalayam, Kakapalayam, Theerthampalayam, Pothiyampalayam, Machampalayam, Mallegoundenpalayam, Salair, Podanur, Chettipalayam, Kallpalayam, Edayarpalayam, Periyakuiali, and Chinnakuilai were the main barren rocks in the study area during 1999 and 2008. But in 2017, many of the places transformed into settlements and industrial estates. In Pothiyampalayam, Podanur, Chettipalayam, Kallapalayam, and

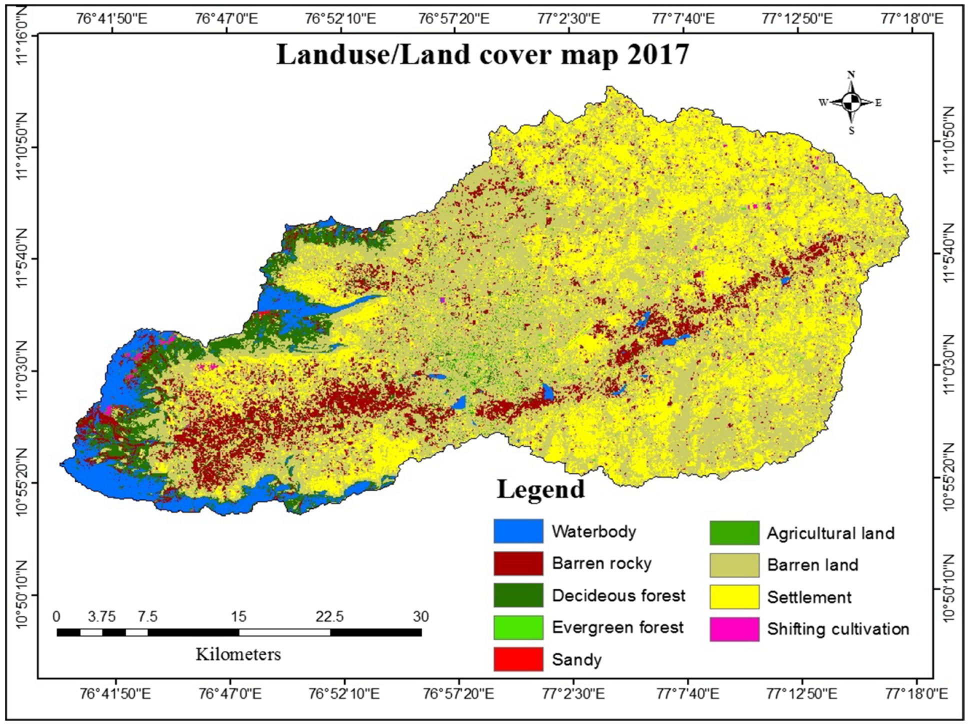

Fig. 5 Land use/land cover map of 2017

Table 1 Land use/land cover change detection during 1999, 2008, and 2017

Year	1999		2008		2017		Change during 1999 to 2017
Classification	Area (Km^2)	Percentage (%)	Area (Km^2)	Percentage (%)	Area (Km^2)	Percentage (%)	Area (Km^2)
Water body	51.99	3.43	79.44	5.25	73.703	4.87	−21.71
Barren rocky	195.63	12.92	157.03	10.38	135.825	8.98	59.81
Evergreen forest	166.24	10.98	177.07	11.70	5.711	0.38	90.61
Deciduous forest	177.29	11.71	186.82	12.35	86.685	5.73	160.53
Sandy	149.48	9.87	288.78	19.09	9.409	0.62	140.08
Agricultural land	270.15	17.85	366.38	24.21	13.139	0.87	257.01
Barren land	261.31	17.27	199.67	13.20	770.633	50.93	−509.31
Settlement	235.95	15.59	47.17	3.12	410.651	27.14	−174.70
Shifting cultivation	5.005	0.33	10.75	0.71	7.295	0.48	2.29

Chinnakuilai, the number of industrial estates was very high, and most of the areas were occupied by several companies for their industrial activities. The low population density, illiteracy, and lack of sufficient waste disposal space were the primary reasons for locating industrial estates in these areas. In 2017, the barren rocky areas covered 135.82 sq.km, accounting for 8.98% of the total area. The change ranges between 1999 and 2017 was 59.81 sq.km. Due to industrialization and urbanization, barren rocky lands were depleted by human beings.

Evergreen forest

Multi-storeyed forests with a number of mature trees in the upper canopy were presented in this area. There was mainly one reserve forest in the study area, which was Thadagam reserve forest. In 1999, the lands covered by evergreen forest

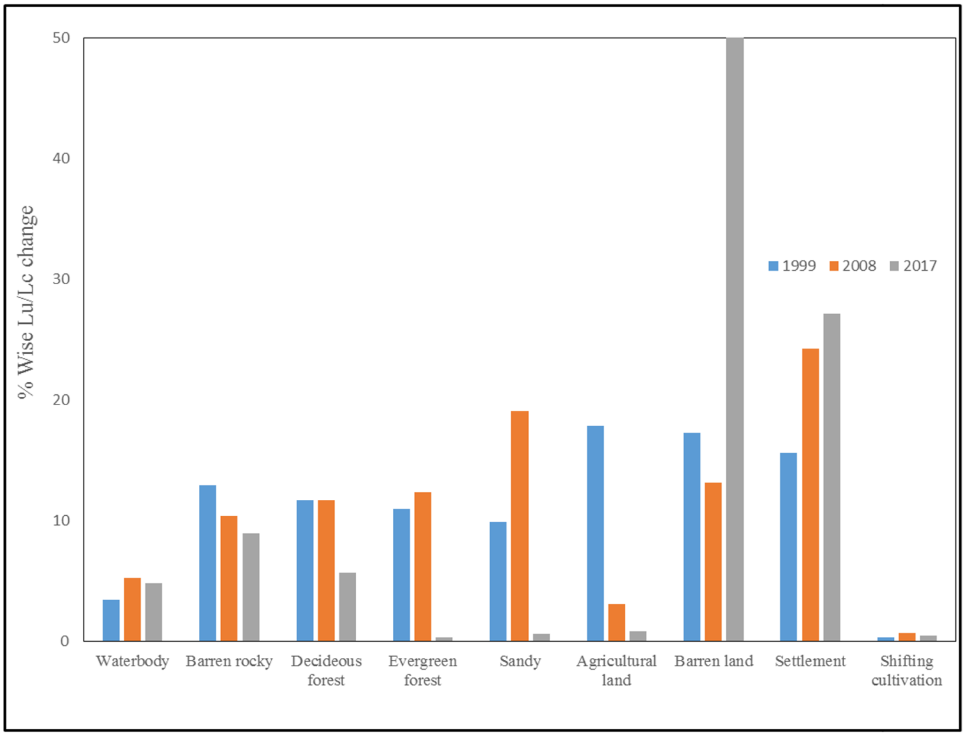

Fig. 6 Land use/land cover change detection 1999, 2008, and 2017

were 166.24 sq.km, which comprises 10.98% of the total area, and 177.07 sq.km, which comprises 11.70% in 2008. Alanthurai, Anaikatti south, Booluvampatti, and Thadagam reserve forest were the main evergreen forest present in 2008. In 2017, the area of evergreen forest was reduced to 5.711 sq.km that is 0.38%. Bombay Nagar, a settlement patch with continuous strips of building was created in the dingle of Thadagam. The size of built-up area in and around Bombay Nagar was increased from the last 10 years. Due to the population growth and anthropogenic activities, the change rate between 1999 and 2017 was 90.61 sq.km. In Mathvarayapuram and Iruttupallam, the forest become patches, and the rate of deforestation and encroachment was very high. Patches of land were devoid of vegetation and design as plots for sale.

Deciduous forest

Deciduous forest covers are less dense forests and shed their leaves during the dry season. The deciduous forest Noyyal watershed was decreased dramatically. In 1999, the deciduous forest cover was 177.29 sq.km (11.71%) of the total area. It is increased to 186.82 sq.km, (12.35%) in 2008. Villupuram, Seengapathi, Thadagam reserve forest, and Pooluvappatti, were the main deciduous forests in the study area in 2008. In 2017, the area was decreased to 86.685 sq.km (5.73%). Vadivelampalayam, Molapalyam, and Mugasimangalam connected forest of Pooluvappatti were transformed in to build up area. Singampathi and Sadivayal connected to the Seengapathi forest area also occupied by several land promoters and converted the land into apartments and avenues. 160.53 sq.km was the rate of change of deciduous forest between 1999 and 2017 which is in agreement with the findings of Koneti et al. (2018).

Sandy

Sandy land includes reddish yellow sand patches. Sandy land in 1999 was 149.48 sq.km. (9.8%) of the total area. In 2008, it was 288.78 sq.km (19.09%) of the total area. Due to build-up, transportation, and other anthropogenic activities, the sandy land reduced to 9.40 sq.km, in 2017, (0.62%) of the total area. Thenkarai, Kuppanur, Veerapandipudur, Chinnathadagam, Nanjundapuram, Dhaliyur, Kempanur, Mankarai, and Madathur were the main sandy regions in the study area. Among these sandy areas, Dhaliyur, Kempanur, and Mankarai were converted to settlements, roads, and other commercial and industrial units. The rate of change of sandy land during 1999 and 2017 was 140.08 sq.km.

Agricultural land

This class includes cropland, plantations, and aquaculture. The rate of change in agricultural land during 1999 and 2017 was very high due to the increase of white-collar jobs and development of technologies and urbanization, and the agricultural practices in Noyyal watershed decreased dramatically. 270.15-sq.km agricultural land was present in 1999 that is 17.8%. 47.17 sq.km was reduced in 2008 (3.12%) of the total area and that of 2017 was 13.139 sq.km, (0.87%) of the total area. Narasampathi, Athuppagoundenpudur, PN Pudur, Thondamuthur, Thenmanallur, Kondayampalayam, Semmedu, Vellamadai, Keeranatham, Athipalayam, Idigarai, Thekkupalayam, Ichinnaputhur, and Irugur were the major areas with agricultural land. Among these places, five places such as Athipalayam, Thekkupalayam, Keeranathan, Idigarai, and Ichinnaputhur, the number of residential units increased and that dramatically decreased the agricultural lands. The rate of change of agricultural land was 257.01 sq.km during 2000 to 2009.

Barren land

Barren land includes open pit mines, quarries and gravel pits, transition zones, and mixed barren land. The barren land in 1999 was 261.31 sq.km (17.2%) of the total area and was 199.67 sq.km (13.20%) in 2008. Karadimadai, Vellimalaipattinam, Kempanur, Achanpalayam, and Kakapalayam were the barren lands in 2008. In 2017, the area of barren land was 770.63 sq.km (50.93%) of the total area. Sooripalayam, Mangalam, Pudupalayam, Kurukkapalayam, Anandhapuram, Segudanthalai, Naduvempalayam, Ichipatti, Sukkampalayam, Arakulam, Idayarpalayam, and Nadupalayam were the newly created barren lands by human beings in 2017. These barren lands were created for the establishment of commercial and industrial units. The rate of change of barren land during 1999 and 2017 was 509.31 sq.km. Due to mining activities, quarries, and deforestation, the total area of barren land is increasing day by day. Between 2000 and 2009, the area of barren land in and around the Coimbatore district of Tamil Nādu expanded from 132.8 to 148.9 sq.km. There are no mining operations in this study, but there are quarries and deforestation in the amount of barren land.

Settlements

A settlement includes urban and rural settlements, transportation, communication, and recreational utilities. In 1999, the settlements of Noyyal watershed were 235.95 sq.km (15.59%) of the total area and that of 2008 was 366.38 (sq. km), i.e., 24.21% of the total area. It was increased to 410.65 sq.km (27.14%) of the total area in 2017. The rate of change of settlements during 1999 and 2017 was 174.70 sq.km. The main areas where buildings apartments, avenues, gardens, and villas were increased day by day in, Sarkar samakulam, Kuppakonampudur, Lakshminagar, Vedapatti, Aishwarya nagar, Kurudampalayam, Bombay nagar, Vinayagapuram, Visuvasapuram, Thoppampattipirivu, Uppilipalayam, PN palayam, Ramasamy nagar, Selvapuram, Sundakkamuthur, Perumal nagar, RS puram, Perur, Sulthanpettai, Somanur, Sulur, and Selvarajapuram. For these areas, the rate of construction of building was very high in and around Chettipalayam. Settlements expanded from 24.3 to 29.2 sq.km between 2000 and 2009, according to this analysis. The rate of change between 2000 and 2009 was 4.9 sq.km. Between 1990 and 2000, the settlements of Coimbatore grew in this study. The settlements increased from 112.16 to 633.02 sq.km. In this study, the settlements of study area increased between 1990 and 2000. The settlements grow up from 112.16 to 633.02 sq.km. Based on these and other examine, it is obvious that the pace of expansion in settlements, construction, transportation, and human activities in the Noyyal watershed is quite high (Geetha Selvarani et al. 2017).

Shifting cultivation

Agricultural system, in which plots of land are temporarily cultivated, then left fallow and allowed to get back to their natural vegetation. The rate of shifting cultivation in 1999 and 2017 was 2.29 km^2, the area of shifting cultivation in 1999 was 5005 km^2, and accounting for 0.33% of the total area, and in 2008 was 10.75 km^2, equivalent to 0.71%. Nanjundapuram, Therkupalayam, Vellamadai, Valiyampalayam, and Idigarai are the main shifting cultivation areas in the study area. In 2017, the area of shifting cultivation was 7.29 km^2, accounting for 0.48% of the total area.

Land use land cover change detection during 1999 and 2017

The result of this study indicates that a significant amount of changes has occurred in the watershed since 1999, and that has an effect on the area's ecosystem and human livelihoods. Due to population growth, industrialization, urbanization, and anthropogenic activities, the land use land cover pattern of Noyyal watershed changed dramatically from 1999 to 2017. Kaswanto et al. (2010) also found that population growth had an important effect on land use changes. During the last 18 years, the rate of deforestation and the number of settlements and barren land were increased dramatically. Industrialization and urbanization lead to poor agricultural practices in and around Coimbatore. These LULC changes have a significant role in the changing climatic condition of Coimbatore. Last 18 years, the temperature rate increased, rate of rainfall decreased, and scarcity of water increased.

The percentage of barren land and settlements was very high in 2017 while compared to 1999 and 2008. The total percentage of barren land was 17.2 in 1999 and that of 2017 was 50.93%. Demolition process was very high during the past 18 years, for the construction of new buildings, roadways, and recreational places. This is the main reason for the increased percentage of barren land. Karadimadai, Vellimalaipattinam, Kempanur, Achanpalayam, Kakapalayam,

Table 2 Rating criteria of Kappa statistics

Kappa statistics	Strength of agreement
< 0.00	Poor
0.00–0.20	Slight
0.21–0.40	Fair
0.41–0.60	Moderate
0.61–0.80	Substantial
0.81–1.00	Almost perfect

Sooripalayam, Mangalam, Pudupalayam, Kurukkapalayam, Anandhapuram, Segudanthalai, Naduvempalayam, Ichipatti, Sukkumpalayam, Arakulam, Idayarpalayam, and Nadupalayam were the main barren lands in the study area in 2017. The total percentage of settlements was 15.59% in 1999 and that of 2017 was 27.14%.

The major areas where buildings were increasing day by day are Sarkar samakulam, Kuppakonampudur, Lakshmi Nagar, Vedapatti, Aishwarya Nagar, Kurudampalayam, Bombay Nagar, Vinayagapuram, Visuvasapuram, Thoppampatti Pirivu, Uppilipalayam, PN Palayam, Ramasamy nagar, Selvapuram, Sundakkamuthur, Perumal nagar, RS puram, Perur, Sulthanpettai, Somanur, Sulur, and Selvarajapuram. Beyond these areas, the rate of construction of building was very high in and around Chettipalayam. This confirms to the results of due to the increase of white-collar jobs, the agricultural practices in Noyyal watershed were decreased from 17.8 to 0.868%. The rate of deforestation is also very high in Noyyal watershed. The total forest cover in 1999 was 22.69% and that of 2017 was 6.09%. These results specify that the deforestation rate is very high in and around study area especially in Vadivelampalayam, Mugasimangalam, Singampathi, Mathvarayapuram, Sadivayal, and Iruttupallam; and that is the great environmental impact of industrialization, urbanization, and growth of population. The overall LULCC in 1999 to 2017 was given in Fig. 6.

Kappa accuracy assessment

The Kappa accuracy assessment technique was chosen to evaluate the accuracy of the 2017 classified maps (Table 2). Landsat 8-OLI 2017 was used to evaluate accuracy; a total of 332 field reference sites were used to verify the type of land cover. Three hundred thirty-two randomized stratified points in each class were created (Table 3). LULC maps created from satellite images for study area consist of nine thematic land cover classes such as water bodies, barren, rocky, evergreen forest, deciduous forest, sandy land, agricultural land, barren land, settlements, and shifting cultivation. Outside of these reference locations are water (48), barren rocky (28), evergreen forest (42), deciduous forest

Table 3 Accuracy assessment error matrix of classified image

Classified data	Water body	Barren rocky	Evergreen forest	Deciduous forest	Sandy land	Agricultural land	Barren land	Settlements	Shifting cultivation	Classified total
Water body	39	1	2	0	1	3	3	0	2	51
Barren rocky	2	20	2	1	2	1	1	2	0	31
Evergreen forest	2	0	31	0	1	2	4	1	0	41
Deciduous forest	0	1	3	23	0	0	0	1	1	29
Sandy land	0	2	1	0	34	1	0	0	3	41
Agricultural land	2	2	1	0	0	22	2	1	2	32
Barren land	1	1	0	4	2	0	28	3	0	39
Settlements	0	0	1	3	2	3	2	27	1	39
Shifting cultivation	2	1	1	1	1	0	3	1	19	29
Reference total	48	28	42	32	43	32	43	36	28	332

(32), sandy land (43), agricultural land (32), barren land (28), settlements (27), and shifting cultivation (28). These reference sites were then compared to classify results created from the satellite images.

The diagonal elements highlighted in yellow on the error matrix represent the areas that were properly classified. These are an indication of the precision of the classification. In the study, only 39 of the 48 water reference sites were adequately identified in classified imagery. Likewise, out of the 28 barren rock reference sites, 20 were exactly recognized; out of the 42 evergreen forest reference sites, 31 were precisely observed; out of the 32 deciduous forest reference sites, 23 were strongly presented; out of the 43 sandy land reference sites, 34 were truly received; out of the 32 agricultural land reference sites, 22 were properly known; out of the 43 barren land reference sites, 28 were accurately identified; out of the 36 settlement reference sites, 27 were exactly noticed; and out of the 28 shifting cultivation reference sites, 19 were precisely recognized. The off-diagonal components of an error matrix represent areas that have not been properly classified. The off-diagonal elements tell us more about how we can improve our classification of remote sensing. Time is required to review these errors to identify where the most common errors occurred in the classification. The overall accuracy is calculated by summing the number of correctly classified sites and dividing them by the total number of reference sites. This study is 73.19% accurate overall.

The overall Kappa coefficient was generated from a statistical analysis to estimate the accuracy of classification. The overall method used for accuracy assessment is a comparative method which is analyzing the checking points with the classified image for all the land cover classes. For this analysis, it is very important to calculate how fit the classification studied as evaluated to randomly assign values that determine the agreement between two ranges—positive or negative. The Kappa coefficient ranges between − 1 and + 1. The value of 0 was found to be significantly less than a random classification. The negative values indicate that the classification is considerably lower than the random quality. The positive value near 1 is observed; the classification is considerably better than random. The overall Kappa coefficient of the present study was observed the value of 0.72. Based on the evaluation criteria of Kappa statistics, this study has proven substantial strength of agreement for the map of 2017.

Conclusion

The study was carried out in the Noyyal watershed in the Coimbatore region. The study concluded that remote sensing data associated with geographic information systems (GIS) can be a valuable tool for mapping and evaluating LULCC in a specific area. During the investigation period from 1999 to 2017, there were several remarkable observations of substantial changes in LULC. Settlements, forest cover, barren land, and agricultural land all showed significant changes, according to the analysis. Water bodies, barren land, settlements, and shifting cultivation exhibited a growing pattern, whereas barren land, rocky, forest cover, agricultural land, and sandy terrain showed a declining tendency. The progressions in the pattern of agricultural activity and extended action of urbanization are ascribed to this area as the causes. During the last 18 years, demolition for the construction of new buildings, streets, and recreational areas has been at an all-time high.

In 1999, the entire percentage of the settlement was 15.59%, whereas in 2017, it was 27.14%. In overall, the LULC data collected in the study area from 1999 to 2017 revealed some substantial changes that may or may not have been caused by the environment. However, these characteristics should be carefully examined for the environment's long-term viability. The study's overall accuracy is 73.19%, while the current study's Kappa coefficient is 0.72. Based on the Kappa statistical evaluation standards, this research found considerable strength of agreement for the 2017 map. The study suggests that it will be extremely beneficial to the general public as well as future environmental best practices.

Author contribution SK identified and specified, compares the theoretical, computational and GIS models, work designs. TA carried out the study performance of an implemented project system, methodology, and GIS. SK implemented a designed work system for the study and assisted the GIS work. MK specified in theoretical and coordinated and implements.

Data availability For this study we used the real-time datasets with the help of USGS.

Declarations

Ethics approval There is no conflict of interest, the author has a close relationship with entire manuscript, and ethical approval is not applicable to this research.

Consent to participate The authors have consented to the submission of the case report to the journal.

Consent for publication I give my consent for the publication of identifiable details, which can include details within the text to be published in the above Journal and Article. Therefore, anyone can read material published in the Journal.

Competing interests The authors declare no competing interests.

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