RETRACTED ARTICLES: Multi-temporal image analysis for LULC classification and change detection

GN Vivekananda*, R Swathi and AVLN Sujithc

*Department of CSE, Madanapalle Institute of Technology & Science, Madanapalle, AP, India; †Department of CSE, S V College of Engineering, Tirupati, AP, India; ‡Department of CSE, Gates Institute of Technology, Anantapur, AP, India

ABSTRACT

Land use/Land cover (LULC) plays a vital role in planning and supervising the utilization of the natural resources based on the gradual increase in the human demands in the current ecosystem. This study mainly focuses on the usage of the geographic information system (GIS) and land usage to identify the changes in Ananthapuramu, which is located in the Ananthapur district of Andhra Pradesh (AP) state, South India. This paper mainly focuses on the classification and identification of the changes in LULC in the period of 1999–2019 based on a survey of India’s topographic map and temporal images gathered from the satellite. The experimental results indicate that over the specified period of study, the rate of increment and decrement in the built-up area, rate of underwater bodies, forest bodies that may demonstrate a significant impact on the environmental ecosystem.

Introduction

Land use/land cover (LULC) changes play an essential role in the studies of regional, local and global environmental change (Gupta & Munshi, 1985; Mas, 1999). Land cover refers to how the Earth’s surface is covered by forests, wetlands, impervious surfaces, agricultural, and other types of land and water (Prakasam, 2010). Land use refers to how humans use the landscape, whether for development, conservation, or mixed uses. Land use includes recreation areas, wildlife habitats, agricultural land, and built-up land (Reis, 2008). Since the past 100 years, the human population and its influence have increased exponentially on land. Human alterations on the Earth’s surface result in changes in the land cover. These changes significantly affect key aspects of Earth system functioning (including the balance of energy, water, and soil). Moreover, the pressure on limited natural resources, which is caused by an increase in population, contributes to changes in the land surface cover (Islam et al., 2018).

There exist numerous sources of LULC changes (Lambin et al., 2001) described forest degradation, agricultural magnification, globalization, and urbanization as the leading causes for regional and global LULC changes. Biophysical attributes, the global climate, and ecosystem activities are associated with significant changes in the land cover (Aansen et al., 2014). (Kaliraj et al., 2017) indicated the necessary information required for understanding the trends in LULC changes in a coastal area. Changes in the LULC are dynamic and continuous. Updated and accurate LULC maps are of considerable significance for proper planning, global change, environment monitoring, and the estimation of forest degradation. Reports related to changes in the LULC play a vital role in the utilization and management of natural resources.

Recently, multispectral and multi-temporal high-and medium-spatial-resolution satellite data have emerged as essential tools for estimating aspects such as the vegetation cover, forest degradation, and urban expansion (Mustafa et al., 2007). Remote sensing and GIS technology provide a platform for studying landscape transformations throughout the surface of the Earth (Estoque & Murayama, 2015). In conventional methods, mapping is performed using available records, field surveys, and maps. Thus, conventional methods are time-consuming and expensive. Moreover, the produced maps become quickly outdated in rapidly changing environments (Dash et al., 2015). In contrast to traditional data acquisition, remotely sensed data provides valuable information in a relatively short time and cost-effective manner. High-resolution satellite imagery or aerial photos are important for studying the LULC changes in large cities. However, such data sets are limitedly available due to financial factors (Dwivedi et al., 2005; Gadrani et al., 2018). However, medium-resolution data, such as the Multi-Spectral Scanner (MSS), TM, and Operational Land Imager (OLI) Landsat data sets, have been used worldwide for LULC change detection analysis (Chandrashekar et al., 2018; Sundarakumar et al., 2012). (Wang et al., 2009) used Landsat TM data to assess the changes in the urban land, bare soil, land under water bodies, and land covered by vegetation in China. (Ondini et al., 2012) used...
Landsat TM data to monitor the LULC changes in Port Elizabeth, South Africa, between 1990 and 2000. Landsat data sets can be obtained free of cost from the United States Geological Survey (USGS) Earth Explorer (http://earthexplorer.usgs.gov) online portal.

Currently, numerous techniques are available for assessing and detecting LULC changes. Among them, remote sensing technology and GIS provide robust tools for acquiring accurate and timely information on land use patterns and their changes (Arveti et al., 2016; Mamun et al., 2013). Remote sensing applications allow land changes to be studied within a limited time and at a low cost. Numerous methods have been developed by many researchers to review changes in the LULC (Jwan Al-doski, 2013; Singh, 1989) including multi-temporal composite image change detection (Carmelo et al., 2012; Eastman & Fulk, 1993), on-screen digitization of change (Sreedhar et al., 2016), vegetation index differencing (Shanmugam & Rajagopalan, 2013), and post-classification change detection (Belal & Moghamm, 2011; Courage et al., 2013; Kafi et al., 2014).

The main contribution of this article is to quantitatively analyse the LULC in Ananthapuramu and its surrounding area from 1978 to 2019 by using multi-temporal Landsat imagery. The main intention of this study is to determine the urbanization pressure and changes within the environment. Even though several studies had contributed pertaining towards LULC detection this study made use of integrated remote sensing and GIS techniques to detect LULC changes in the study area. Application of the Quantum inspired image processing in urban surveillance is considered as a vital aspect in the context of analyzing huge image data.

**Study area**

In this research, the LULC changes in the urban and rural parts of Ananthapuramu were determined using remote sensing and GIS technology. The study area is located in the south eastern part of Andhra Pradesh state and the north eastern part of Ananthapur district. Ananthapuramu is considered as one of the major districts in rayalaseema region and its geographical location based on GIS is located at 78° 30’ and 76° 60’ East; 15° 15’ and 13° 40’ North. It is surrounded by chittoor and kadapa at the east, Kurnool and Bellary on the north, chitradurga and thumkur at the west and kolar at the south. The geographical area of the ananthapur district contributes around 7% of area in the state of Andhra Pradesh with an area of around 19,130 sq. km. In is considered as one among the biggest district in Andhra Pradesh that includes around 11 towns and 972 villages.

Based on its topographical details the district is classified in to three natural regions that include red soils at the southern region, enormous expanse of arid along with the treeless poor red soil at the central region, black cotton soils at the northern region. The major rivers that surpasses through the district include pennar river and chitravathi that are originated from the state of Karnataka. Ananthapur district includes two distinct geological formations, of those the initial one is sedimentary rocks in the eastern part of Tadipatri and archaean rocks at the northern part of Gooty. Later parts of anantapur mostly include gneisses and granites along with the minerals like barites, limestone and diamonds of gem quality. In a generic perspective red and black soils constitute around 76% and 24% of the geographical area respectively. The geographical area of the forest is around 10.3% of the total area with undulating and hilly topography. The climate of this area is categorized as semi-arid [19]. The study area experiences a maximum temperature of 33°C–45°C in the summer (April–May) and minimum temperature of 15°C in the winter (December–January). It receives rainfall due to the...
southwest monsoon (June–September) as well as the northeast monsoon (November–December). Table 1 indicates LULC pattern of the anantapur district from 1951 to 1978.

**Methodology**

This study specifically focused on interpreting the changes in the land use through satellite imagery and demographic data. The quantitative method of change detection was used in this research. In the change detection method, each satellite image is classified. The resulting LULC maps obtained after the classification are then compared according to the pixel-by-pixel approach by using a change detection matrix. The methodology adopted in this study is as follows: (1) data collection, (2) pre-processing, (3) LULC classification scheme, (4) selection of training data samples, (5) image classification, (6) accuracy assessment, and (7) change detection. Every step except the data collection step was performed using ERDAS Imagine 14 software and Arc Map 10.1. Figure 2 depicts the flow chart that illustrates the methodology included in this present study.

**Data collection**

The collected data were divided into ancillary and satellite data. The data were used to assess the temporal changes and develop a thematic LULC map of the study area. The auxiliary data was used for the analysis and validation of results. The ancillary data included the (1) ground reference data obtained from field surveys, (2) Toposheet No. 57 0/6, and (3) Google Earth data. The toposheet was of 1982, had a scale of 1:50,000, and was prepared by the Survey of India (SOI), Hyderabad. The sheet was converted to a digital map by using a scanner and saved in the .jpg file format (Praveen Kumar & Sreenivasula Reddy, 2013). Satellite images from 1978 and 2018 were used to assess the changes in the LULC. The 1978 satellite image of the study area covers one scene of the Landsat MSS data set (path 153 and row 5). The 2018 satellite image was obtained from path 143 and row 51 of the Landsat 8 OLI–Thermal Infrared Sensor (TIRS) data set. The Landsat data sets were downloaded free of cost from the USGS Earth Explorer online archive (freely downloadable worldwide). The Landsat MSS data set has four spectral bands (4–7) with a spatial resolution of 60 m, and the Landsat 8 OLI data set has nine spectral bands (2–7) with a spatial resolution of 30 m. These data sets were used for preparing the LULC map. The downloaded data was in the Geo tiff file format. Each image band exhibits intensity values for a certain wavelength in the form of a greyscale image of the study area. The spectral characteristics of the Landsat data are listed in Table 1. Images with cloud cover and undesired shade significantly reduce the accuracy result of classification. Therefore, good-quality and cloud-free scenes were used in this research.

Quantum GIS is an open-source framework that enables efficient collection of image data from various sources that include the vector, database and raster, which are used in the context of building a single project for seamless spatial analysis (Vivekananda and Chenna Reddy, 2018, 2019). This process enhances the capability of the data collection that meets the requirements and basic functionalities of GIS. Additionally, Quantum GIS is considered as an option for improving the features through plugins using python language which is regarded as and programmer-friendly nowadays. Application of quantum GIS leads to the efficient development of a systematic model to process multi-temporal images for LULC.

**Image subsetting and pre-processing**

Image analysis enables information to be extracted from data sets. A scanned toposheet image is not georeferenced to the surface of the Earth (Manonmani & Mary Divya Suganya, 2010). Therefore, the toposheet was georeferenced to longitudes and latitudes by using well-distributed Ground Control Points (GCPs) and projected to the Geographic (Lat/Lon) WGS 1984 datum. Finally, the study area was clipped from the georeferenced toposheet image. Satellite imagery was overlaid in one image (single layer) by using the layer stack tool of ERDAS software. Due to this process, a False Colour Composite (FCC)
image was developed (Erdas Imagine Tour Guides, 2014). Extracting the image of the study area involved three significant steps: geometric rectification, sub-setting, and enhancement. The georeferenced toposheet was used as reference data for the geometric rectification of the single-layered image. In geometric rectification, GCPs were detected in both the toposheet and satellite image (2018 photograph). The satellite image was rectified using the total Root Mean Square (RMS) error estimated below one pixel. Multi-temporal images (1978 and 2018), as shown in Figure 3(a, b), were then registered using the Auto Sync work station tool (Yuan et al., 2013). The Landsat 8 image of 2018 was considered as the reference image. Based on

Figure 2. Flowchart demonstrating the methodology followed in present study.

Figure 3. (a) FCC images of the study area 1978 Landsat MSS image. (b) FCC images of the study area 2018 Landsat OLI–TIRS image.
the reference image, the Landsat MSS image was registered and projected to the Universal Transverse Mercator (UTM) WGS 1984 datum and resampled to a resolution of 30 m by using the nearest neighborhood classification. The study area was masked and clipped from the registered multitemporal images by using the subset tool of ERDAS Imagine 14. Each subset image was enhanced using the histogram equalization technique to improve spectral responses. The 120-km² subset area of 1978 and 2018 (Figure 3) was obtained from the Landsat MSS and Landsat OLI data sets, respectively. The images of the subset area were used for subsequent analysis and image classification.

**Image classification scheme**

The USGS Level I LULC classification scheme was used in this study. The study area was broadly classified into five different classes. The detailed description of the classes is provided in Table 2. Each class was derived according to texture, tone, and color (Radhakrishnan et al., 2014). These classes were assigned to pixels in image classification.

**Selection of training data samples**

Data sets were trained using different band combinations of the satellite images, field survey data, and Google Earth data. The satellite image of the Ananthapuramu region and the Landsat 8 subset image were linked and synced using the Google Earth tool of ERDAS software. This process enabled the unique features in the study area to be recognized. Different band combinations were used to determine the color tone of a specific class. The band combination 5–4–3 was used for vegetation, forests, crops, wetlands analysis. The band combination 7–6–4 was used for analyzing the built-up land. Data sets were trained according to the tone of the pixel color. Training sites were created in the imagery by drawing polygons, which were placed in an AoI (Area of Interest) layer. To train each specific class, 15 polygons were brought and placed in the signature editor. These 15 polygons were merged and specified by a particular class name. The signature editor file was then saved as a signature file (.sig format). Two signature files were developed in this study to train the two data sets (1978 and 2018). Finally, the trained data sets were used in the supervised image classification process.

**Image classification**

Multi-temporal Landsat images of the study area were used to study and classify the land cover types. Remote sensing includes three main image classification techniques: unsupervised classification, supervised classification, and object-based image classification. The Maximum Likelihood Classifier (MLC) algorithm of supervised classification was used in this study. The MLC has been widely used for the classification of medium-resolution satellite imagery (Anil et al., 2011; Bayarsaikan et al., 2009; Brahmbhatt et al., 2000; Ratnaparkhi et al., 2016; Zubair Iqbal & Javed Iqbal, 2018). The spectral signature files developed for all the classes were used during classification.

The classification was performed using the MLC. This algorithm, according to ERDAS, computes the weighted distance \( D_w \) of an unknown vector \( X \) belonging to one of the known class “i” is based on the Bayesian equation:

\[
D_w = \ln \left( \frac{\sum_{j=1}^{c} \ln \left( \frac{p_j}{\pi_j} \right) \pi_j}{c} \right)
\]

Where \( c \) is particular class, \( \pi_j \) is Percent probability of any pixel is a member of class \( i \). The datasets obtained from Landsat are classified based on the dates in which they are received. Then, a majority filter with a 4 × 4 size kernel was applied to the classified data to minimize the salt and pepper effect (Kantakumar et al., 2016; Lillesand & Kiefer, 1999). The classified images generated after using the majority filter display the LULC types of the study area. The classified images were compared with each other to determine the variation in the LULC pattern.

In the context of Quantum inspired image processing, initially, the input image is transformed into 8 × 8 and 16 × 16 blocks, further in which a two-dimensional Discrete Cosine transformation is applied on each block. In this context, the coefficients of DCT are transmitted, coded and quantized.

**Table 2. Image classification details.**

| S. No. | Class                  | Description                                                                 |
|-------|------------------------|-----------------------------------------------------------------------------|
| 1     | Built-up               | Land covered by concrete, including low-, medium, and high-density road networks; residential, industrial, and commercial buildings; educational institutes; transportation; open-roof concrete structures; other human-made structures; and solid waste landfills. |
| 2     | Forest                 | Land characterized by relatively sparse forest vegetation.                    |
| 3     | Agriculture land       | Areas characterized by a high density of grasses, herbs, and crops, including parks and regularly tilled, planted croplands. |
| 4     | Barren land/Other lands| Areas with or without sparse vegetation that are likely to change or be converted to other users in the future. This category includes land without crops, land with barren rock, and sand areas along rivers/stream beaches. |
| 5     | Water                  | Areas covered by water, including rivers, reservoirs, ponds, lakes, and streams. |
Classification accuracy assessment

After generating the classified images, the accuracy of the classified images was determined using the ERDAS Imagine 14 software. Classification accuracy assessment is an essential step after image classification. The accuracy assessment tool of the supervised classifier randomly generated 176 and 324 reference points through stratified random sampling of the 1978 and 2018 classified images, respectively. Each point had a specific color and pixel value, which were automatically identified by the software. The classes in the classified image were considered as reference classes. Randomly generated points were then identified, and the corresponding class was assigned by the user manually. The error matrix and kappa statistics for the two classified images were generated from the self-generated report section of ERDAS Imagine 14. This process was performed for two classified images (i.e., 1978 and 2018). The error matrix indicates the accuracy of classification (Foody, 2002). The rows represent the classes resulting from the classified image, whereas the columns represent the classes identified by the user from the reference values. The diagonal cells of the error matrix indicate the total number of correctly identified pixels for each class of the reference and classified data. The off-diagonal cells represent the incorrectly identified pixels, which indicate the error between reference data and classified data. There are two types of errors, namely omission and commission error, are occurred during the classification process.

Errors of commission occurred when a classification process assigns pixels to a specific class that doesn’t belong to it. The number of pixels that are mistakenly assigned to a class was found in column cells of the class above and below the main diagonal. The Producer’s accuracy also described the number of errors of commission. For every class, errors of omission occurred when pixels that belong to one class, are included in other classes. In the confusion matrix, the number of omitted pixels was found in the row cells to the left and the right from the main diagonal. The user’s accuracy is another indicator characterizing the errors of omission. The adopted equations calculated producer’s efficiency and user’s accuracy:

\[
\text{Producer’s accuracy} = \left( \frac{x_{kk}}{x+k} \right) \times 100 \quad (2)
\]

\[
\text{User’s accuracy} = \left( \frac{x_{kk}}{x+k} \right) \times 100\% \quad (3)
\]

The overall accuracy and kappa coefficient of the two data sets were calculated using the following equations.

\[
\text{Overall accuracy} = \frac{1}{N} \sum_{k=1}^{r} n_k \quad (4)
\]

\[
\text{Kappa coefficient} = \frac{N \sum_{k=1}^{r} x_{kk} - \sum_{k=1}^{r} (x_{kk} \cdot x_{k+k})}{N^2 - \sum_{k=1}^{r} (x_{kk} \cdot x_{k+k})} \quad (5)
\]

Where \( N \) represents the total number of pixels, \( r \) represents the number of classes, \( x_{kk} \) represents the total pixels in row “k” and column “k,” \( x_{k+k} \) represents total samples in a row “k,” and \( x_{k+k} \) represents the total samples in column “k” in the error matrix.

Change detection

Remote-sensing and GIS-based change detection approaches are widely used due to their cost-effectiveness and high temporal resolution. The post-classification comparison technique, which is based on maximum likelihood supervised classification, is the most commonly used method for detecting LULC changes. A high overall classification accuracy has been achieved with this technique for a variety of data (Muttitanon & Tripathi, 2005; Torahi & Rai, 2011). The post-classification comparison technique involves classifying images and comparing the corresponding classes to determine the areas where change has occurred. In a comparative study of different techniques, the post-classification comparison technique had the highest classification accuracy. (Landsat 8 dataset, 2019; Sun & Wang, 2009; Team, 2014) used the post-classification comparison technique based on the MLC algorithm to verify the land-use changes in the Datong basin, China, through Landsat data. In this study, two registered and independently classified images were used to calculate the changes in LULC. The degree of accuracy of the results depends on the accuracy of the thematic maps prepared through image classification. The magnitude of change (C) in each class was determined using the following equation:

\[
C_i = L_i - B_i \quad (6)
\]

The percentage change (C %) in each land-use class was calculated by dividing the change in a class by the coverage area in the base year and multiplying by 100, by the simple equation.

\[
P_i = \frac{L_i - B_i}{B_i} \times 100 \quad (7)
\]

Where: \( i = \) Number of classes in an image
\( C_i = \) Magnitude of change in class “\( i \)”
\( P_i = \) Percentage of change in class “\( i \)”
\( L_i = \) Base image (1978)
\( B_i = \) Latest image (2018)
Results and discussion

The data sets of the Ananthapuramu region (Landsat MSS for 1978 and Landsat 8 OLI for 2018) were registered using the AutoSync workstation module in ERDAS IMAGINE 14. The data sets were registered by georeferencing the images with latitude and longitude values from the already georeferenced SOI toposheet of the study area. After registration, both the data sets were trained through visual interpretation. The identified classes were digitized by drawing polygons to produce signature files. In the next step, supervised classification was performed according to the signature file in ERDAS Imagine 14 for producing the LULC maps. The accuracy assessment results for the two data sets are presented in Tables 3 and 4. The area occupied by different classes in both years was obtained from the attribute table. After-image classification, the post-classification comparison technique was performed, where a LULC map from one data set (1978) was compared with a LULC map from another data set (2018). According to the comparison, the changes occurring between the two study years are presented quantitatively. After-image classification, maps were prepared on a 1:50,000 scale by using ArcMap 10.1.

LULC pattern of Ananthapuramu in 1978

The LULC map layout generated from the Landsat MSS data set is displayed in Figure 4. The land categories for the year 1978, and their statistics are listed in Table 3. According to the results, the largest category was agriculture land (47.83 km², 39.84% of the total area), followed by forest (37.66 km², 31.38% of the total area). The remaining land use categories were settlements with homestead trees (6.81 km², 5.7% of the total area), barren land/other lands (17.87 km², 14.89% of the total area), and water (9.83 km², 8.19% of the total area).

Table 3. Confusion matrix indicating the overall accuracy and Kappa statistics of the 1978 LULC map of the study area.

| Classified data          | Reference data | Water | Agriculture | Built-up | Forest | Barren land/other lands | Row total | User Accuracy (%) |
|-------------------------|----------------|-------|-------------|----------|--------|-------------------------|-----------|-------------------|
| Water bodies            | 30             | 0     | 0           | 0        | 0      | 30                      | 100       |                  |
| Agriculture land        | 5              | 28    | 3           | 3        | 5      | 41                      | 68.29     |                  |
| Built-up                | 0              | 1     | 30          | 0        | 2      | 33                      | 90.29     |                  |
| Forest                  | 3              | 3     | 0           | 29       | 0      | 35                      | 82.85     |                  |
| Barren land/other lands | 0              | 3     | 3           | 2        | 36     | 44                      | 77.77     |                  |
| Column Total            | 36             | 35    | 35          | 34       | 35     |                         |           |                  |
| Producer's accuracy (%) | 83.33          | 80    | 85.71       | 85.29    | 80     |                         |           |                  |
| Overall Classification Accuracy (%) | 82.85 |         |              |          |        |                         |           |                  |
| Overall kappa statistics | 78.5           |       |              |          |        |                         |           |                  |

LULC pattern of Ananthapuramu in 2019

The classified image for 2018 (Figure 5) was produced using the Landsat 8 data set. According to the 2018 results, the land area mainly comprised barren land/other lands (41.55 km², 34.63% of the total land), followed by settlement land (31.55 km², 26.29% of the total area). The land-use categories were forest land (18.25 km², 15.21% of the total area), agriculture land (18.25 km², 15.21% of the total area), and water bodies (2.65 km², 2.21% of the total area). The land-use categories for 2018 and their statistics are listed in Table 4. From 1978 to 2018, the LULC patterns changed considerably.

Table 4. Confusion matrix indicating the overall accuracy and Kappa statistics of the 2018 LULC map of the study area.

| Classified data          | Reference data | Agriculture | Built-up | Forest | Barren land/other lands | Row total | User Accuracy (%) |
|-------------------------|----------------|-------------|----------|--------|-------------------------|-----------|-------------------|
| Water bodies            | 63             | 1           | 0        | 0      | 1                       | 65        | 96.92             |
| Agriculture land        | 0              | 54          | 3        | 1      | 4                       | 62        | 87.09             |
| Built-up                | 0              | 1           | 62       | 0      | 2                       | 65        | 95.38             |
| Forest                  | 2              | 6           | 0        | 52     | 0                       | 60        | 86.66             |
| Barren land/other lands | 1              | 6           | 9        | 1      | 55                      | 72        | 77                |
| Other land              |                |             |          |        |                         |           |                   |
| Column Total            | 66             | 68          | 74       | 54     | 62                      | 324       |                  |
| Producer's accuracy (%) | 95.45          | 80          | 83.78    | 94.29  | 88.7                    |           |                  |
| Overall Classification Accuracy (%) | 87.46 |         |          |        |                         |           |                  |
| Overall kappa statistics | 857            |             |          |        |                         |           |                  |
bodies, built-up land, and forest) categories was more than 80%. The agriculture land and barren/other land categories have a user’s accuracy of 68.25% and 77.77%, respectively.

For the 2018 LULC map, 324 pixels were selected randomly. The overall kappa statistics and overall accuracy of the 2018 LULC map were 0.857 and 87.46 %, respectively (Table 4). The producer’s accuracy of each class was higher than 80%. The user’s accuracy of all the classes except barren/other lands (77%) was more than 80%. The accuracy of each class was observed to be satisfactory in the two classifications. The overall classification accuracy results and kappa statistics for the 1978 and 2018 LULC maps are presented in Tables 3 and 4, respectively.

**Change detection from 1978 to 2018**

The area under the LULC classes and its changes from 1978 to 2018 are presented in Table 5. Figure 3 displays the spatial expansion of the built-up area. In 1978, the area covered by built-up land was minimal and mainly located in the center of the study area. Positive and negative changes were observed over 40 years in the area under the LULC categories. The water bodies, forest, and agriculture land categories exhibited a decrease in their area, whereas the built-up land and barren land/other land categories exhibited an increase in their area. As presented in Table 5, the most substantial changes in area were observed for the built-up/other land categories, followed by the water bodies, agriculture land, and forest categories.

Figure 4. LULC map of the study area in 1978, which indicates a relatively small built-up area.

Figure 5. LULC map of the study area in 2018, which indicates the level of urban expansion from 1978 to 2018.
Water bodies
The area under water bodies declined from 9.83 km² in 1978 to 2.65 km² in 2018, which represents a net decrease of 7.18 km². The area under water bodies decreased due to the conversion of water bodies into other land and the reduction in the rainfall received by the study area over the past 40 years.

Agriculture land
The area under agriculture land decreased from 47.83 km² in 1978 to 18.25 km² in 2018, which represents a net decrease of 29.58 km². The available agriculture land within the study area rapidly decreased during the study period. The area under agricultural land decreased due to the demand for urban shelter and socio-economic development activities inside the study area. Another reason for the decrease is that farmers in the study area have neglected to farm and reserved their lands for other businesses.

Built-up land
The area under built-up land increased from 6.81 km² in 1978 to 31.55 km² in 2018, which represents a net increase of 24.74 km². The area under built-up land increased due to the rise in population, tourism activities, and the demand for shelter by inhabitants. Another reason for the growth is that the study area is a center point to reach the world-famous Tirumala temple.

Forest land
The area under forest land decreased significantly from 37.66 km² in 1978 to 26 km² in 2018, which represents a net decrease of 11.66 km². The decrease in forest land is attributed to the conversion of forest lands into built-up areas, such as parks, roads, and parking places. The decrease can also be attributed to the use of forest land for other development activities.

Barren land/other lands
The area under barren land/other land increased from 17.29 km² in 1978 to 41.55 km² in 2018, which represents a net increase of 23.26 km². The growth in barren land/other land is attributed to the fact that farmers in the study area have neglected agriculture activities and used agriculture land for other businesses. Although some barren regions were converted into the settlement and agriculture land, the area under other land increased considerably in the study period.

Conclusion and future work
In this research, remote sensing and GIS were integrated for quantifying and understanding the LULC changes in Ananthapuramu over 40 years from 1978 to 2018. The technique used in this study is simple and inexpensive. The extent of land-use changes in Ananthapuramu was determined using multi-temporal satellite imagery. In this study, classification accuracy was measured using the confusion matrix. The overall classification accuracy of this study was acceptable. Significant changes in the LULC were observed in the study area between 1978 and 2018. During these 40 years, the area under built-up land and other land increased considerably, whereas the area under agriculture land and water bodies drastically decreased. The causes of the LULC changes in the study area include the decrease in agricultural activities and the increase in built-up activities.

The LULC changes may not have a considerable environmental impact on the study area. However, the LULC changes should be closely monitored in the future for the sustainability of the environment. Further, the work could be extended by using the various machines and deep learning algorithms like CNN, R-CNN that could enhance the performance of the algorithm.

Disclosure statement
No potential conflict of interest was reported by the authors.

Funding
This work was supported by the National Natural Science Foundation of China [51872023].

ORCID
GN Vivekananda http://orcid.org/0000-0001-7292-7436

Table 5. The area under each LULC class in the 1978 and 2018 data sets and change in the area of each LULC class over 40 years (in km² and percentage).

| Land use/Landcover | Area, (Km²) | Area Changed (Km²) | Percent change% |
|--------------------|-------------|--------------------|-----------------|
| No                | 1978        | 2018               | (2018–1978)     |
| 1 Water bodies    | 9.83        | 2.65               | −7.18           | −73.04 |
| 2 Built-up        | 6.81        | 37.75              | +30.94          | 454.33 |
| 3 Forest          | 37.66       | 26                 | −11.66          | −31    |
| 4 Barren land/other land | 17.27 | 35.35              | +18.08          | 104.7  |
| 5 Agriculture     | 47.83       | 18.25              | −29.58          | −61.84 |
| Total             | 120         | 120                |                 |

(+) Indicates an increase and (−) indicates a decrease in the area under a LULC class over 40 years (1978–2018).
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