Change Detection in Land Use/Cover of Pennar Sub basin in Andhra Pradesh using Satellite Data and GIS

ANUSHA SANKARA, TRIPATHI M. P., MANI A.
Department of Soil and Water Engineering
Indira Gandhi Krishi Vishwavidyalaya & Acharya N. G. Ranga Agricultural University
Raipur, Chhattisgarh-492012 & Lam, Guntur, Andhra Pradesh-522034
INDIA

Abstract: - There is a rapid change in land use/cover which drastically affects on the environment, through the flow of water, energy, greenhouse gases from the land to the atmosphere, deforestation, etc. An attempt has been made to study the temporal changes in land use/cover for the three periods viz. 2011 and 2020 to identify the changes in the Pennar sub-basin, Anantapur district, Andhra Pradesh. The study was carried out using Erdas Imagine 2015 software with Landsat 8 and Landsat 5 imageries of 2020 and 2011. The study area was categorized into seven classes which are reservoirs, water bodies, agricultural lands, barren lands, fallow lands, built-up lands, and forests. Maximum likelihood classification of supervised classification was used in the present research. The accuracy assessment was carried out by Kappa coefficient statistics of the years 2011 and 2020. The results indicate the annual rate of change (ARC) from 2011 to 2020 is on a rising trend for agricultural lands, built-up, barren lands, forest and water bodies with 9.49 km^2/yr (11.97%), 0.47 km^2/yr (1.63%), 1.09 km^2/yr (7.15%), 1.30 km^2/yr (2.17%) and 0.16 km^2/yr (0.59%), respectively. Furthermore, it was in decreasing trend for reservoir and fallow land 0.07 km^2/yr (0.73%) and 12.47 km^2/yr (6.09%). The kappa coefficient statistics of classified supervised imageries for 2011 and 2020 were 0.89 & 0.82, respectively which shows the classified imageries are almost perfect [13].

Key-Words: - GIS, Land use/cover change, Remote sensing data, Kappa Statistics

Received: April 9, 2024. Revised: August 5, 2024. Accepted: September 9, 2024. Published: October 23, 2024.

1 Introduction

Land use/cover are two different terminologies that are often used indistinguishably (*Dimyati et al. 1996*). Land cover generally refers to the physical characteristics of the land surface, expressed in soil, water, vegetation, etc., and also developed by human inferences such as settlements. Whereas land use describes the land that has been utilized by human daily activities as the role of land for economic activities (*Rawat and Kumar, 2014*). The rapid increase of population growth may directly affect the changes in land use patterns like increasing built-up lands, water resources, agricultural farming, deforestation, etc.

Land use/cover change analysis plays a vital role in better understanding of land surface dynamics with sustainable management with space and time. Understanding the earth's surface patterns, the changes, and interactions with human activities and the environment are mainly useful for proper decision-making and implementing land management practices (*Mahapatra, 2013, Rao et al. 1996 & Jaman et al. 2022*). The land use directly impacts on the hydrological water resources and its drainage system (*Singh et al. 2014*). *Balakrishnan and Ilanthirayan (2017)* reported that land use and land cover of a watershed have a great effect on water quality and stream strength.

Land cover classification is one of the major uses of distance interest identification of features such as land use, usually using multispectral satellite images. However, the use of multi-temporal data can also cause problems while using traditional automated classification algorithms (*Suryawanshi and Bhutada, 2010*). The major problem is to get cloudless images of certain places in specific years. Therefore, Landsat satellite imageries are usually taken at an interval of 5 or 10 years. The remote sensing data made feasible for the study of land use/cover variations at low cost, with better accuracy and in less time (*Kachhwala, 1985*) also GIS provided a suitable platform for the data understanding, evaluation, renovation, and retrieval (*Chilar, 2000*).

To acquire a more informative analysis of land use land cover, Remote Sensing data should be combined with the Geographic Information System

(GIS) technique. Landsat and aerial images are used to study the variations in land cover distributions and to update existing geospatial features (*Rwanga and Ndambuki, 2017*).

In earlier studies, the accuracy assessment was not given prior importance; however, the accuracy assessment plays a vital role in the present studies due to the chances for errors in digital processing images (*Congalton, 1991*). The accuracy assessment has been made through kappa statistics by comparing the correctly classified pixel to the defined land cover pixels obtained by ground truth data (*Rwanga and Ndambuki, 2017*).

So, based on the literature cited above, helps in understanding the effect of land use/cover changes and proper management of watersheds by implementing suitable measures. An attempt has been made to study the actual status of land use/cover in the Pennar sub-basin, Andhra Pradesh, and the changes that took place in the years 2011 to 2020.

1.1 Study Area

The present research was carried out in one of the sub-basins of Pennar located in Anantapur district of Andhra Pradesh. It comprises three manuals of Anantapur district, namely, Uravakonda, Vajrakarur and Kuderu having an area of 424 km², the region between Penna Ahobhilam Balancing Reservoir (PABR), Korrakodu village, Kuderu Mandal and Mid Pennar Reservoir (MPR), Penakacharla village, Garladinne Mandal covers 26 villages. The study area is situated between 77 º 14' 52" E to 77 º 26' 38" E longitude to 14º 42' 29" N to 14º 58' 57" N latitude. The culturable area is about 55% whereas; the net sown area is 36% of the total basin area. The average annual rainfall in the Pennar drainage basin is about 550 mm in Anantapur district. Majorly grown crops are paddy, groundnut, jowar, cotton, sunflower, and rabi crops. The Mid Pennar Reservoir (MPR) is at 338 m MSL while the Penna Ahobhilam Balancing Reservoir (PABR) is at 349 m above MSL. The annual temperatures are 36.1ºC in summer and 31.7ºC in winter. The climate of the Pennar basin is characterized by the mean maximum temperature of 40.3ºC observed at Kadapa district to 34.7ºC observed at Arogyavaram and mean minimum temperature of 20ºC observed at Nellore district to 15.3ºC observed at Arogyavaram. Relative humidity ranged in between 21-84%. The majority of soils found in the Pennar basin are sandy soils, black soils, red soils, and mixed soils. The location map of the study area is shown in Fig.1.

2 Problem Formulation

2.1 Data Used

Satellite data and secondary data were used to examine the historical changes of LULC in the study area for a period of 9 years from 2011 to 2020. Two Landsat satellite images i.e., 2011 and 2020 of Path/Row 144/50 were downloaded from the USGS website (https://earthexplorer.usgs.). The attributes of Landsat satellite images for the present study are given in Table 1. To satisfy the best change detection, the Landsat images of wet season viz. October and November were used which enabled cloud-free imagery with the best visibility.

2.2 Image Processing and analysis

The downloaded image data was processed in the environment of Erdas Imagine 2015 and ArcGIS 10.1. The systematic flow chart for data processing is given in Fig.2.

This study was followed by a series of data analysis steps using ArcGIS and Erdas 2015. These steps include atmospheric, geometric corrections, radiometric sub-setting, gap filling, and enhancement. The selection of suitable bands to be used in image classification also includes preprocessing. The satellite imageries were then projected to the projected coordinate system, WGS 1984, UTM zone 43 N.

Landsat 8 OLI imagery is accelerated to increase the image resolution from 30 m to 15 m by combining color information in the multispectral bands and high-resolution panchromatic bands using a layer stack tool to achieve FCC (False Color Composite) image which improves mapping resources and classification accuracy. Yet it is impossible to carry out in Landsat 5 TM, 2011 images as the panchromatic band is absent.

2.3 Image Classification

Image classification is an important remote sensing technique used to represent all the pixel values present in the satellite imagery data into individual groups of LULC classes which are used to generate beneficial thematic maps. Generally, it assigns various spectral signatures from the imagery to different classes depending on the spectral reflectance values of different types of LULC classes.

Although there are many ways to classify image data, the commonly used methods are supervised and unsupervised methods. In this study, maximum likelihood statistics was used for image classification. Improved visualizations of various characteristics to easily detect LULC layers in images using True and False color composites (FCC). The LULC training sets are created by visual interpretation of Landsat images (2011 and 2020) based on Google Earth images, knowledge of the field of study, and field observations. After developing a set of instructions, the maximum likelihood classification is followed to generate a spectral signature, which is used to classify all the pixels in the image. The FCC images of 2011 and 2020 are shown in Fig.3.

Mainly 7 classes are classified i.e., reservoirs, built-up lands (rural), agricultural lands (shallow crop, dense crop), fallow lands, barren lands, shrub forests, and water bodies (streams, canals, and ponds).

2.4 Accuracy Assessment

The accuracy assessment was computed using the Kappa Coefficient by analyzing the pixel is correctly classified using historical high-resolution Google Earth imageries acquired from Google Earth Pro (*Jaman et al. 2022, Rwanga, S. S. and Ndambuki, J. M. 2017*). The Google Earth images captured during October 2011 and November 2020 have been used to study the accuracy assessment of LULC maps of 2011 and 2020, respectively. The accuracy assessment was computed by the following formulae.

A total of 230 points (locations) were located on the classified images of the study area. The accuracy assessment reference column was selected to the best guess of each reference point. With the help of Google Maps, topographic maps, and Google Earth imageries the accuracy assessment has been made.

Users' accuracy = $\frac{\text{Number of correctly classified pixels in each class}}{\text{Total number of classified pixels in that class (Row Total)}} \times 100$

Producers' accuracy = $\frac{\text{Number of correctly classified pixels in each class}}{\text{Total number of reference pixels in that class (Column Total)}} \times 100$

Kappa Co-efficient = $\frac{(TS \times TCS) - \Sigma(\text{Column Total} \times \text{Row Total})}{TS^2 - \Sigma(\text{Column Total} + \text{Row Total})}$

Where, TS = Total Sample and TCS = Total Corrected Sample

2.5 Change Detection

Change detection is defined as "the process of identifying differences in the state of an object or phenomenon by noticing them at various times" (*Alawamy et al. 2020*). Change detection not only explores the changes that have taken place but also determines their nature, spatial extent, and pattern. It also contributes maximum information acquired from the complete matrix of LULC change which expresses the magnitude of change (MC) and change rates. Change detection determines the broad range of differences between the pair of images from the initial period to the final period (*Pande and Moharir, 2014*). To determine the number of conversions from a particular land cover to another land cover category and their corresponding area over the evaluated period, cross-tabulation analysis on a pixel-by-pixel basis was conducted (*Butt et al. 2015*).

Although, the degree of change detection mainly depends on the accuracy of individual classifications. Based on the several studies conducted, the change detection of LULC in various parts of the world, maximum likelihood classification has been used which attains high accuracy. The developed classified LULC maps for two time periods (2011 and 2020) were compared by applying the detection algorithm using Erdas 2015. The Magnitude of Change (MC), the Percentage of Change (PC), and the Annual Rate of Change (ARC) for individual LULC classes for two time periods were calculated by using the following equations:

$$\text{MC (km}^2\text{)} = A_i - A_f \quad \dots (1)$$

$$\text{PC (\%)} = \frac{Ai - Af}{Ai} \times 100 \quad \dots (2)$$

$$\text{ARC (km}^2\text{/yr)} = \frac{\text{Ai} - \text{Af}}{n} \quad \dots (3)$$

$$\text{ARC (\%)} = \frac{Ai - Af}{Ai \times n} \times 100 \quad \dots (4)$$

Where, A_i is the initial time class area (km^2), A_f is the final time class area (km^2) and n is the number of years of the period.

3 Problem Solution

The classified LULC maps of the Pennar Sub-basin of two different periods i.e., 2011 and 2020 depicted in Fig. 4 and Fig. 5, respectively.

About 2.18 % of the area was occupied by the reservoirs in 2011 whereas 2.03% in 2020 in the Pennar sub basin. The area under the reservoir was initially high and gradually decreased in 2020. Streams and water bodies (ponds, streams) in 2011 and 2020 were found to be 6.38% and 6.71%, respectively which indicates the area had been increased from 2011 to 2020.

On average 6.73% of the area was occupied by built-up land in 2011 whereas it was found to be 7.74 % in 2020. The built-up land in rural areas gradually increased spatially and temporally. Barren lands in 2011 and 2020 occupied 3.61% and 5.94 % of the area, respectively. There was a rapid increase from 2011 to 2020. The area occupied by agricultural land (shallow crop + dense crop) was 18.69% in 2011 whereas it was 38.84% in 2020, respectively. The area under cultivation of crops has been increased from 2011 to 2020. The area occupied by fallow land in 2011 and 2020 was 48.22% and 21.75%, respectively. There was a decrease in area from 2011 to 2020. The area under fallow lands and barren lands may have been converted into croplands thus there was an increase in agricultural lands from 2011 to 2020.

The forest area in the Pennar sub-basin was found to be 14.18% and 16.95 % during 2011 and 2020, respectively. The above classification reveals that there was little increase in shrub forest area from 2011 to 2020.

The achieved overall accuracy was 91.30% & 86.08% and Overall Kappa Co-efficient statistics were 0.89 & 0.82 respectively for the classified images of 2011 and 2020 which were almost perfect. According to *Rwanga and Ndambuki, 2017* accuracy assessment requires an overall kappa co-efficient above 0.81 (Table 3) which was successfully carried out in this research. The classification results of 2011 and 2020 are summarized in Table 4.

The Magnitude of Change (MC) during the period 2011 to 2020 was found to be in the increasing trend for agricultural lands, built-up, barren lands, forest, and water bodies area was 85.47 km^2, 4.33 km^2, 9.87 km^2, 11.76 km^2, and 1.44 km^2 respectively. However, it was in the decreasing trend for reservoir and fallow lands as the area was observed to be 0.61 km^2 and 112.25 km^2, respectively.

The Percentage of Change (PC) from 2011 to 2020 for reservoirs was 6.59%. Built-up area, agriculture land, fallow land, barren land, forest, and water bodies have registered the PC as 14.75%, 107.75%, 54.88%, 64.38%, 19.54%, and 5.32% respectively.

The Annual Rate of Change (ARC) from 2011 to 2020 was found to be on a rising trend for agricultural lands, built-up, barren lands, forest and water bodies with 9.49 km^2/yr (11.97%), 0.47 km^2/yr (1.63%), 1.09 km^2/yr (7.15%), 1.30 km^2/yr (2.17%) and 0.16 km^2/yr (0.59%) area, respectively. Furthermore, it was in decreasing trend for the reservoir as the area was 0.07 km^2/yr (0.73%) whereas the fallow land area was recognized to be 12.47 km^2/yr (6.09%).

4 Conclusion

This research was mainly undertaken to study the changes in land use/cover in two different periods viz. 2011 and 2020. The cultivation area was increased from 2011 to 2020 by 18.69 % to 38.84%. It indicates that there was a double increment of agricultural land by effective utilization of land and water from the Pennar tributaries for agricultural purposes. The water bodies, built-up, forests, and barren lands increased from 2011 to 2020 due to the increase in population. Furthermore, fallow land was decreased due to the conversion into agricultural lands. This research also reveals that the quantification of land use/cover can be effectively done by Remote sensing and GIS which proves that in the present scenario, it plays a very important role in the analysis of changes in land use.

References:

[1] Alawamy, J.S., Balasundram, S.K., Hanif, A.H.M. and Sung, C.T.B. 2020, Detecting and Analyzing Land Use and Land Cover Changes in the Region of Al-Jabal Al-Akhdar, Libya Using Time-Series Landsat Data from 1985 to 2017, *Sustainability 2020*, Vol.12, 4490: doi:10.3390/su12114490.

[2] Balakrishnan, M. and Ilanthirayan, A. 2017, Land Use/ Land Cover Mapping With Change Detection Analysis of Walayar Watershed Using Remote Sensing and GIS, *Indian Journal of Natural Sciences*, Vol.8, No.43, pp. 12581-12588.

[3] Butt, A., Shabbir, R., Ahmad, S.S. and Aziz, N. 2015, Land use change mapping and analysis using Remote Sensing and GIS: A case study of Simly watershed, Islamabad, Pakistan. *The Egyptian Journal of Remote Sensing and Space Sciences*, Vol.18, pp. 251-259.

[4] Chilar, J. 2000, Land cover mapping of large areas from satellites: status and research priorities. *International Journal of Remote Sensing*, Vol. 21, No.67, pp. 1093-1114.

[5] Congalton, R.G. 1991, A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data. *Remote Sensing of Environment*, Vol.37, pp. 35-46. https://doi.org/10.1016/0034-4257(91)90048-B

[6] Dimyati, M., Mizuno, K., Kitamura, T 1996, An Analysis of Land Use/Cover Change using the combination of MSS Landsat and Land Use Map: A Case Study in Yogyakarta, Indonesia: *International Journal of Remote Sensing*, Vol.17, No.5, pp. 931 - 944.

[7] Jaman, T., Dharanirajan, K. and Rana, S. 2022, Land use and Land cover Change detection and Its Environmental Impact on South Andaman Island, India using Kappa coefficient Statistical Analysis and Geospatial Techniques.

International Research Journal of Engineering and Technology, Vol. 9, No.4, pp. 281-288.

[8] Kachhwala, T.S. 1985, Temporal monitoring of forest land for change detection and forest cover mapping through satellite remote sensing, *In Proceedings of the 6th Asian conference on Remote Sensing*, National Remote Sensing Agency, Hyderabad (1985), pp. 77- 83.

[9] Mahapatra, M., R. Ramakrishnan and A.S. Rajawat 2013, Mapping and monitoring of land use and land cover changes using Remote sensing and GIS techniques, *International Journal of Geomatics and Geosciences*, Vol.4, No.1, pp. 242- 248.

[10] Pande, C. and Moharir, K.N. (2014). Analysis of Land Use/Land Cover Changes Using Remote Sensing Data and GIS Techniques of Patur Taluka, Maharashtra, India. *International Journal of Pure and Applied Research in Engineering and Technology*, Vol. 2, No.12, pp. 85-92.

[11] Rao, D.P., Gautam, N.C., Nagaraja, R. and Mohan, P.R. 1996, IRS-IC application in land use mapping and planning. *Current Sciences*, Vol.70, pp. 575-578.

[12] Rawat, J.S. and Kumar, M. 2015, Monitoring land use/cover change using remote sensing and GIS techniques: A case study of Hawalbagh block, district Almora, Uttarakhand, India. *The Egyptian Journal of Remote Sensing and Space Sciences* Vol.18, pp. 77-84.

[13] Rwanga, S.S. and Ndambuki, J.M. 2017, Accuracy Assessment of Land Use/Land Cover Classification Using Remote Sensing and GIS. *International Journal of Geosciences*, Vol.8, pp. 611-622. https://doi.org/10.4236/ijg.2017.84033

[14] Singh, P., Gupta, A. and Singh, M. 2014, Hydrological inferences from watershed analysis for water resource management using remote sensing and GIS techniques. *The Egyptian Journal of Remote Sensing and Space Sciences,* Vol.17, pp. 111-121.

[15] Suryawanshi, S.L. and Bhutada, S.H. 2010, Development of thematic maps for a watershed using remote sensing and geographic information system. *International Journal of Agricultural Engineering*, Vol.3, No.1, pp. 147-152.

Appendix

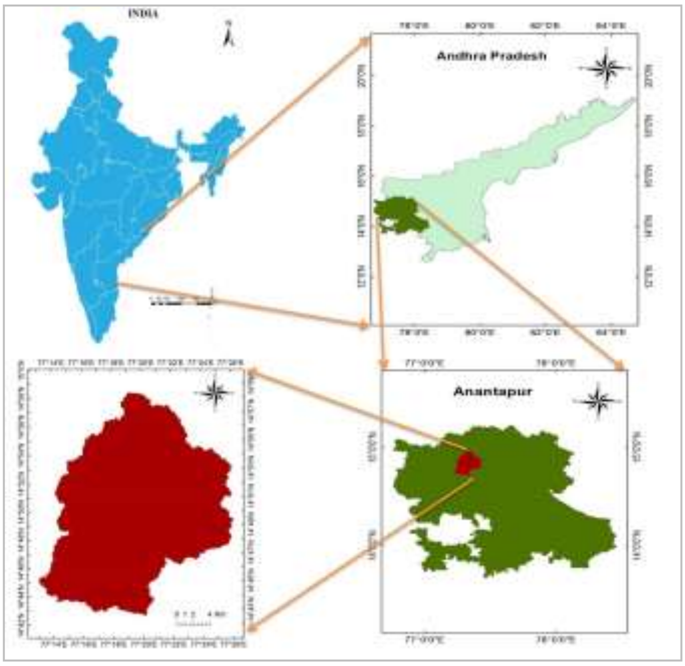

Fig.1 Location map of the study area

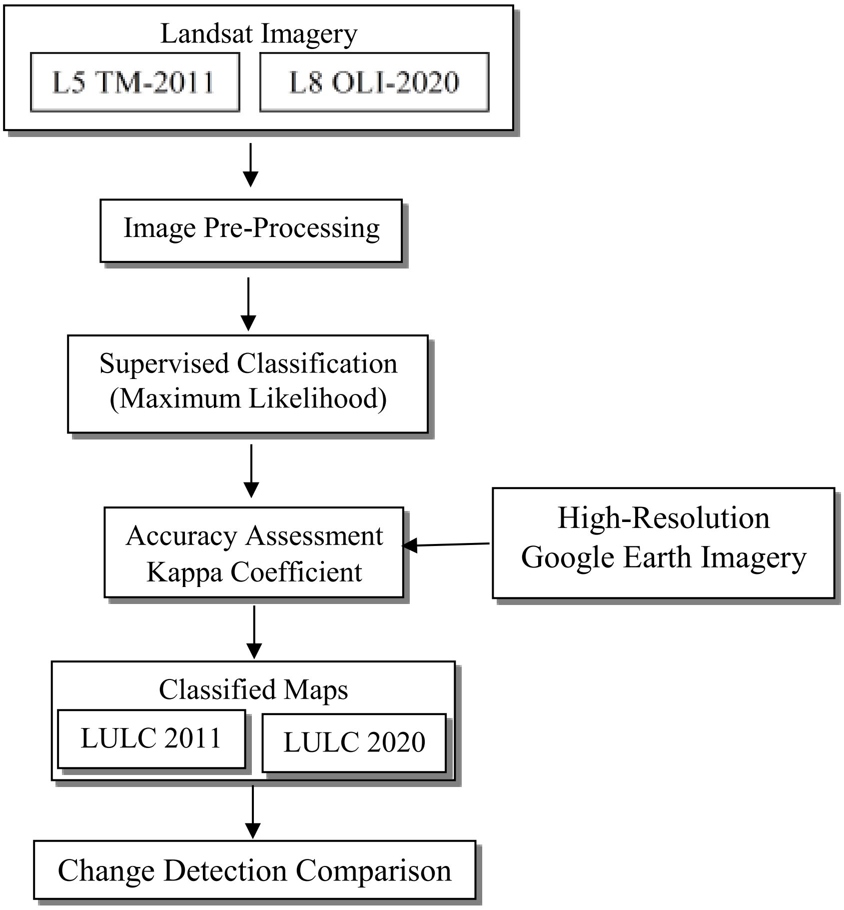

Fig.2 Flow chart of data processing steps

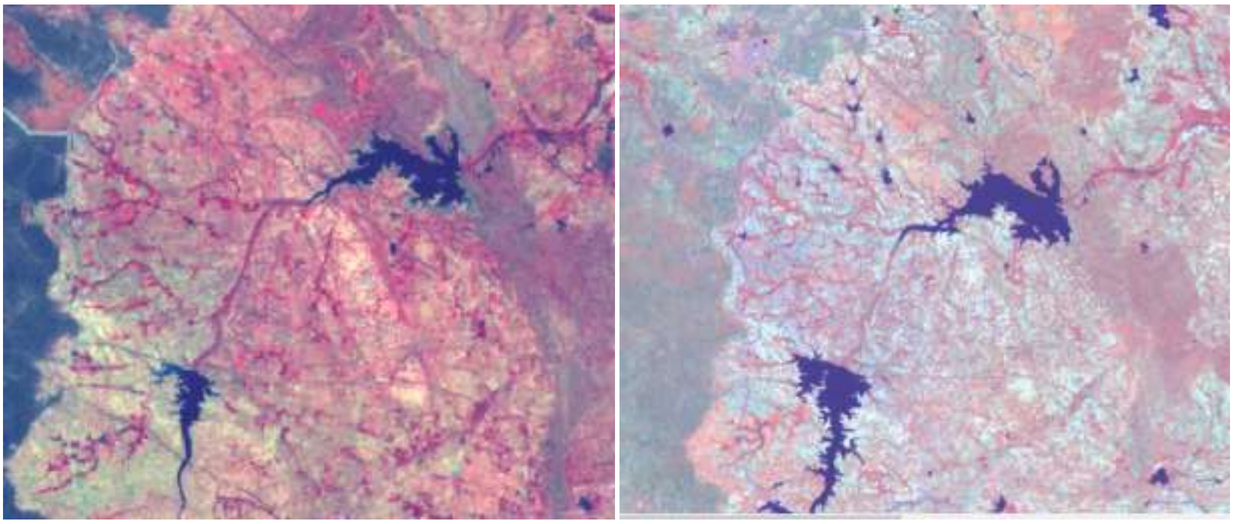

Fig.3 FCC images of 2011 and 2020

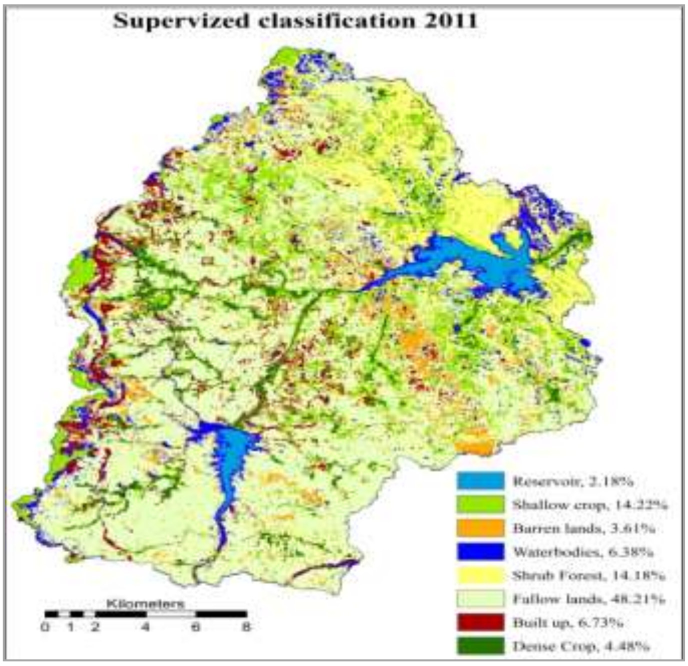

Fig.4 LULC during the year 2011

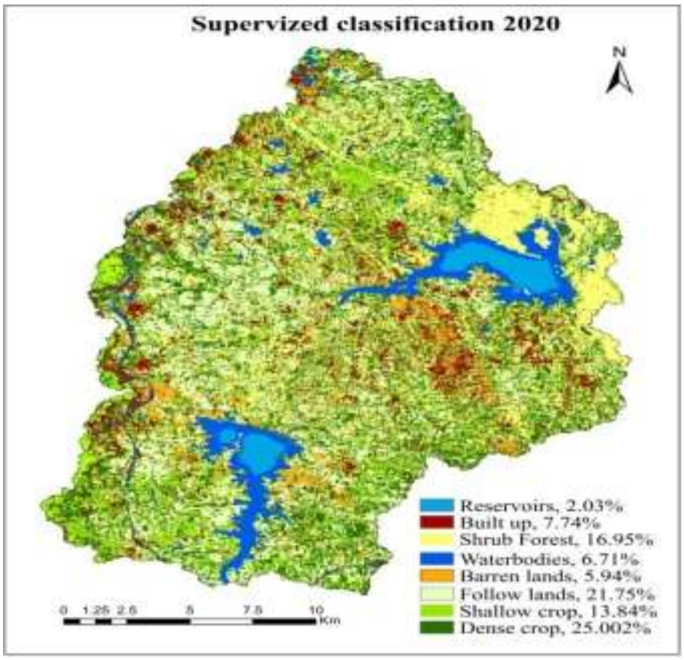

Fig.5 LULC during the year 2020

Table 1 Source and characteristics of satellite imagery

Satellite data	Path/Row	Date	Number of bands	Resolution
L5 TP	144/50	01/10/2011	7	30m
L8 OLI	144/50	10/11/2020	11	30m

Table 2 Rating Criteria for Kappa Co-efficient Statistics

S. No.	Kappa statistics	Strength of Agreement
1.	<0.00	Poor
2	0.00-0.20	Slight
3	0.21-0.40	Fair
4	0.41-0.60	Moderate
5	0.61-0.80	Substantial
6	0.81-1.00	Almost Perfect

Table 3 Accuracy assessment of supervised classification images of 2011 & 2020

LULC Class	Kappa Co-efficient Statistics (2011)		Kappa Co-efficient Statistics (2020)	
	User Accuracy	Producer's Accuracy	User Accuracy	Producer's Accuracy
Water bodies	100	100	100	95.83
Forest	85.71	92.30	92.85	86.67
Barren land	76.47	86.67	69.23	75.00
Fallow land	100	76.92	100	75.86
Cropland	97.37	97.37	74.19	88.46
Built up land	66.67	100.00	81.81	100.00
	Overall Accuracy (2011) = 91.30		Overall Accuracy (2020) = 86.08	
	Kappa Co-efficient = 0.89		Kappa Co-efficient = 0.82	

Table 4 Land use/cover categories during 2011 & 2020 and Area

LULC class	2011 (Km^2)	Area (%)	2020 (Km^2)	Area (%)	Area Change from 2011 to 2020	
					Km^2	%
Reservoir	9.25	2.18	8.64	2.03	-0.61	-0.15
Built up	28.54	6.73	32.87	7.74	+4.33	+1.01

Agriculture	79.32	18.69	164.79	38.84	+85.47	+20.15
Fallow land	204.54	48.22	92.29	21.76	-112.25	-26.46
Barren land	15.33	3.61	25.20	5.94	+9.87	+2.33
Forest	60.16	14.18	71.92	16.95	+11.76	+2.77
Water bodies	27.05	6.38	28.49	6.71	+1.44	+0.33
Total	424.21	100	424.21	100		