Industrial area mapping and decadal change detection by means of LANDSAT data and Image processing methods in parts of YSR kadapa district, Andhra Pradesh, India

Abstract

Limestone mine includes the removal of natural vegetation and the overlying soil to extract Limestone for cement production and for building construction. The dynamics of the Limestone mines and cement plant dust impacts on land, water, and air at local, regional, and global levels. Therefore, mapping and change assessment of the mining area, including the condition of leachates, land usage, vegetation, water and environment provide information about environment in and around the Limestone mines and cement plants for sustainable mining and industrial practices. Over the past few years remote sensing data has become vital in mapping the Earth's features, infrastructures, managing natural resources and studying environmental changes. This research work is focused on the Landsat image processing methods for Limestone mines and industries mapping and Land use/cover change assessment, in parts of YSR kadapa district, Andhra Pradesh, India over the period 1991 to 2019.The results of Landsat image Hybrid classification using ERDAS 2015 and ArcGIS 10.5 showing an overall accuracy of 92 % and kappa index 0.9 in comparison to conventional methods of classification.

Keywords: Limestone mines, cement and Thermal power Industries, Landsat data, Hybrid classification, Band ratio.

1. Introduction

The Growing population, Town/village sprawl, rapid industrialization and growth in infrastructure during the past three decades the demand for Limestone increased. The Limestone is the principal raw material for cement production and building (house) construction, it also used as flux in metallurgical processes (in Glass, Ceramic, Paper, Textile and Tanning Industries), used for manufacture of calcium carbide, alkali, bleaching powder, sugar refining, in fertilizer (calcium ammonium nitrate) and as soil conditioning agent in agriculture [6].

Limestone mines, cement plants and Thermal power plant contributed a great part to Local people and government of Andhra Pradesh revenue. Unsupervised Limestone mining activity and cement production causes to incredible change in land use /land cover, environmental degradation beyond acceptable limits and can affect long term socio-economic factors of the study area [1]. Hence, information on land use /cover and possibilities for their optimal use is essential for the selection, planning and implementation of land use schemes for limestone mining activity to meet the increasing demands for human needs and welfare. Therefore, monitoring the regions at multi-temporal and high spatial resolution is important for local governments to gain information that is needed for the policies of economic and environmental protection [1, 3, and 4].

Remote sensing data with high spatial resolution (≤30 m) provides an opportunity to achieve better insight into industrial Limestone quarry area dynamics, to access the social implications of mining and cement production at the local community level to regional spatial scales. Multi-temporal remote sensing data archives can provide a valuable source of data to reveal historical trends in land use patterns, which is a vital factor in managing contradictory land demands [3].

2. The Limestone mining and processing area

Major industries like The India Cements Limited (Coromandal Cements)-Chilamakur, The India Cements Limited-Yerraguntla, Zuari cements- Yerraguntla, Bharathi Cements Limited-Nallalingayapalli, Rayalaseema Thermal Power Plant (RTPP) and huge quarries of Napa slab stones (Limestones) are located in and around the Yerraguntla town. Yerraguntla town is 47 km towards west from YSR kadapa district head quarters and located between the Geographical Co-ordinates 14.6333°N latitude and 78.5333°E longitude. As per the 2011 census total population of Yerraguntla Mandal is 77,072 out of which urban population is 32,574 while rural is 44,498. It has an average elevation of 152 meters (501 feet).

Limestone occur all over India but the present study is limited to mapping and evaluation over the 684KM^2 area as shown in figure1and 2.where cement-grade, slab-grade limestone mines and Major industries present [7].

Figure 1: Location map of Industrial area in and around yerraguntla town

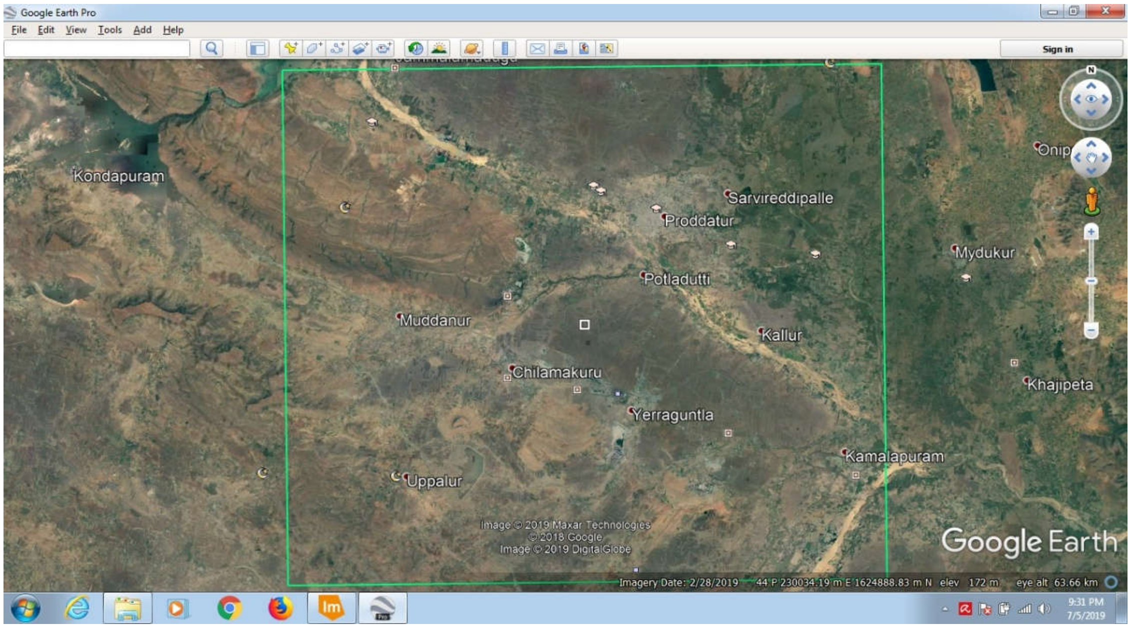


Figure 2: Industrial area map from Google earth

3. Landsat data selection and acquisition

Remote sensing is the only cost effective, precise, monitoring tool to map the Land use/cover pattern on a varied scale. The Landsat series of satellite launches began in 1972 provides an enormous wealth of data with high temporal frequency for the scientific analysis and change detection. Landsat data are well suited for surface feature analyses because of the long history of earth observation and rich spectral bands with ample spectral information [1].

Limestone mines growth or decline rate is slow hence in this study decadal observation carried out for mapping and change assessment of industrial area. Landsat 5 (TM), landsat 7(ETM+) and Landsat 8 (OLI) images with low cloud coverage were picked from the US Geological Survey's (USGS) Earth Explorer platform (https://earthexplorer.usgs.gov), representing years 1991,2001,2011 and 2019 for decadal observations.

The images from TM, ETM+ and OLI Landsat sensors have a common spatial resolution (30m) and six overlapping spectral bands (blue, green, red, near-infrared (NIR), shortwave infrared 1 (SWIR1), and shortwave infrared 2 (SWIR2)) were used for analysis while the remaining bands were excluded from further processing. Images from the first Landsat sensor generation (Multispectral Scanner/MSS) were not taken into consideration at this point because of their coarser spatial resolution and lower spectral fidelity. Remote sensing data used in the study is Landsat data (cloud-free) in the months of March/April in the years 1991, 2001, 2011 and 2019.Table 1 indicates the sensor, sensor ID, spacecraft ID, path/raw and the Sun elevation angle at the time of the acquisition of each image. All the images were Level 1T processed (L1TP) and provided in GeoTIFF format with 30m pixel size and UTM WGS84 map projection.

Table 1: Detailed information of all Landsat images that were used in this study

Image acquisition date	**Sensor**	**Spacecraft**	**Path /Row**	**Sun elevation angle (degrees)**	**Sun azimuth angle (degrees)**
6th March 2019	OLI_TIRS	LANDSAT_8	143/050	55.87	124.46
1st April 2011	TM	LANDSAT_5	143/050	60.32	106.98
29th April 2001	ETM	LANDSAT_7	143/050	64.18	86.55
10th April 1991	TM	LANDSAT_5	143/050	55.29	97.33

4. Classification approach

The main aim of this study is to use image classification schemes to obtain cement plant, Thermal power plant and Limestone Mines dynamics and impact on Land use/cover of the study area. The methodology adopted in this study is summarized in the flow chart (Figure). The methodology include Image Pre-processing, Image Classification, Change Detection Analysis and Prediction of land cover change.

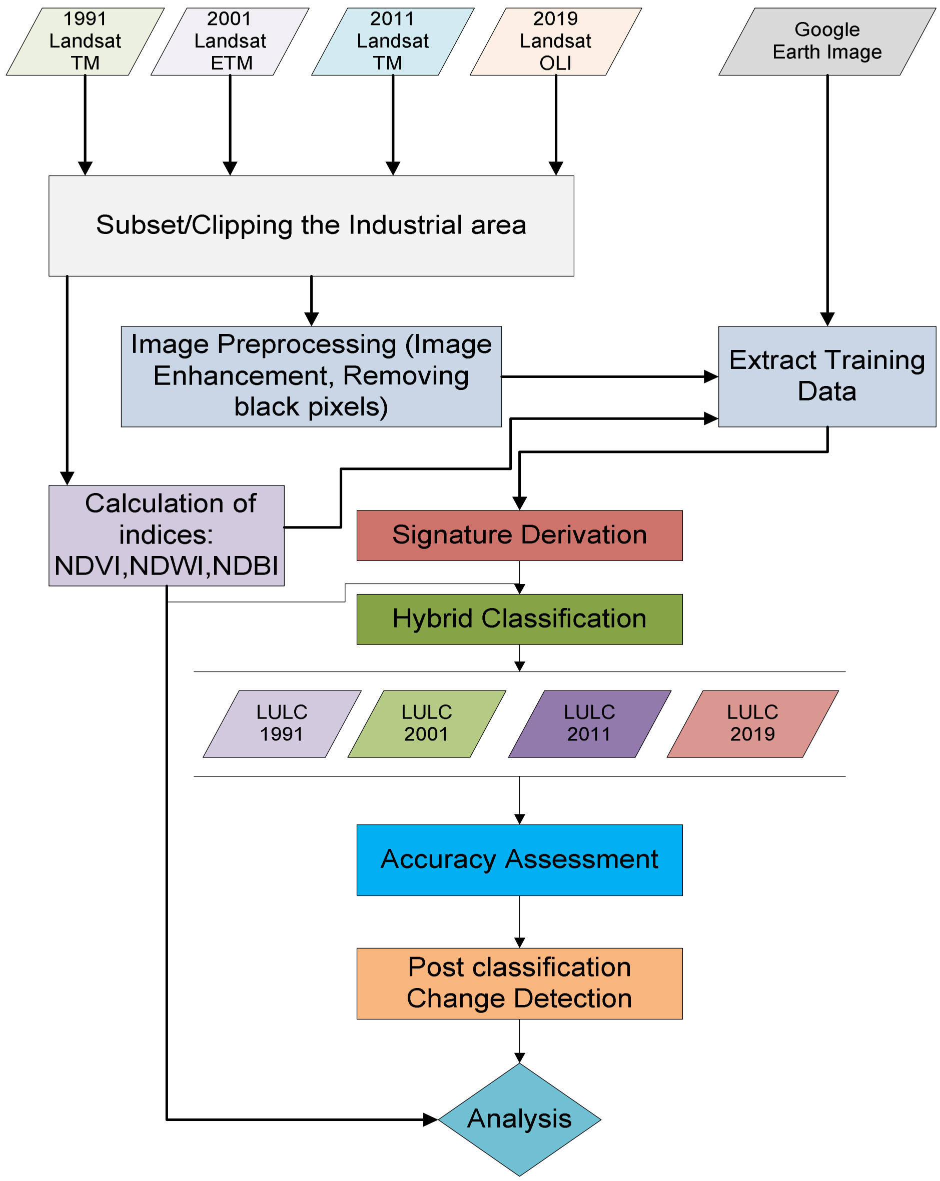


Figure 3: Hybrid supervised/unsupervised classification approach

4.1 Pre-processing

Preprocessing of satellite images is an essential step prior to image classification and change detection. Preprocessing operations include: atmospheric correction, geometric corrections, radiometric corrections, stacking of image bands. In this study, we are used Level-1 Precision Terrain (L1TP) processed Tier 1 Landsat data. It was systematically, radio-metrically, geometrically and topographically corrected using ground control points; the scenes suitable for time series pixel level analysis.

The landsat 5, 7 & 8 images are obtained for the study area were recorded in bands ranging from 1 to 9 for Landsat 8, Bands 1 to 8 for Landsat 7 and Bands 1 to 7 for Landsat 5. In Landsat8 band 8 does not have color (i.e. Panchromatic) that will help in analyzing the data, visually. Landsat 8 individual bands 1 to 9 (1 to 8 for Landsat 7 and 1 to 7 for Landsat 5) are combined (Layer stacking) except band 8 to form multispectral images which can therefore be viewed in different color combination (RGB combination). Upon careful examinations, band combination NIR-5, Red-4 and Blue-3 for Landsat 8 image and NIR-4, Red-3, Blue-2 for Ladsat 5&7 images was used as it revealed clearly all the land cover classes distinguishable on the images.
Subset image extracted from multi-band image with the help of industrial area vector polygon shape file developed in ArcGIS for cropping the image to cover only the study area.

4.2 Multispectral indices

For the study area, we calculated NDVI, NDWI and NDBI which are serving as proxies for different land surface properties such as vegetation status, surface water and Barren land and built-up [14]. The calculation was performed using the following equations. Table 2 shows statistical values of indices computed for the years 1991 and 2019; these values are used for extracting training data and Land use and Land cover analysis.

$$\text{Normalized Difference Vegetation Index, NDVI} = \frac{NIR-Red}{NIR+Red}$$

$$\text{Normalized Difference Water Index, NDWI} = \frac{NIR-SWIR}{NIR+SWIR}$$

$$\text{Normalized Difference Building Index, NDBI} = \frac{SWIR-NIR}{SWIR+NIR}$$

$$\text{Modified NDWI} = \frac{Green\ band-SWIR\ band}{Green\ band+SWIR\ band}$$

$$\text{Built-up Index BU} = \text{NDBI} - \text{NDVI}$$

NDVI image classified into two classes: (1) NDVI values below to 0.18 were considered as no vegetation and (2) NDVI values from 0.19 to 0.48 were considered as vegetation

Table: Green, Red, NIR, SWIR Bands of Landsat satellites

Satellite	**Green Band**	**Red Band**	**NIR Band**	**SWIR Band**	**TIR Band**
Landsat 5 & 7	2	3	4	5,7	6
Landsat 8	3	4	5	6,7	10,11

Table 2: Indices statistics for the years 1991 and 2019 of the study area

	2019					1991				
Index	**Minimum**	**Maximum**	**Dynamic range**	**Mean**	**Standard deviation**	**Minimum**	**Maximum**	**Dynamic range**	**Mean**	**Standard deviation**
NDVI	-1.00	0.48	1.48	0.13	0.06	-0.16	0.65	0.81	0.06	0.07
NDBI	-0.32	1.00	1.32	0.05	0.07	-0.5	0.47	0.97	0.31	0.07
NDWI	-1.00	0.32	1.32	-0.05	0.07	-0.47	0.50	0.97	-0.30	0.07
MNDWI	-1.00	0.39	1.39	-0.11	0.06	-0.89	0.51	1.40	-0.43	0.06
BU	0.68	0.52	0.16	0.09	0.06	-0.34	-0.18	0.16	0.18	0.07

4.3 Image Enhancement

Image enhancement is the process of making important features of raw, remotely sensed data more interpretable by increasing the apparent distinction between the features in the scene for a particular application. Spatial enhancement modifies pixel values based on the values of surrounding pixels. Convolution-edge enhancement filters are the most commonly used filters for an image quality enhancement in the spatial domain. Here we are used a 3x3 kernel matrix to average small sets of pixels across an image for deriving the modified DN value to replaces the centre pixel and a 3x3 edge enhancement filter used to deduce shape information and to extract edges formed by ridges, rivers, roads, railways and canals.

4.4 Image Classification

Generally, either supervised or unsupervised classification techniques are used for land use/ cover class extraction. A supervised maximum likelihood classification alone revealed a serious problem caused by spectral confusion in mine waste and barren lands. The problem was solved by using hybrid supervised/unsupervised classification approach. The Hybrid classification is performed to improve the accuracy and efficiency of the classification (Lillesand and Kiefer, 2015, pp. 487). The hybrid supervised/unsupervised classification approach involves three steps:

(1) unsupervised classification using the ISODATA (Iterative Self-Organizing Data Analysis) algorithm for land use/cover except settlement and bare land; (2) a supervised maximum likelihood classification for settlement and bare land; and (3) finally an overlay of the two classifications [(1) + (2)].The Table 3 describes the 10 Land Use/cover classes of Level-I and Level-II in the Industrial area of Yerraguntla Region, YSR Kadapa District, Andhra Pradesh, India. Figure 4 illustrates the 10 Land Use/cover classes of Satellite Images taken from Google Earth.

Table 3: Description of the 10 Land use/cover classes in the Industrial area

S.No.	Land use/ cover class	Description
1	Limestone Mines/ Quarries	Areas include both Cement Grade and Slab Grade Limestone mining activities with significant surface expression. The main cement grade limestone mines are Thippaluru Limestone Mines (Bharati cements) Zuvari cement Limestone mines Coromandel Limestone Mine (ICL)
2	Mine waste	Mine waste extracted from the Napa slab quarry and cement grade Limestone mine are dumped close to the quarry and surroundings
3	Town/villages/ Roads/ Rails	Included in this category are Residential, Non building structures, systematic street patterns, Transportation such as Roads and Rails and utilities.
4	Industrial area	This area included major cement and power plants like The India Cements Limited (previously Coromandal Cements)-Chilamakur, The India Cements Limited-Yerraguntla, Zuari cements- Yerraguntla, Bharathi Cements Limited-Nallalingayapalli, Rayalaseema Thermal Power Plant (RTPP)
5	Fallow land	A piece of land that is normally used for farming but that is left with no crops on it for a season in order to let it recover its fertility.
6	Crop land	Agricultural lands under crop, the main crop lands in this study include rice, groundnut ,vegetables, Bengal gram, red gram etc.
	Natural vegetation	Natural vegetation included plant community which has grown naturally without human aid and cultivated fruits trees
8	Barren land/ Hill shade	Lands included which do not support for any vegetation, one third of the area having vegetation or other cover and Hill areas
9	Water bodies	Included reservoirs, Rivers , ponds and significant accumulation of water in Mines
10	Dry/ parched water bodies	Dried up water bodies, including man-made lakes, reservoirs and River

(1). Limestone Mine

(2).Mine waste

(3).Town/villages/ Roads/ Rails

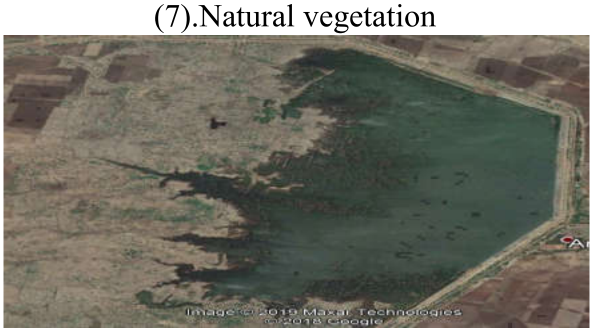
(4).Industrial area

(5).Fallow Land

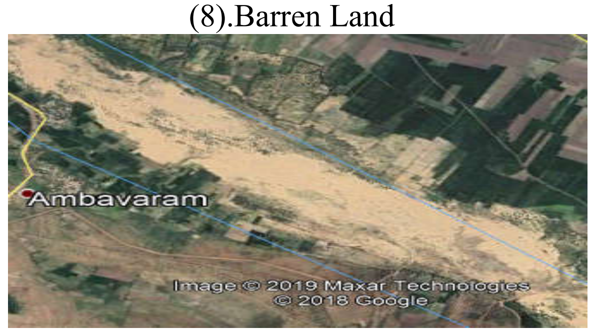
(6).Crop land

(7).Natural vegetation

(8).Barren Land



(9).Water bodies



(10).Parched water bodies

Figure 4: Satellite Images of 10 LULC classes of Industrial area from Google Earth

4.5 Accuracy assessment

Accuracy assessment is an important to have faithful results in precise change detection from outcome of classification of data. Evaluation of the accuracy is derived from thematic map. In the classification process the checkpoints are courtesan from the Google Earth. Accuracy assessment is accomplished by using a supervised Classifier toolbar called ERDAS Imagine 2015. We have taken fifty random reference points from the Google Earth and used to assess the accuracy of the classified images of the years 1991, 2001, 2011 and 2019. An error matrix is generated and compared the relationship between known reference data (ground truth) and the results of an automated classifier [13].The proportionate reduction of error generated by a classifier is expressed by the Kappa coefficient. Processed resultant is compared with the error of a completely random classifier.

Kappa coefficient is computed as

$$K = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r}(X_{i+} * X_{+j})}{N^{2} - \sum_{i=1}^{r}(X_{i+} * X_{+j})}$$

Where *r* is the number of rows in the error matrix

X_{ii} is the number of observations in ith row and ith column

X_{i+} and X_{+j} are the marginal totals for ith row and jth column

N is the total number of samples in the error matrix

4.6 Post-classification comparison for change detection

Matrix operation of GIS, the land use/cover of each pixel in a date is cross tabulated with another date.The change detection matrix comprise n x n cells with a land use/cover change map 'from 1991 to 2001'. Subsequently 'from 2001 to 2011', 'from 2011 to 2019' and 'from 1991 to 2019' class change matrices of land use/cover are produced with 10 land use/cover classes in each image resulted of 100 possible sequence changes, 10 static elements for each time period. The pixel by pixel nature of this change allows both the areal extent and spatial distribution of land use/cover changes to be quantified [12].

6. Results and discussion

Four Land use/cover maps are obtained through the analysis of the Four Multi-Temporal images (1991, 2001, 2011 and 2019) of the study area; using Imagine unsupervised / supervised classification approach in ERDAS 2015. Table 2 depicts land use/cover classes of the study area in 10 categories. The resultant land cover maps are shown in Figure 5. On clear examination of these four land use/ cover maps, it revealed that the Fallow Land and Barren Land constitute the highest portion of the study area. Industries, Town/Village/Roads/Rails Land use classes are seen to be interrelated. Few water bodies found to be part of Limestone Mine site.

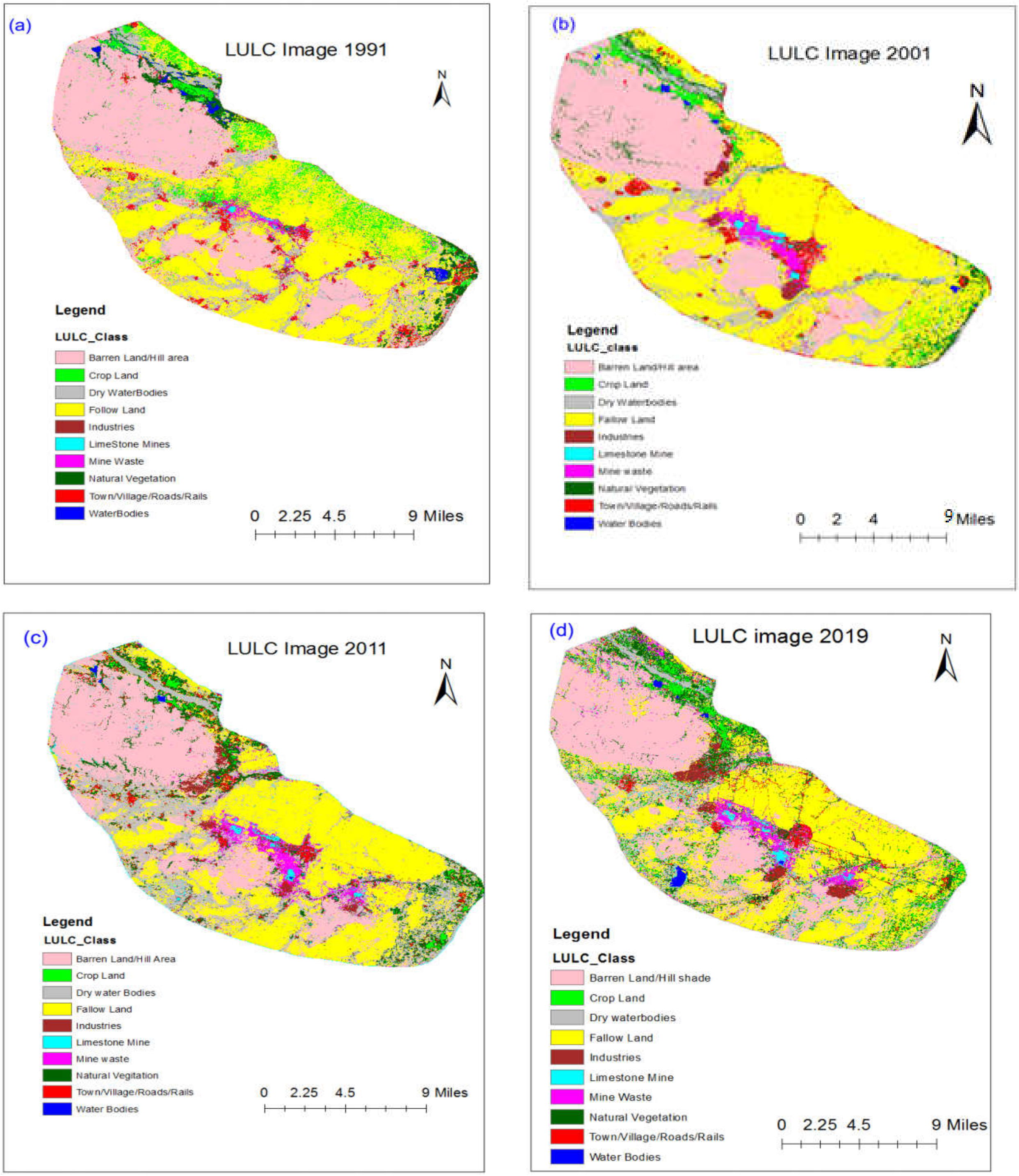


Figure 5: (a) 1991 LULC map of Industrial area, (b) 2001 LULC map of Industrial area, (c) 2011 LULC map of Industrial area, (d) 2019 LULC map of Industrial area,

The Table 4 shows the areal extent of the area of the individual land use/cover categories in square Kilometer (KM^2) and the percentage they occupied. Figure 6 (bar graph) depicting the trends of land use/cover changes in the four years 1991, 2001, 2011and 2019.

Table 4: land use / cover categories spatial area (Total study area 684 KM^2)

Land Use/cover class	1991		2001		2011		2019	
	Area in Sq. KM	Area (%)	Area in Sq. KM	Area (%)	Area in Sq KM	Area (%)	Area in Sq KM	Area (%)
Limestone Mines/ Quarries	2.39	0.35	6.28	0.92	9.00	1.32	11.18	1.64
Mine waste	10.50	1.53	16.67	2.44	19.90	2.91	25.56	3.74
Town/Village/ Roads/ Rails	21.45	3.14	17.92	2.62	19.25	2.81	17.37	2.54
Industries	5.73	0.84	10.21	1.49	11.09	1.62	12.31	1.80
Fallow Land	261.07	38.17	312.65	45.71	228.61	33.42	227.62	33.28
Crop land	46.64	6.82	13.91	2.03	5.91	0.86	29.12	4.26
Natural vegetation	23.76	3.47	25.25	3.69	54.57	7.98	64.98	9.50
Barren land/ Hill shade	226.79	33.16	210.61	30.79	207.92	30.40	228.10	33.35
Water bodies	7.60	1.11	2.94	0.43	0.98	0.14	2.92	0.43
Dry water bodies	78.73	11.51	68.20	9.97	127.41	18.63	64.68	9.46

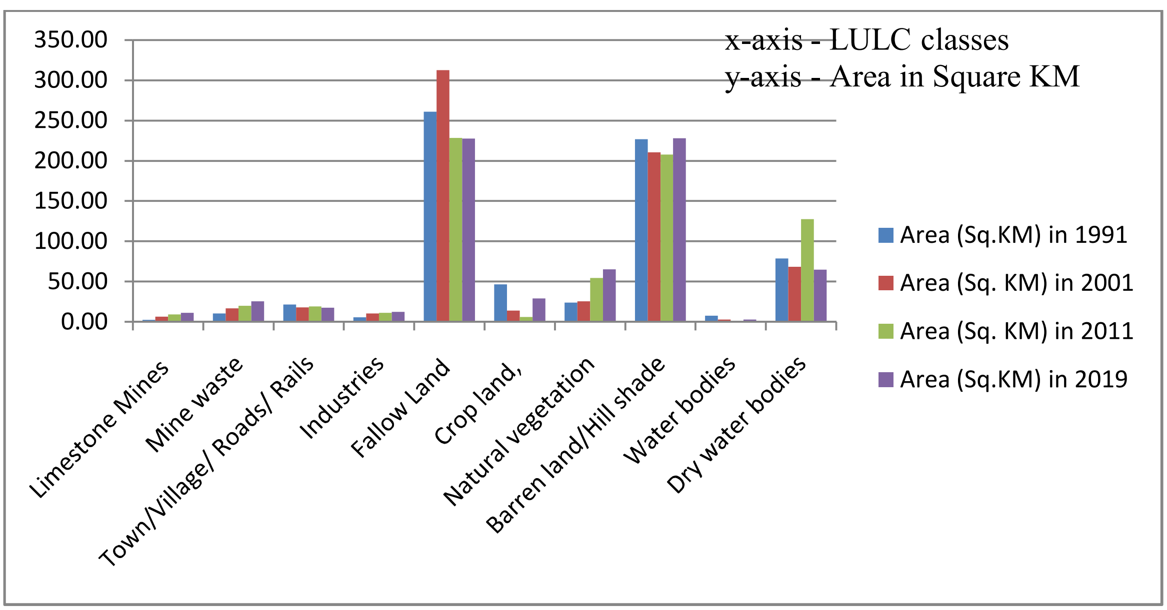


Figure 6: Spatial extent of area occupied by the Land use/cover class in the years 1991, 2001, 2011 and 2019.

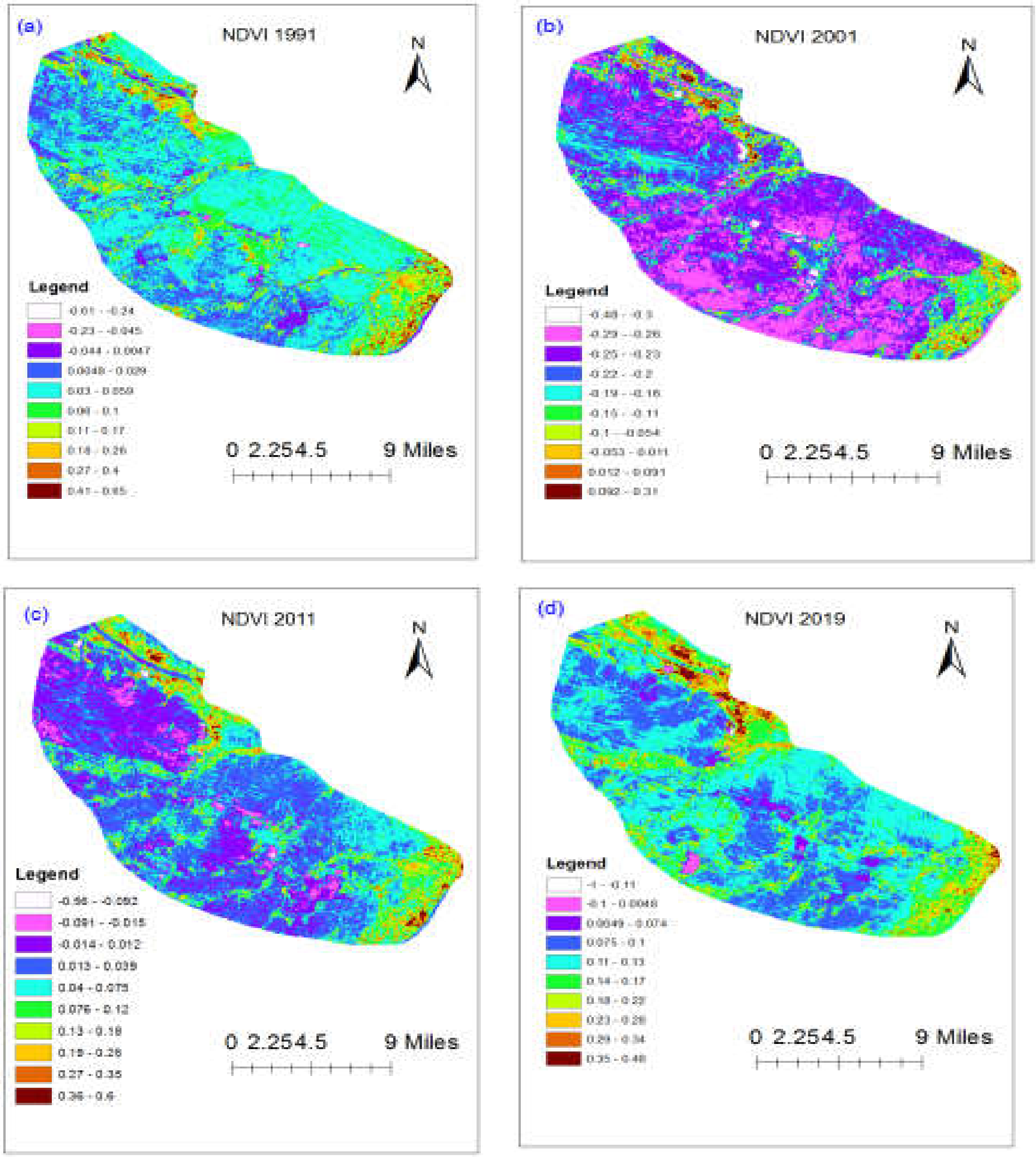


Figure 7: NDVI maps of study area for (a) 1991, (b) 2001, (c) 2011, (d) 2019

The statistics Table 2 and figure 7 shows that lesser the NDVI value from -1 to 0.18 usually represent water bodies (ranging from -0.0175 to -0.328), Built up (ranging from -0.019 to 0.060) and bare soil (ranging from -0.001 to 0.166). The NDVI value of the vegetation is ranging from 0.19 to 0.48.

6.1 Change Detection Matrix

Change detection matrix provides the information on the frequencies with which each land use/ cover classes remained either unchanged or has changed to one of the other classes, using two thematic maps of different dates. Four change detection tables are generated from thematic maps

1991-2001, 2001 – 2011, 2011-2019 and 1991-2019 using the ArGIS 10.5 and Microsoft Excel. In the Transition matrix, elements in the diagonal represent the land cover classes that remain unchanged including total area and those in the off-diagonal are the changed land use/cover classes. The column element represents land cover class in the earlier date and the row element represents land cover class in the later date [13]. Tables from 5 to 8 shows the Land use/cover Transition matrices for decadal change from 1991 to 2019.

Change detection matrix in Table 4 shows the total Limestone mining in the year 1991 is 2.39KM^2 but this Limestone mining area in the year 2019 is 11.18KM^2. To make this 11.18KM^2 Limestone mining area in the year 2019, it taken 0.86 KM^2 from Mine waste, 0.51 KM^2 from Towns/ villages/Roads/Rails, 0.91 KM^2 from Industrial area, 3.74 KM^2 from fallow land, 0.51 KM^2 from crop land, 0.3 KM^2 from natural vegetation, 1.69 KM^2 from barren land, 0.19 KM^2 from water bodies and 2.78 KM^2 from Dry water bodies. Similarly Limestone Mine waste area increases from 10.49 KM^2 to 25.56 KM^2, Town/Village/Roads/Rails area decreases from 21.44 KM^2 to 17.37 KM^2, Industrial area increases from 5.71 KM^2 to 12.31 KM^2, Fallow Land decreases from 261.04 KM^2 to 227.62 KM^2, Crop Land decreases from 46.63 KM^2 to 29.12 KM^2, Natural vegetation increases from 23.76 KM^2 to 64.98 KM^2, Barren Land/Hill shade area slightly increases from 226.05 KM^2 to 228.10 KM^2, Water bodies decreases from 7.60 KM^2 to 2.92 KM^2, Dry water bodies decreases from 78.72 KM^2 to 64.68 KM^2 . The reason for decrease in Town/Village/Roads/Rails area is increase in Natural vegetation; it covers the most of the residential buildings, streets, Roads. Industrial area increases because one ICL cement plant at Chilamkur villge and other plant at Yerraguntla commissioned in 1998 and 1999 respectively and expanded in 2010, Zuari Cement plant commissioned in 1998 in Krishnanagar which is 7 km away from Yerraguntla town, Bharathi Cement plant was established in the year 2006 at Nallalingayapalli near to yerraguntla and RTPP stage-I(Unit-I) commercial operation started in 1994 subsequently expanded to stage-V((Unit-V)) in 2010.With establishment of cement plants crop and follow land decreases consequently the surrounding Town/village people got employment.

Table 5: Change detection matrix from 1991 to 2019 in sq.KM

class No.	class Name	Limestone Mines	Mine waste	Town/Village/Roads/Rails	Industrial area	Fallow land	Crop land	Natural vegetation	Barren land/ Hill shade	Water bodies	Dry water bodies	Total area 2019
1	Limestone Mines	0.41	0.86	0.51	0.19	3.74	0.51	0.30	1.69	0.19	2.78	11.18
2	Mine waste	0.52	2.64	1.40	0.15	10.22	2.05	0.74	4.43	0.33	3.09	25.56
3	Town/Village/ Roads/Rails	0.28	0.95	2.59	0.36	6.69	0.83	0.32	1.74	0.20	3.41	17.37
4	Industrial area	0.14	0.40	0.20	1.40	1.50	0.52	0.03	7.20	0.05	0.87	12.31
5	Fallow land	0.28	1.96	4.03	0.60	151.03	24.35	4.82	20.52	2.17	17.85	227.62
6	Crop land	0.05	0.18	1.88	0.14	7.98	3.30	5.20	5.67	0.84	3.88	29.12
7	Natural vegetation	0.24	1.13	5.21	0.56	20.79	7.51	6.39	11.87	1.70	9.59	64.98
8	Barren land/ Hill shade	0.19	1.45	2.60	0.75	39.10	4.44	2.50	160.81	0.43	15.84	228.10
9	Water bodies	0.02	0.06	0.08	0.06	1.40	0.01	0.16	0.10	0.52	0.51	2.92
10	Dry water bodies	0.25	0.86	2.96	1.50	18.60	3.10	3.30	12.02	1.18	20.91	64.68
	Total area 1991	2.39	10.49	21.44	5.71	261.04	46.63	23.76	226.05	7.60	78.72	683.84

Table 6: Change detection matrix from 2011 to 2019 in sq.KM

class No.	class Name	Limestone Mines	Mine waste	Town/Village/Roads/Rails	Industrial area	Fallow land	Crop land	Natural vegetation	Barren land / Hill shade	Water bodies	Dry water bodies	Total Area 2019
1	Limestone Mines	1.90	1.68	0.54	0.31	1.31	0.03	0.41	1.67	0.07	3.26	11.18
2	Mine waste	1.09	6.88	1.26	0.34	5.07	0.08	1.68	3.87	0.03	5.26	25.56
3	Town/Village/ Roads/Rails	0.45	1.30	4.81	0.54	3.94	0.02	1.32	0.70	0.01	4.27	17.37
4	Industrial area	0.20	0.82	0.86	4.82	0.92	0.03	0.98	2.07	0.06	1.56	12.31
5	Fallow land	0.64	2.69	2.16	1.33	158.00	1.04	8.92	18.41	0.19	34.24	227.62
6	Crop land	0.04	0.32	1.55	0.14	4.38	2.30	10.47	3.44	0.00	6.48	29.12
7	Natural vegetation	0.24	2.27	3.83	0.92	13.37	1.51	19.01	7.22	0.03	16.60	64.98
8	Barren land/ Hill shade	0.47	2.26	1.22	1.79	30.34	0.36	6.21	158.86	0.00	26.60	228.10
9	Water bodies	0.28	0.00	0.08	0.14	0.21	0.01	0.20	0.12	0.49	1.39	2.92
10	Dry water bodies	3.54	1.66	2.94	0.75	11.06	0.52	5.37	10.97	0.10	27.76	64.68
	Total Area 2011	8.83	19.88	19.24	11.09	228.59	5.91	54.57	207.34	0.98	127.41	683.84

Table 7: Change detection matrix from 2001 to 2011 in sq.KM

class No.	class Name	Limestone Mines	Mine waste	Town/Village/Roads/Rails	Industrial area	Fallow land	Crop land	Natural vegetation	Barren land / Hill shade	Water bodies	Dry water bodies	**Total Area 2011**
1	Limestone Mines	**1.58**	0.70	0.33	0.21	1.48	0.08	0.18	0.77	0.16	3.51	9.00
2	Mine waste	1.16	**5.69**	2.38	1.05	5.54	0.05	0.31	1.91	0.06	1.74	19.90
3	Town/Village/ Roads/Rails	0.77	0.36	3.31	1.04	5.66	0.88	1.64	2.92	0.08	2.58	19.25
4	Industrial area	0.17	0.40	0.29	3.00	2.01	0.03	0.08	4.23	0.05	0.82	11.09
5	Fallow land	0.88	4.57	2.20	1.01	190.66	1.90	2.39	11.45	0.47	13.10	228.61
6	Crop land	0.01	0.02	0.11	0.10	1.39	2.25	1.16	0.48	0.06	0.34	5.91
7	Natural vegetation	0.20	0.35	2.87	1.37	18.21	5.40	9.91	9.40	0.63	6.23	54.57
8	Barren land/ Hill shade	0.54	1.99	1.76	0.94	24.26	1.20	4.30	160.46	0.15	12.32	207.92
9	Water bodies	0.09	0.00	0.00	0.04	0.00	0.07	0.01	0.06	0.57	0.14	0.98
10	Dry water bodies	0.88	2.60	4.68	1.45	63.45	2.04	5.26	18.93	0.71	27.43	127.41
	Total area 2001	6.28	16.67	17.92	10.21	312.65	13.91	25.25	210.61	2.94	68.20	684.64

Table 8: Change detection matrix from 1991 to 2001 in sq.KM

class No.	class Name	Limestone Mines	Mine waste	Town/Village/Roads/Rails	Industrial area	Fallow land	Crop land	Natural vegetation	Barren land / Hill shade	Water bodies	Dry water bodies	**Total Area 2001**
1	Limestone Mines	0.91	1.27	0.29	0.15	1.48	0.31	0.08	0.61	0.04	1.15	6.28
2	Mine waste	0.10	2.59	0.43	0.12	8.33	1.51	0.12	1.05	0.07	2.37	16.67
3	Town/Village/ Roads/Rails	0.18	1.01	3.77	0.21	5.47	0.80	0.80	2.43	0.23	3.03	17.92
4	Industrial area	0.21	0.69	0.51	1.75	1.84	0.48	0.11	3.10	0.11	1.41	10.21
5	Fallow land	0.36	2.82	7.36	1.14	200.60	32.93	7.48	23.62	2.43	33.92	312.65
6	Crop land	0.04	0.10	0.46	0.04	1.92	3.45	3.48	1.96	0.96	1.50	13.91
7	Natural vegetation	0.06	0.20	2.74	0.06	4.74	2.05	5.47	5.91	0.78	3.23	25.25
8	Barren land/ Hill shade	0.29	1.00	2.47	0.69	14.41	3.22	4.15	174.62	0.50	9.26	210.61
9	Water bodies	0.05	0.05	0.16	0.08	0.33	0.14	0.31	0.21	1.39	0.23	2.94
10	Dry water bodies	0.19	0.78	3.26	1.49	21.94	1.77	1.77	13.30	1.09	22.63	68.20
	Total area 1991	2.39	10.5	21.45	5.73	261.06	46.64	23.76	226.79	7.60	78.73	684.64

Conclusions

The Hybrid classification approach combines the advantages of the supervised and unsupervised classification, with this classification approach we are achieved 92% overall land use/cover classification accuracy for the years 1991, 2001, 2011 and 2019, with 0.91 Overall Kappa index. Classified images are dominated by follow lands and Barren lands because the major cultivation is seasonal rail fall dependent and in the moths of April and May no rain fall record in the study area. The results indicate change of LULC classes over the period of 30 years. Limestone mining area increases from 0.35 %(2.39 km^2) to 1.64% (11.18km^2), Limestone mining waste area increases from 1.53 %(10.50 km^2) to 3.74% (25.56km^2), Industrial area increases from 0.84 % (5.73 km^2) to 1.80% (12.31km^2). Follow Land decreases from 38.17%(261.07 km^2) to 33.28% (227.62km^2) and crop land decreases from 6.82 %(46.64 km^2) to 4.26% (29.12km^2).Indices are computed to extract training samples in the present work and the NDVI to estimate the Land Surface Emissivity (LSE) and Land Surface Temperature (LST) over the three decades in the study area in future work.

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