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TIME SERIES ANALYSIS OF MAJOR LAND RESOURCES USING LANDSAT IMAGES IN A PART OF DISTRICT JHANSI, UTTAR PRADESH, INDIA

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Abstract
Space born technology, with its repetitive nature, uses electromagnetic energy to capture digital data from the Earth's surface by remote sensing systems. The purpose of this research is to track changes in land resources with six time series (2003-2009, 2003-2015, 2003-2021, 2009-2015, 2009-2021 and 2015-2021) over a period of 18 years. Multi-date Landsat images of 2003, 2009, 2015 and 2021 have been used to monitor the changing pattern. Level – I classification scheme composed by NRSC/ ISRO and supervised Maximum Likelihood Classification (MLC) techniques were used to identify and classify land use/ land cover features located in Jhansi Tehsil. The findings show that there have been significant changes in land resources over the years. The area under agriculture land, built-up and waterbodies were increased by 48.83%, 53.53% and 106.73% while forest/ tree outside forest and wastelands were reduced by 59.74% and 38.68% respectively It is concluded that, the expansion of key land resources indicates the growth in population and socio-economic activities whereas the loss in some land resources might be due to human induced progressive activities.

Keywords: Change detection; Jhansi tehsil; Landsat images; LULC; Remote Sensing

1. Introduction

Land is mankind's one of the most valuable resource; which provides food, fibre, medicine, minerals and other necessities. The socio-economic growth of a country is influenced by its accessible land resources. Land resources are crucial to determine economic, social and cultural advancement. Land resource definition is based on the interpretation of connected physical qualities for human activity or usage, and dynamic factors of both the natural environment and the occupying civilization are taken into account in each given case. Land is prone to varying functions and/or values due to differences in both circumstances, particularly the action of man in time and space (Highsmith & Land, 1965).

Rapid urban expansion, land degradation and conversion of agricultural land to prawn farming are associated with large environmental costs. All of these are the main indicator of the faster changes in land resources (Sankhala & Singh, 2014). These types of changes have a significant impact on the local, regional, and finally global environments. In particular, the global carbon cycle is impacted by human-induced changes to land cover, which results in an increase in atmospheric carbon. (Alves & Skole, 1996). Therefore, it is imperative to investigate changes in land use to see the impact on terrestrial ecosystems as well as to prepare sustainable land use plans for researchers. (Muttitanon & Tripathi, 2005).

Space born technology uses electro-magnetic energy to capture data from the Earth's surface by remote sensing systems. The use of Remote Sensing and Geographic Information Systems (GIS) in the context of comprehensive geoenvironmental challenges to monitor and manage land resources that can be detected using satellite images. It is also being developed as a significant instrument for capturing data on any and all aspects on the earth's surface. Satellite data with extremely high resolution (both spatial and spectral) has been accessible in recent years. For decades, remote sensing and GIS have provided significant financial support to India's progressive initiatives (Kumar et al., 2013).

Landsat images have been utilised for a wide range of applications, including several concerned with human-induced, bio-physical changes and the influence of the geo-physical environment on civilization. Another key application of Landsat images is to monitoring the temporal changes on the earth's surface due to its repeatability (Townshend, 2006). Change in land resources as a result of human activities have had a significant impact on global environmental changes and have become a hot issue among academics (Liu et al., 2002).

2. Materials and Methods

The present study precisely dedicated to analysing temporal changes on land resources using space-born platform. Temporal Landsat images for 2003, 2009, 2015 and 2021 were used to achieve the goal. The comprehensive implemented methodology are as follows:

Study Area

Jhansi district is located in south-west portion of Uttar Pradesh, India. There are 5 tehsils under Jhansi district viz., Jhansi, Mauranipur, Moth, Garautha and Tehrauli. The Jhansi tehsil is further divided in to two blocks name as Babina and Baragaon for administrative purposes. In India, the block is often the next level of administrative division after the tehsil (Census of India, 2011). The study area i.e., Jhansi tehsil lies between 25°7'27.676" to 25°35'26.175"N and 78°18'3.760" to 78°49'14.816"E (Fig. 1). Jhansi is a part of the plateau of Southern Bundelkhand, and slopes generally in the direction to the northeast. The elevation varies from 200 m above mean sea level in the north to about 345 m in the south. The moderately weathered pediplain, residual hills, linear quartz reefs, and historic meanders make up the northern highly erodible plain province. The pediplain is moderately and thoroughly weathered, with an overburden of 5 to 20 m, and formed moderate aquifers. The prospective aquifer system is made up of the shallow alluvial sediments and the granite/gneiss mantle underneath, which has an average thickness of 40 metres. Average pediplain thickness is 0 to 5 metres, and it is fragmented and crisscrossed by lineaments. It offers fair to excellent chances for ground water. The Betwa River (a tributary of the Yamina River) and the Pahuj River (a tributary of Sind River) have drained in Jhansi. Both of these rivers are perennial in nature. The river flow direction and slope are north to north-east, and the drainage system is dendritic in form (CGWB, 2017).

Granite formations usually include quartz, feldspar, plagioclase, biotite, chlorite, hornblende, pyroxene, olivine, muscovite, apatite, zircon, and magnetite (Mishra & Sharma, 1975). Agricultural regions rely on rainwater. Similarly, soil health is normally determined by soil quality, but in Jhansi, the Vindhyan range's combination of red and black soil is not particularly productive. As a result, during the Kharif season, the major crops of Jhansi Tehsil are Juwar and toor, and during the Rabi season, Wheat, Gram, and Masoor (Census of India, 2011).

In the sub-humid area, the climate is characterised by a hot, dry summer and a frigid winter. May is the warmest month, with maximum average temperatures about 42° degrees Celsius and lowest average temperatures around 28°C. Similarly, January has a highest average temperature of around 24°C and a low average temperature of around 9°C. The air is very dry and scorching throughout the summer, while the moisture content of the air is very high during the monsoon. The average yearly humidity is 41%. The average wind speed is 4.8 km/h. The evapotranspiration potential is 1603mm. During the South-West monsoon, annual rainfall varies between 700 and 1100 mm. From June through September,

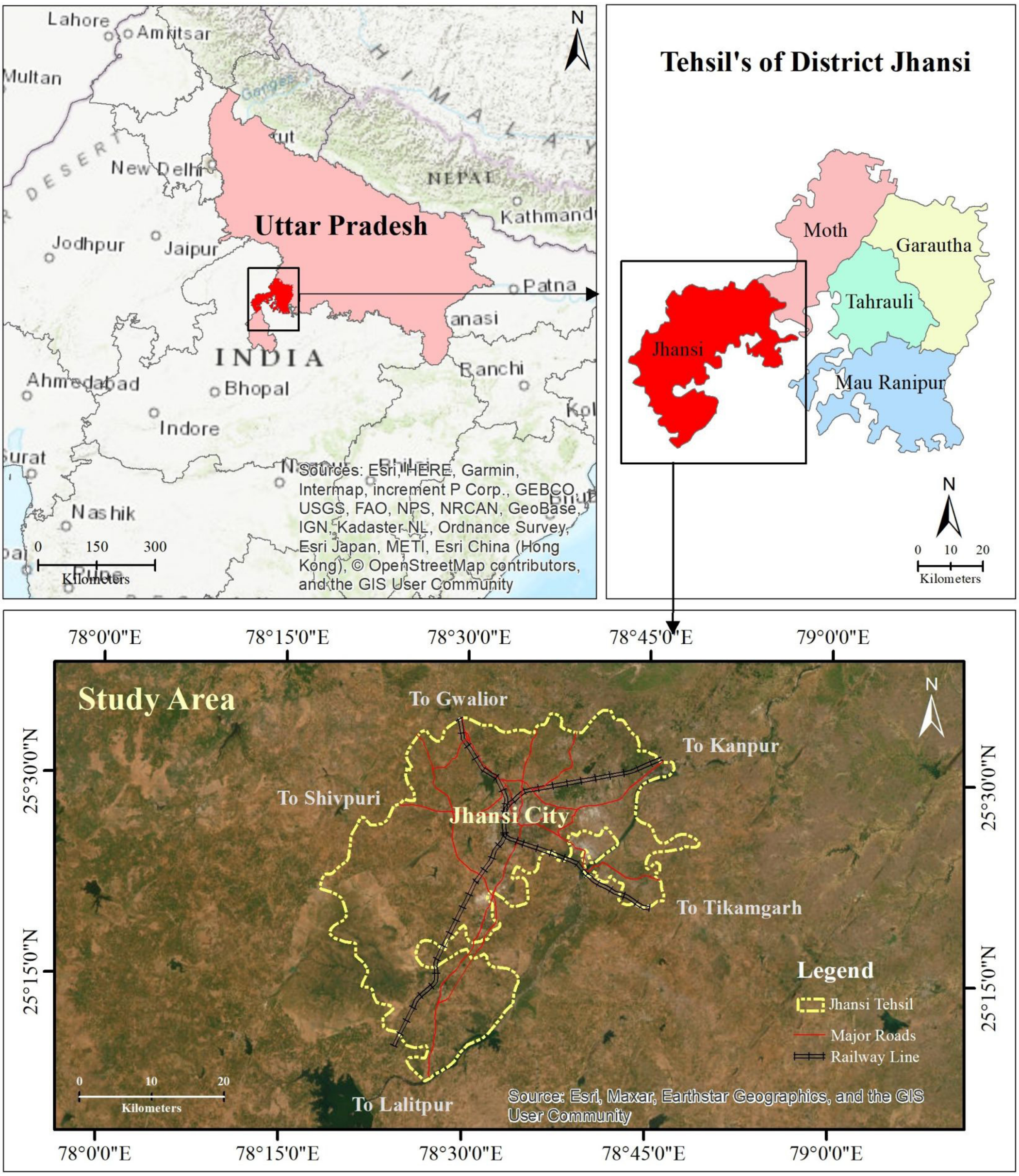

Fig. 1. Administrative Settings of Jhansi Tehsil

almost 91 percent of the rainfall is recorded, and precipitation is the only source of groundwater replenishment. High rainfall intensity causes moderate to undecorated soil health deterioration and increases silt concentration in waterbodies. The Jhansi Tehsil's rainfall pattern is very erratic, contributing to drought conditions (CGWB, 2008).

Data collection

Numerous data were used to prepare thematic layers and evaluate the temporal changes. Total eight temporal images of the study area with spatial resolution 30m has been downloaded from https://earthexplorer.usgs.gov. To achieve the goal, full care has been taken that the data should be cloud free and or same season/ month. For the reason of that, it is essential as per the objective, there should be minimum time interval as well as geometrically/ atmospherically corrected for all time/ interval (2003, 2009, 2015 and 2021) hence the date from January last week to first week of February has been selected (Table 1). To validate the image classification accuracy, ground control points were collected from various land use classes using google earth pro.

Image processing

Image processing is the processes where the operations deal directly with the pixels of the digital image. Over real-world position to each pixel of the raster file can be determine as every pixel on the raster image is positioned on the Earth's surface (USGS, 2018). Particularly in Landsat images, the subsequent steps has been followed i.e., layer stacking, mosaic and subset/ masking using area of interest (Stack Exchange, 2022). Layer stacking of all Landsat images have been done using ERDAS Imagine. Image mosaic of Landsat images has been completed using Mosaic Pro Tool of ERDAS imagine (IEEE, 2021). A subset of the specified study area (Fig. 2) have been done using Mask tool of ArcGIS.

Record of the precise locations of different land resources

Total 100 ground control points have been validated in different land use/ land cover classes with the help of Garmin GPS for accuracy assessment of classified Landsat images.

Table 1. Details of downloaded satellite images

S. No.	Satellite Name	Path/Row	Passing Date	Downloaded File/Folder
1	Landsat 7	145/042	27.01.2003	LE07145042200301270 1T1-SC20200522070134
2	Landsat 7	145/043	27.01.2003	LE071450432003012701T1-SC20200522073148
3	Landsat 5	145/042	04.02.2009	LT05_L1TP_145042_20090204_20161028_01_T1
4	Landsat 5	145/043	04.02.2009	LT05_L1TP_145043_20090204_20161028_01_T1
5	Landsat 8	145/042	05.02.2015	LC081450422015020501T1-SC20200601061158
6	Landsat 8	145/043	05.02.2015	LC081450432015020501T1-SC20200601065152
7	Landsat 8	145/042	21.02.2021	LC08_L2SP_145042_20210221_20210303_02_T1
8	Landsat 8	145/043	21.02.2021	LC08_L2SP_145043_20210221_20210303_02_T1

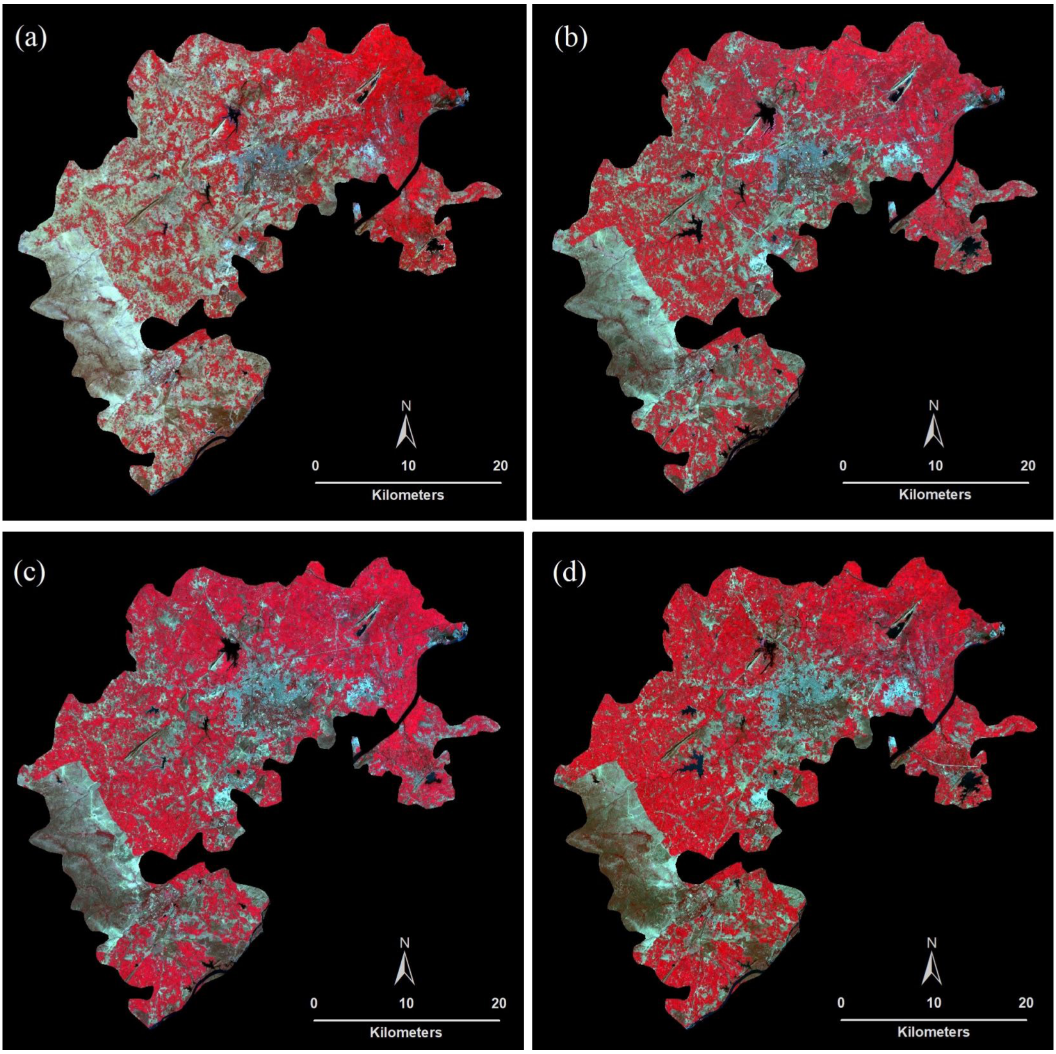

Fig. 2. Multi-date satellite images (a) Landsat 7; Passing Date: 27/01/2003; RGB: B3, B2, B1; (b) Landsat 5; Passing Date: 04/02/2009; RGB: B3, B2, B1; (c) Landsat 8; Passing Date: 05/02/2015; RGB: B4, B3, B2; and (d) Landsat 8; Passing Date: 21/02/2021; RGB: B4, B3, B2

Classification of land resources

The classification of land resources is very important for selection of different features presented on earth surface. In this study, Level – I classification scheme developed by NRSC/ ISRO (NRSC/ ISRO, 2014) was used to identify and classify the land use/ land cover features. In the Level – 1 classification scheme, land has divided in five categories i.e., built-up, agricultural land, forest, waterbodies and wastelands. For the drive of Level-I classification, supervised Maximum Likelihood Classification (MLC) technique has been used through training sample method in ArcGIS. Maximum Likelihood Classification (MLC) uses statistics to determine the likelihood of pixel values belonging to a certain feature class. The highest chance of each assigned pixel of the specified feature class is the maximum likelihood (Vanderkelen, 2015). This classification is purely based on the cluster/ group of spectral signature hence some of the classes has been club under another representative class i.e., built-up including existing constructional/ transportation/ industrial/ mining activities, agricultural land includes active cropland only, forest including huge amount of trees outside forest, waterbodies includes active surface water only and wastelands including barren rocky surface and scrubland.

Accuracy assessment

To assess the accuracy of all classified images based on field reference data, total 100 random sample points (20 points in each class) using equalized stratified random category were created using ArcGIS. In the land use/ land cover classifications, the minimum acceptable accuracy level is of < 50% (Maps and GIS Library, 2014). The map's accuracy level was assessed by picking equally distributed reference locations in the imagery and comparing them to the test pixel or comparable reference position of a ground observation. The reference points were spread at random in the ArcGIS imagery before being converted to MS Excel to assess the accuracy. The exported data were then used to calculate the error matrix for the categorized pictures, which included the kappa coefficient (k), overall accuracy, commission error (user's accuracy), and omission error (producer's accuracy). The entire accuracy of the categorized pictures is referred to as overall accuracy. The likelihood of a given class being mistakenly categorized on the map is known as commission error (user accuracy), whereas the probability of a single class being wrongly classified on the ground is known as omission error (producer accuracy). The Kappa coefficient (K) is a discrete multivariate approach used in accuracy evaluation; K > 0.80 indicates high accuracy or agreement of the class examined, 0.60-0.80 indicates moderate to high, 0.40-0.60 indicates moderate accuracy and < 0.40 indicates low accuracy (Agariga et al., 2021).

The Kappa Coefficient (K), overall accuracy, user's accuracy, and producer's accuracy were all calculated using the formulas shown below:

$$K = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_i + X_{x+1})}{N^2 - \sum_{i=1}^{r} (x_i + X_{x+1})} \quad (1)$$

where:

N – total number of observations in the matrix,

r – number of rows in the matrix,

x_{ii} – number of observations in row i and column i,

$x + i$ – total for row i and

x_{i+} – total for column i

$$Overall\ accuracy = \frac{Total\ number\ of\ individual\ pixels\ correctly\ classified}{Total\ number\ of\ classified\ cells} X\ 100 \quad (2)$$

$$User's\ accuracy = \frac{Total\ number\ of\ correctly\ classified\ individual\ cell\ (row)}{Total\ number\ of\ pixel\ in\ a\ given\ class\ (row)} X\ 100 \quad (3)$$

$$Producer's\ accuracy = \frac{Total\ number\ of\ correctly\ classified\ individual\ cell\ (column)}{Total\ number\ of\ classified\ pixel\ (column)} X\ 100 \quad (4)$$

(Jenson, 2014)

Change detection

Temporal data has been of considerable improvement to monitoring the temporal changes in land resources over the year. The following formula was used to evaluate change detection (Kashaigili & Majaliwa, 2010; Kleemann et al., 2017). A negative value represents a reduction in land use/cover size, whereas a positive value represents an increase (Abubakar & Anjide, 2012).

$$Area\ change = Area_{i\ year\ x+1} - Area_{i\ year\ x} \quad (5)$$

$$Area\ change\ (\%) = \frac{Area_{i\ year\ x+1} - Area_{i\ year\ x}}{\sum_{i=1}^{n} Area_{i\ year\ x}} X\ 100 \quad (6)$$

$$Annual\ rate\ of\ change = \frac{Area_{i\ year\ x+1} - Area_{i\ year\ x}}{t_{years}} \quad (7)$$

$$Annual\ rate\ of\ change\ (\%) = \frac{Area_{i\ year\ x+1} - Area_{i\ year\ x}}{\sum_{i=1}^{n} Area_{i\ year\ x}\ X\ t_{years}} X\ 100 \quad (8)$$

where:

$Area_{iyear\ x+1}$ – Area of LULC for the following year

$Area_{i\ year\ x}$ – Area of LULC of the current year

$\sum Area_{i\ year\ x}$ – The total area of LULC of the current year

t_{years} – the years' difference between the first and second period

3. Results

Assessment of temporal status and changes were calculated between six time series i.e., 2003-2009, 2003-2015, 2003-2021, 2009-2015, 2009-2021 and 2015-2021. The time series analysis of land resources for Jhansi tehsil are as follows-

Status and error matrix analysis of land resources in 2003

The study reveals that out of the total geographical area (118500 ha), wasteland accounts 43.51% (51555.09 ha) of the total area. The next main feature was agriculture covering about 38.66% of land which accounts about 45815.98 ha. The rest of land resource features such as forest/ tree outside forest (TOF), built-up and waterbodies accounts 12893.89 ha (10.88%), 6607.79 ha (5.58%) and 1627.26 ha (1.37%) respectively (Table 2). The graphical presentation and spatial distribution of land in 2003 is shown in Fig. The overall accuracy and kappa coefficient was found 91% and 88.75% respectively. User's and producer's accuracy of individual classes for Landsat – 7 image are presented in appendix A.

Status and error matrix analysis of land resources in 2009

The study reveals that out of the total geographical area (118500 ha), agriculture covering about 53.38% (63254.23 ha) and wasteland accounts for 28.87% (34208.37 ha) of the total geographic area. The rest of land resource features such as forest/ tree outside forest (TOF), built-up and waterbodies accounts 11653.66 ha (9.83%), 6637.01 ha (5.60%) and 2746.74 ha (2.32%) respectively (Table 3). The graphical presentation and spatial distribution of land resources in 2009 is shown in Fig. 4. The overall accuracy and kappa coefficient was found 89% and 86.25%. User's and producer's accuracy of individual classes for Landsat – 5 image are presented in appendix B.

Status and error matrix analysis of land resources in 2015

Out of the total geographical area (118500 ha), wasteland accounts for 26.65% (31580.31 ha) of the total area. The next main land use feature was agriculture covering about 57.42% of land which accounts about 68045.54 ha out of total geographic area. The rest of land resource features such as forest/ tree outside forest (TOF), built-up and waterbodies accounts 5981.17 ha (5.05%), 9882.08 ha (8.34%) and 3010.89 ha (2.54%) respectively (Table 4). The graphical presentation and spatial distribution of land resources in 2015 is shown in Fig. 5. The overall accuracy and kappa coefficient was found 90% and 87.5%. User's and producer's accuracy of individual classes for Landsat – 8 image are presented in appendix C.

Status and error matrix analysis of land resources in 2021

Agriculture covering about 57.54% (68185.77 ha) and wasteland accounts for 26.68% (31614.95 ha) of the total geographic area (118500 ha). The rest of land resource features such as forest/ tree outside forest (TOF), built-up and waterbodies accounts 5190.45 ha (4.38%), 10144.73 ha (8.56%) and 3364.11 ha (2.84%) respectively (Table 5). The graphical presentation and spatial distribution of land resources in 2021 is shown in Fig. 6. The overall accuracy and kappa coefficient was found 92% and 90%. User's and producer's accuracy of individual classes for Landsat – 8 image are presented in appendix D.

Table 2. The status of land resources in 2003

Land resources	Area (000'ha)	Area (%)
Built-up	6.60779	5.58%
Agriculture	45.81598	38.66%
Forest/ TOF	12.89389	10.88%
Waterbodies	1.62726	1.37%
Wastelands	51.55509	43.51%
Total	118.500	

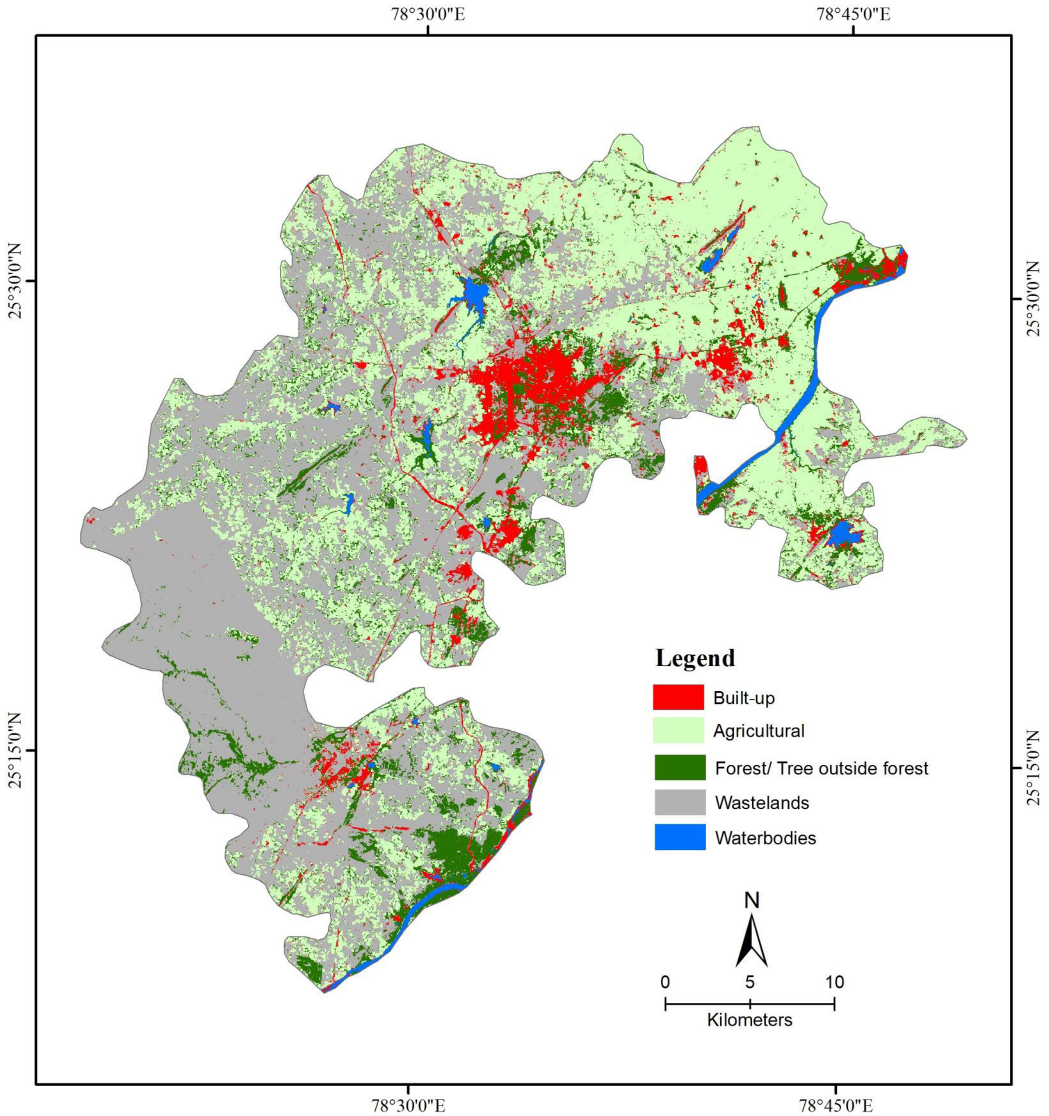

Fig. 3. Spatial distribution of land resources in 2003

Table 3. The status of land resources in 2009

Land resources	Area (000'ha)	Area (%)
Built-up	6.63701	5.60%
Agriculture	63.25423	53.38%
Forest/ TOF	11.65366	9.83%
Waterbodies	2.74674	2.32%
Wastelands	34.20837	28.87%
Total	118.500	

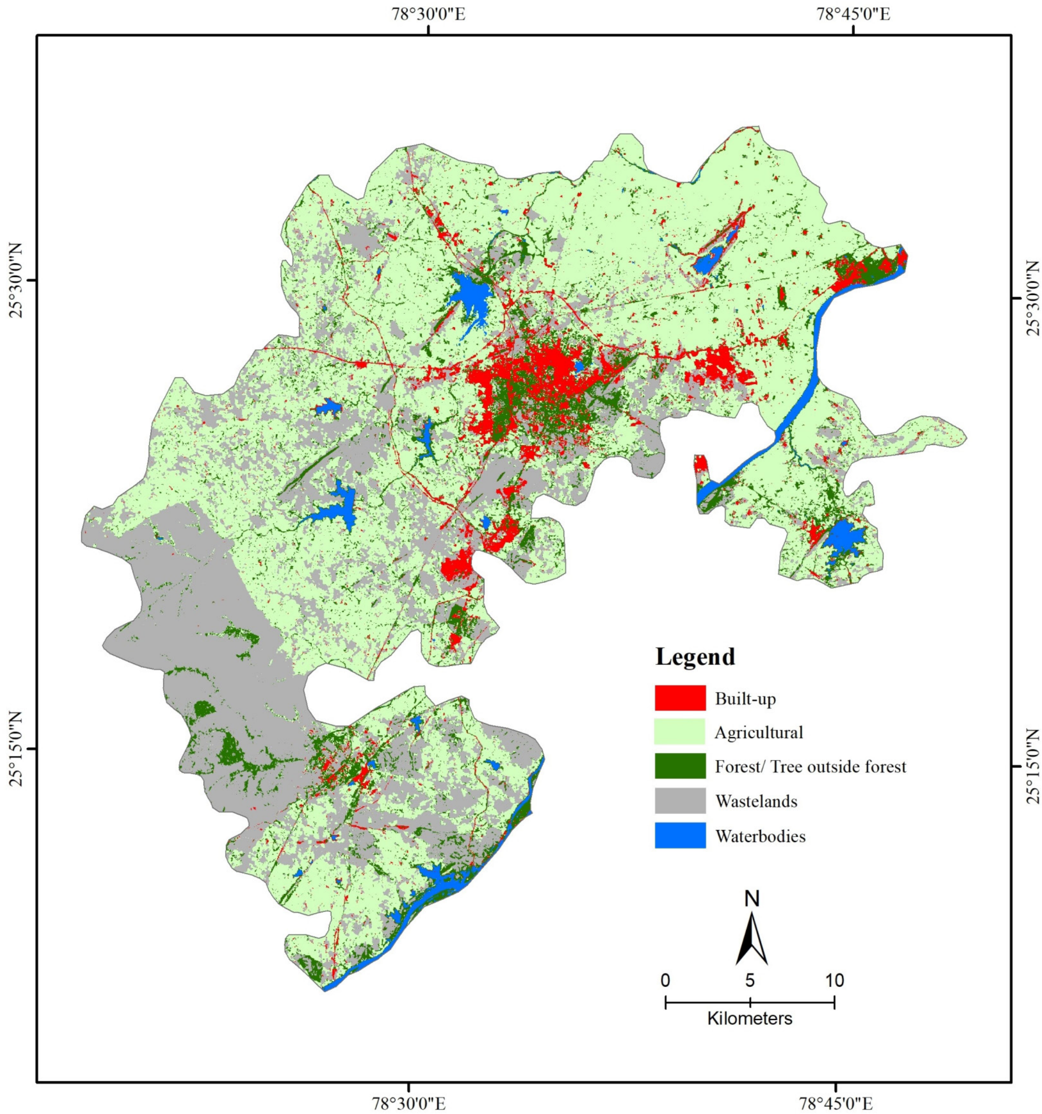

Fig. 4. Spatial distribution of land resources in 2009

Table 4. The status of land resources in 2015

Land resources	Area (000'ha)	Area (%)
Built-up	9.88208	8.34%
Agriculture	68.04554	57.42%
Forest/ TOF	5.98117	5.05%
Waterbodies	3.01089	2.54%
Wastelands	31.58031	26.65%
Total	118.500	

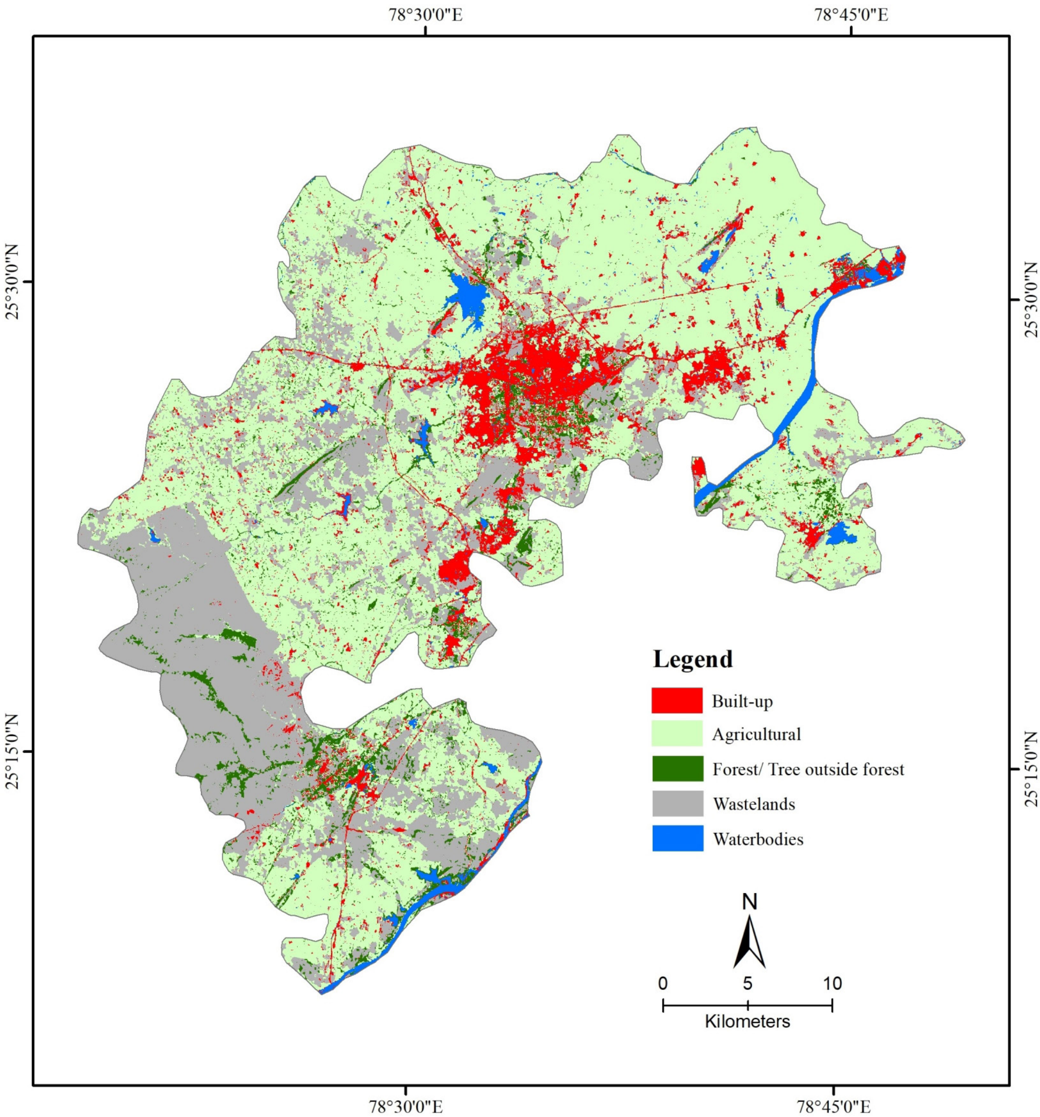

Fig. 5. Spatial distribution of land resources in 2015

Table 5. The status of land resources in 2021

Land resources	Area (000'ha)	Area (%)
Built-up	10.14473	8.56%
Agriculture	68.18577	57.54%
Forest/ Tree Outside Forest (TOF)	5.19045	4.38%
Waterbodies	3.36411	2.84%
Wastelands	31.61495	26.68%
Total	118.500	

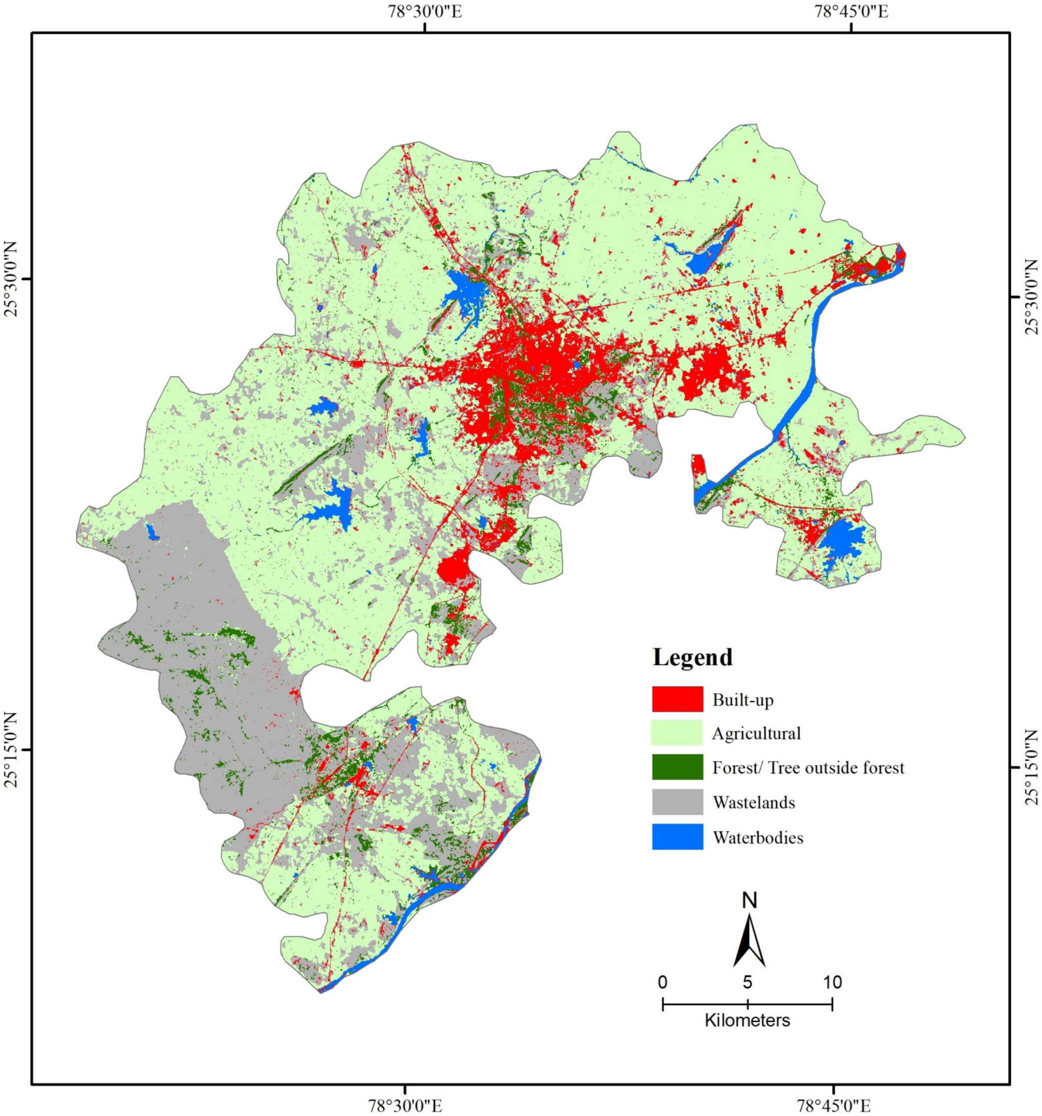

Fig. 6. Spatial distribution of land resources in 2021

Temporal change assessment

The area under agricultural land increased from 38.66% in the year 2003 to 53.38%, 57.42%, and 57.54% in 2009, 2015 and 2021 respectively. Built-up area were slightly increased from 5.58% (in 2003) to 5.60% (in 2009) because of the mining activities and construction/ transportation was slow down in this period. In 2015 and 2021, the area under built-up were found 8.34% and 8.56% respectively. The area under forest/ tree outside forest (TOF) have in decreasing trend during 2003 to 2021. The area under forest/ tree cover was found 10.88%, 9.83%, 5.05% and 4.38% in 2003, 2009, 2015 and 2021 respectively. Wastelands account 43.51%, 28.87%, 26.65% and 26.68% in 2003, 2009, 2015 and 2021 respectively. However, it is slightly increased from 26.65% in 2015 to 26.68% in 2021 due to mining waste and under construction roads/ highways. The area under waterbodies were increased from 1.37% in 2003 to 2.32%, 2.54% and 2.84% in 2009, 2015 and 2021 respectively. The graphical presentation and spatial distribution of change in land resources are shown in Fig. 7 and Fig. 8.

Time series analysis on temporal change assessment of land resource

Time series analysis on temporal changes assessment for last 18 years were calculated between six time series i.e., 2003-2009, 2003-2015, 2003-2021, 2009-2015, 2009-2021 and 2015-2021 (Fig. 9). The area under agricultural and waterbodies have been increased by 38.06% and 68.80% between 2003-09 while forest/ tree outside forest, wastelands showed the decrease of 9.62% and 32.87% respectively. There are some minor change has been recorded in built-up area i.e., about 0.44% during above time series. The area under agricultural, built-up and water bodies showed the increase of 48.52%, 49.55% and 85.03% from 2003 to 2015 while forest/ tree outside forest and wastelands showed the decrease of 53.61% and 38.74% respectively. For the duration between 2003 to 2021 the area under agricultural, built-up and waterbodies showed the increase of 48.83%, 53.53% and 106.73% while forest/ tree outside forest and wastelands showed the decrease of 59.74% and 38.68% respectively. From 2009 to 2015, the area under agricultural, built-up and waterbodies presented the increment of 7.57%, 48.89% and 9.62% while forest/ tree outside forest and wastelands presented the reduction of 48.68% and 7.68% respectively. For the duration between 2009 to 2021, the area under agricultural, built-up and water bodies secure the growth by 7.80%, 52.85% and 22.48% while forest/ tree outside forest and wastelands were fall down by 55.46% and 7.58% respectively. The area under

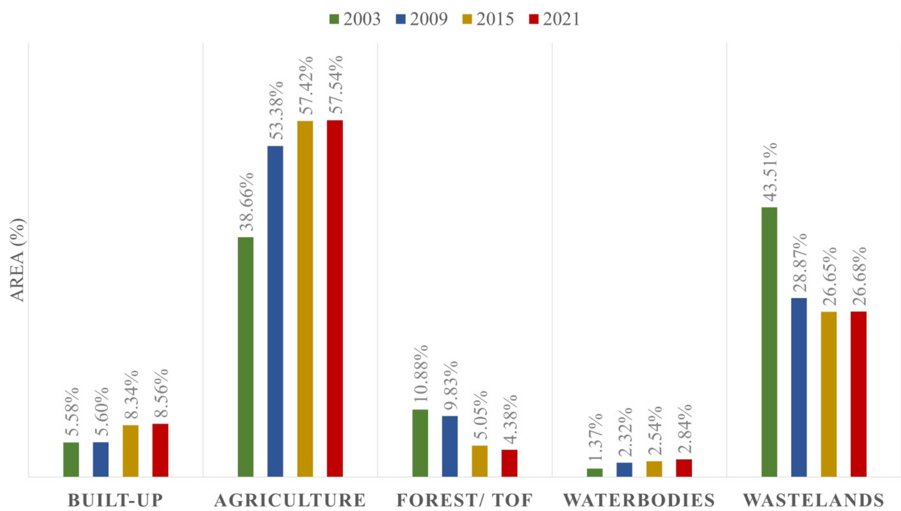

Fig. 7. Graphical presentation: Temporal changes in land resources

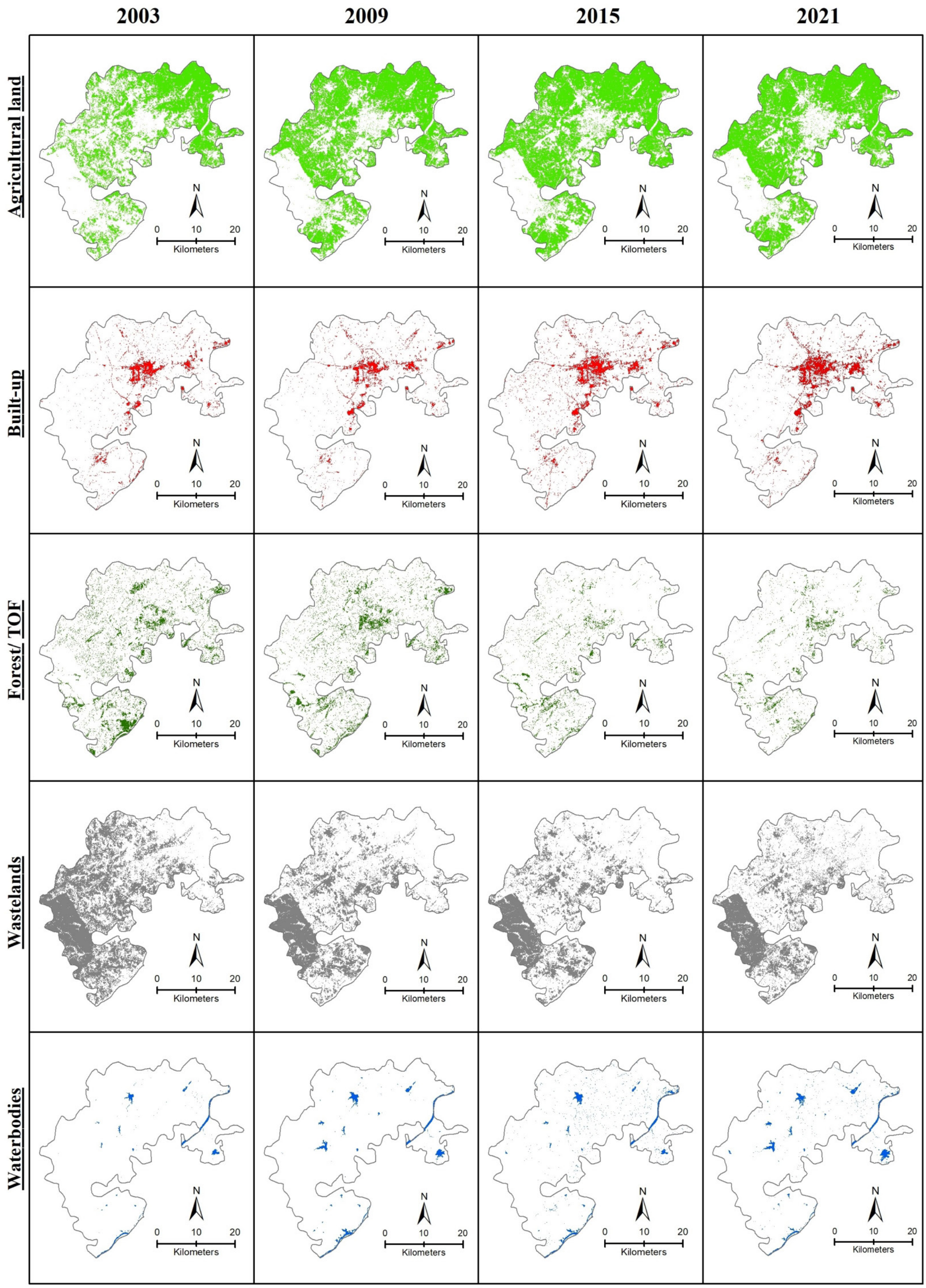

Fig. 8. Spatial distribution: Temporal changes in land resources

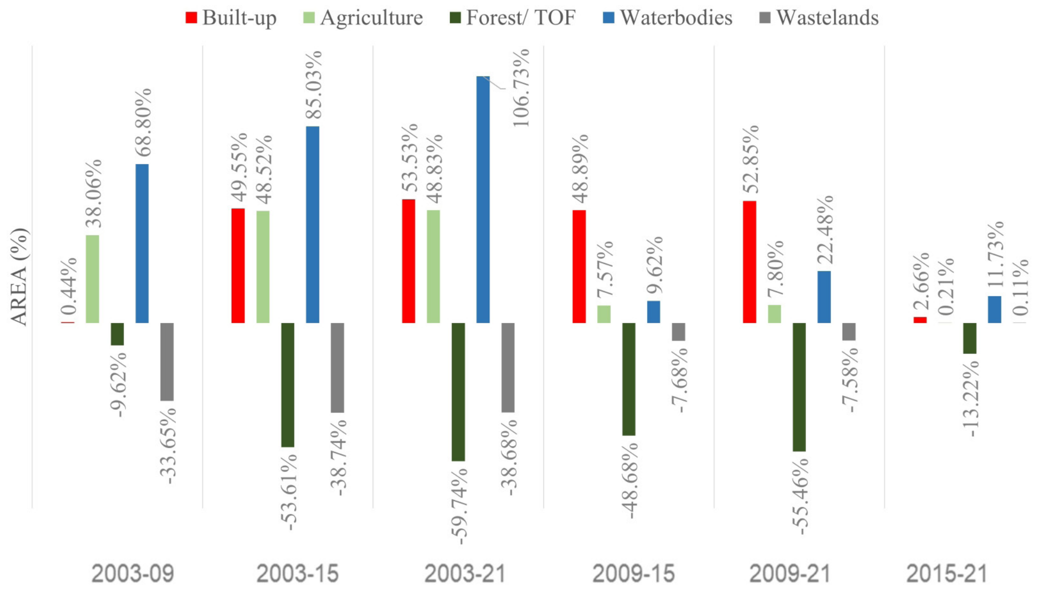

Fig. 9. Time series analysis on change assessment in land resources

agricultural, built-up, wastelands and water bodies have been raised by 0.21%, 2.66%, 0.11% and 11.73% from 2015 to 2021 while forest/ tree outside forest was fall down by 13.22% (Table 6). Table 7 shows the annual rate of change in land resources during different time interval.

4. Discussion

Agricultural land under land resource is the most numerous of the listed classes in the region. The area increased from 45815.98 ha in 2003 to 68185.77 ha in 2021. During this period due to government initiatives canal/ irrigation network widened which enhanced the reach of farmers for irrigation. Irrigation has been the main limiting factor for agriculture due to occurrence of frequent drought in Bundelkhand region hence high crops yield has been recorded. Intensive agriculture due to better irrigation facilities has been started in the region. Conversion of forestlands into agriculture lands and adoption of alternate land use system could possibly explain the increase in agriculture during the period. Built-up area have slightly increased by 0.44% in 2003-09 and 2.66% in 2015-21 however it is recorded as 53.53% growth from 2003-2021 due to urbanization etc. The increase in built up area can be attributed to expanding roads and peripheral zones in the forest area and wastelands. And also because of the increase in population, tourism activities and residents desire for housing, the area under built-up land has to increased (Vivekananda et al., 2021). Apart from these factors, socio-economic factors like migration, urbanization, population growth and other developmental initiatives are also drivers of land use/ land cover change in the region (Kashaigili & Majaliwa, 2010). Wastelands decreased from 51555.09 ha in the year 2003 to 34208.37 ha, 31580.31 ha and 31614.95 ha in 2009, 2015 and 2021 respectively. This may be due to conversion of waste land to prosperity land through adoption of alternate land use systems or use of these neglected land for any other purpose like agriculture or built-up. The land use pattern observed indicates that habitation and farming growth were on the horizon. The area under waterbodies during the period increased from 1627.26 ha (1.37%) in the year 2003 to 3364.11 ha (2.84%) in 2021. This is an interesting point because as a

Table 6. Temporal change assessment of land resources for different time interval

Land resources	2003-09		2003-15		2003-21		2009-15		2009-21		2015-21	
	Area		Area		Area		Area		Area		Area	
	ha	%	ha	%	ha	%	ha	%	ha	%	ha	%
Built-up	29.22	0.44%	3274.30	49.55%	3536.94	53.53%	3245.08	48.89%	3507.72	52.85%	262.65	2.66%
Agriculture	17438.25	38.06%	22229.56	48.52%	22369.79	48.83%	4791.31	7.57%	4931.54	7.80%	140.23	0.21%
Forest/ TOF	-1240.23	-9.62%	-6912.72	-53.61%	-7703.44	-59.74%	-5672.49	-48.68%	-6463.21	-55.46%	-790.72	-13.22%
Waterbodies	1119.48	68.80%	1383.63	85.03%	1736.85	106.73%	264.16	9.62%	617.37	22.48%	353.21	11.73%
Wastelands	-17346.72	-33.65%	-19974.77	-38.74%	-19940.14	-38.68%	-2628.05	-7.68%	-2593.42	-7.58%	34.64	0.11%

Table 7. Annual rate of change in land resources for different time interval

Land resources	2003-09		2003-15		2003-21		2009-15		2009-21		2015-21	
	Area		Area		Area		Area		Area		Area	
	ha	%	ha	%	ha	%	ha	%	ha	%	ha	%
Built-up	4.87	0.07%	272.86	4.13%	196.50	2.97%	540.85	8.15%	292.31	4.40%	43.77	0.44%
Agriculture	2906.38	6.34%	1852.46	4.04%	1242.77	2.71%	798.55	1.26%	410.96	0.65%	23.37	0.03%
Forest/ TOF	-206.70	-1.60%	-576.06	-4.47%	-427.97	-3.32%	-945.41	-8.11%	-538.60	-4.62%	-131.79	-2.20%
Waterbodies	186.58	11.47%	115.30	7.09%	96.49	5.93%	44.03	1.60%	51.45	1.87%	58.87	1.96%
Wastelands	-2891.12	-5.61%	-1664.56	-3.23%	-1107.79	-2.15%	-438.01	-1.28%	-216.12	-0.63%	5.77	0.02%

general trend in other parts of India usually area under waterbodies have been decreased due to changing climatic conditions, poor management practices and anthropogenic interventions. More importantly, common perception about Bundelkhand region has been water scarcity emanated from frequent droughts prevailing in the region. Number of rainy days has also been decreased. As during this period various government initiatives has been launched in the region regarding rainwater harvesting, development and protection of dams. Betwa-Ken River interlinking project and development of irrigation networks which has positively influenced the area under water bodies. The conversion of more water bodies indicates a water scarcity (Gupta et al., 2014). In general, a significant increase in cultivated land to meet the high demand for food due to population growth and resulting in a high demand for food production to meet basic human needs (Al-Faraj & Scholz, 2015). The area under forest/ tree cover showed the decreasing trend during the whole period from 2003 to 2021. The area under forest/ tree cover was found 12893.89 ha (10.88%) in 2003 which gradually decreased to 5190.45 ha (4.38%) in 2021. About 59.74% area under forest/ tree cover has been decreased during 2003-21. The loss in the forest cover may be due to conversion of forest lands into agricultural land, illegal logging and loss of forest lands, expansion of road network and other developmental activities. Indian forest scenario during this period also resonates these facts. Human activities are the principal driver of forest degradation (Ali et al., 2006; Butt et al., 2015). Further support these findings, pointing out that agriculture is the primary cause of annual forest clearance (Wasige et al., 2013)

5. Conclusion

Land is the most significant valuable resource for mankind and it can be measured as an upper layer of earth crust that modified by both natural and human induces operations. The changes are successfully assessed using maximum likelihood classification of multi-temporal Landsat images (2003, 2009, 2015 and 2021). This study reveals the pattern of change in land resources from 2003 -2021 between six time series i.e., 2003-2009, 2003-2015, 2003-2021, 2009-2015, 2009-2021 and 2015-2021 for Jhansi tehsil. The evaluation of change in land resources from past 18 years (2003 to 2021) were observed as agricultural land increased by 48.83%, built-up area increased by 53.53%, forest/ tree outside forest decreased by -59.74%, wastelands decreased by -38.68% and waterbodies increased by 106.73%. The results summarized that, the expansion in agriculture land, built-up and waterbodies were the indication of growth in urbanization and the loss in the forest cover and wastelands may be due to conversion of representative lands into agricultural land, illegal logging, expansion of road network and other developmental activities.

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