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Quantifying LULC change and landscape fragmentation in Prayagraj district, India using geospatial techniques

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Abstract
Spatial temporal change of LULC alter landscape pattern and affect the ecosystem. The present study aimed to quantify the change in LULC of Prayagraj using satellite data and Fragstats. Landsat satellite images from 1990, 2007 and 2017 were used to calculate the changes of LULC using supervised classification. Classified maps were used to calculate different landscape indices using Fragstats. The results showed that during the whole study period, agricultural land, settlement, barren land and salt affected area showed increasing trend whereas forest and water body showed decreasing trend. Further spatial analyses by using landscape metrics are able to assess the trend of spatial patchiness over the studied period.

Keywords: LULC: landscape index: Landsat images

1. Introduction

Change in composition of LULC is dynamic, widespread and accelerating process mainly driven by natural phenomena and anthropogenic activities (Southworth *et al*., 2004) [15]. Over the last few decades Urbanization has emerged as one of the most dominant factor of the losing arable land, devastating habitats, and the decline in natural vegetation cover (Dewan and Yamaguchi, 2009) [3]. As a result, rural areas have been converted into urban land and ultimately effect the natural functioning of ecosystems (Turner, 1994) [14].

India is the second largest populated country in the world showing continuous population growth has played a major role in landscape fragmentation (Kumar *et al.* 2018) [6]. To understand and quantify changes in landscape structure, pattern and dynamics, it is important to have a clear understanding of landscape indices. These indices include area, patch density and size, edge, shape, nearest neighbour, diversity and interspersion, which have been developed in the past few decades to provide useful information about the composition and configuration of landscape (Olsen *et al*., 2006; Paudel and Yuan, 2012) [9, 10]. In explaining landscape dynamics, there are various methods that can be used in the collection, analysis and presentation of data. However accurate, faithful, timely and less cost information have been a challenge for scientist, local communities and policy decision makers. The use of remote sensing (RS) and geographic information system (GIS) technologies can greatly facilitate an excellent promise for data collection because of its faithful, synoptic repetitive coverage over the same area at various spatial and temporal scales, even datasets are available for inaccessible locations at low cost (Sun *et al*., 2009; Hansen & Loveland 2012) [13, 4]. On the other hand, some spatial statistics programs like FRAGSTAT have been effectively used for landscape metrics calculation. Earlier works have demonstrated the applications of this tool to illustrate spatiotemporal dynamics of landscape change (Cayuela *et al*., 2006; Singh *et al*., 2016; kumar *et al*., 2018) [6, 1, 11].

The Prayagraj has been identified as Holy place of India which is the major attractions of the city. Prayagraj is also famous for educational & literary activities hence also referred as Oxford of east. However population and infrastructure development of the area is increasing rapidly. In this context Prayagraj comes under high priority for systematic development. Therefore analysis of these areas will have broad applications. Paryagraj is selected for study because area is known worldwide for its magical confluence of history, culture, and religion. We have aimed to address the LULC change and landscape fragmentation for 1990, 2007 and 2017 in the Prayagraj (Northern part of India) using Landsat imageries.

2. Material and method

2.1 Study area

The study area is located in the southern part of the state, at Latitude 25°45′ N and Longitude 81°85′ E and stands at the confluence of three rivers, Ganga, Yamuna and the invisible Saraswati. Prayagraj is the seventh most populous city in Uttar Pradesh as well as the 32nd most populous city in India. According to 2011 India census, Prayagraj city had a population of approximately 1,316,719. The density of people in Prayagraj is 1,087 per km^2 in 2011, compared to 901 in 2001 (2011; www.censusindia.gov.in). The annual mean temperature is 26.1°C (79.0°F) and monthly mean temperatures are 18-29°C (64-84°F). Prayagraj experiences all seasons with climate varying from extreme hot to extreme cold. The climate is marked by high relative humidity i.e. 70 to 80 percent during monsoon and progressive decrease in humidity (during the summers humidity is very low i.e. 15 to 20 percent only). Rainfall mainly occurs during the period of June to September. The highest monthly rainfall total, 296 mm (12 in), occurs in August. The normal annual rainfall here is 1027 mm (40 in) but the variation from year to year is appreciable on an average there are about 48 rainy days in a year.

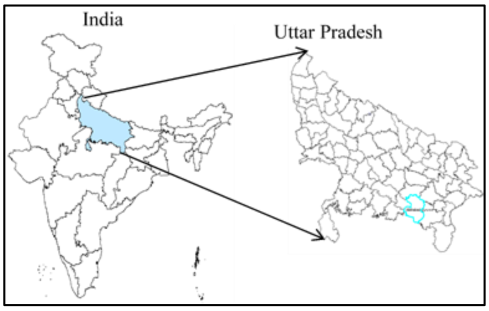


Fig 1: Location map of study area

2.2 Satellite data acquisition and preprocessing

The Ortho-rectified Landsat images of three different years were downloaded from United States Geological Survey (USGS) portal (http:// www.usgs.gov/in) and details are given in Table 1. Top of Atmospheric Correction was applied for radiometric normalization of multi-temporal data. By using district boundary, a subset of the study area was made and extracted from the satellite scenes.

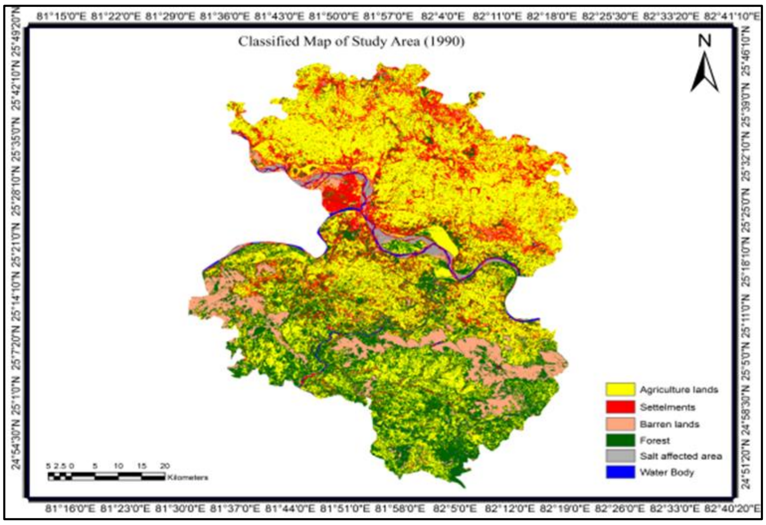
Table 1: satellite images used for the study

Satellite/ Sensor	Year/date	Number of bands used	Spatial Resolution(m)
Landsat5/TM	2nd February 1990	Blue, Green, Red, NIR	30
Landsat7/ETM	14th April 2007	Blue, Green, Red, NIR	30
Landsat 8/ OLI	28th February 2017	Blue, Green, Red, NIR	30

2.3 Land use land cove classification and change analysis

After the image processing LULC maps were prepared using supervised classification method based on training areas and maximum likelihood decision rule, used by many researcher (Yuan *et al.* 2005; Paudel and Yuan 2012,) [15, 10]. Supervised classification is the process of using a known identity of specific sites in the remotely sensed data to classify the remaining part of the image. In this study, supervised classification was carried out using ERDAS IMAGINE 10 and prepared six LULC classes (Figure2).

Accuracy assessment of different classified image was performed based on overall accuracy, producer's accuracy, user's accuracy and Kappa coefficient. Kappa analysis is a discrete multivariate technique used in accuracy assessments (Jensen, 1996) [5]. In order to determine the accuracy of the different classified images a stratified random sampling methodology was used for selection of reference points/ground control points. A total of 60 ground control points were selected. For each sample point, changes were separately assessed. The information of change for different classified image has been determined by Survey of India topographic maps, Survey of published literature.



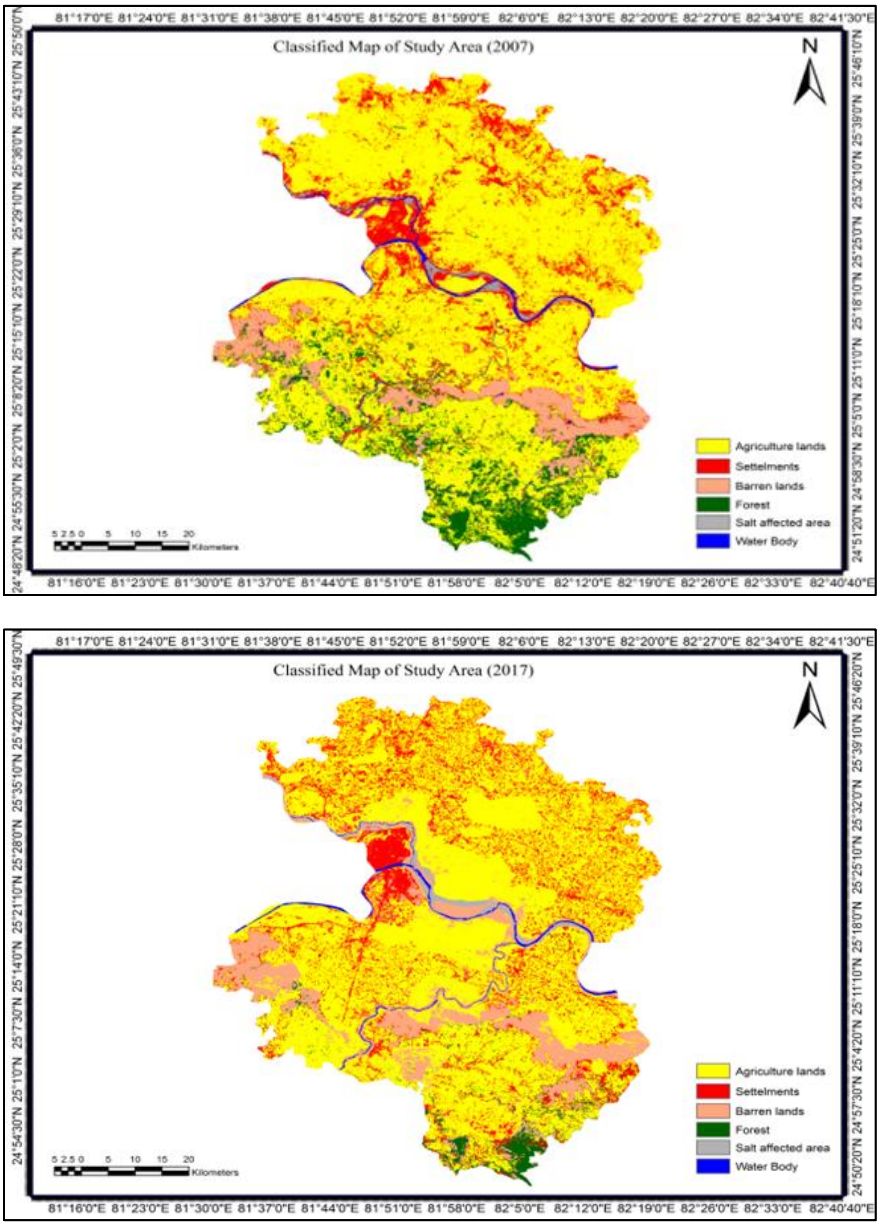


Fig 2: The classified land use/land cover (LULC) maps of study area of years (a) 1990 (b) 2007 (c) 2017

2.4 Landscape metrics analysis

Landscape metrics are algorithms that quantify specific spatial characteristics of patches, classes of patches, or entire landscape mosaics. In this study, landscape metrics such as area, perimeter, core area, shape and fragmentation at patch and class level were calculated using the software FRAGSTATS 4.2.1 for each individual image classification (1990, 2007, 2017). FRAGSTATS, a spatial pattern analysis programme developed by the Forest Science Department, Oregon State University, U.S.A, has been widely used for quantifying landscape structure (McGarigal and Marks, 1994) [8].

At the class level, descriptive metrics of land use land cover pattern between different classes were compared across the four date's classified maps. Table2 lists the set of nine metrics (Number of patches – NP, Patch Density – PD, Largest patch index –LPI, Total edge–TE, Edge Density–ED, Landscape shape index–LSI, Interspersion-juxtaposition index–IJI, MESH effective mesh size, Percentage of like adjacencies–Pland) chosen in the present study.

Table 2: Metrics used at class level to quantify fragmentation (Mc Garigal and Marks, 1995) [7]

Metrics and Units	
PLAND-Percentage of like adjacencies as proportion of a given class type related to the total area.	PLAND = $P_i = \frac{\sum_{j=1}^{n} a_{ij}}{A}(100)$ P_i = proportion of the landscape occupied by patch type (class) i. a_{ij} = area (m^2) of patch ij. A = total landscape area (m^2)
NP Total number of patches in this class	NP = n_i n_i= number of patches in the landscape of patch type (class) i.
PD- (per unit per ha) Ratio of number of patches and the area of investigated	PD = $\frac{n_i}{A}$(10,000)(100) n_i = number of patches in the landscape of patch type (class) i.

	A = total landscape area (m^2).
LPI –Ratio of largest patch area to investigated area	LPI = $\frac{\max_{j=1}^{n}(a_{ij})}{A}(100)$ a_{ij}= area (m^2) of patch ij. A =total landscape area (m^2)
TE (m)-Sum of length of all edge segments for the class	TE = $\sum_{k=1}^{m} e_{ik}$ e_{ik} = total length (m) of edge in landscape involving patch type(class) i; includes landscape boundary and background segments involving patch type i.
ED - Edge Density, m/ha Total length of edge involving the corresponding land use land cover class divided by total area (ha).	ED = $\frac{\sum_{k=1}^{m} e_{ik}}{A}(10{,}000)$ e_{ik} = total length (m) of edge in landscape involving patch type (class) i; includes landscape boundary and background segments involving patch type i. A = total landscape area (m^2).
LSI- Landscape shape index average complexity of the landscape as a whole	LSI = $\frac{.25\sum_{k=1}^{m} e^{*}_{ik}}{\sqrt{A}}$ e^{*}_{ik} = total length (m) of edge in landscape between patch types (classes) i and k; includes the entire landscape boundary and some or all background edge segments involve class I
IJI- Interspersion-juxtaposition index Degree of interspersion of patches of this class, with all other classes.	
MESH, ha (Effective Mesh Size)	MESH= $\frac{\sum_{j=1}^{n} a_{ij}2}{A}\left(\frac{1}{10{,}000}\right)$ a_{ij} = area (m^2) of patch ij. A = total landscape area (m^2).

The indices of LPI, TE, ED, PD, NP and PLAND correspond to area metrics which provide indications of the degree of fragmentation for different land cover types and change images. Specifically NP is an excellent measure of the fragmentation of a given class within the landscape since the landscape size is constant. IJI provide metrics of shape and interspersion. MESH is in high correlation with landscape division which expresses the probability that two randomly placed landscapes are in the same patch.

3 Result and Discussion

3.1 Land Use Change and Accuracy Assessment

The LULC maps of study area were generated for years 1990, 2007 and 2017 (Figure 2) and classification area statistics were summarized in Table3.The accuracy assessment of LULC maps for all three years was found to be 84.22%, 85% and 87.67% whereas Kappa coefficient was found to be 0.8102 and 0.8177 and 0.8444 respectively (Table 5). The percentage area for year 1990, 2007 and 2017 for agriculture land, water body, Settlements, forest, Salt-affected area and Barren land are 59.2%, 63.5%, 64.2%; 0.979%, 0.970%, 0.8%; 11.2%, 15.4%, 16.5%; 14.7%, 5.2%, 3.2%; 1.23%, 1.25%, 1.31%; 12.5%, 13.4%, 13.7% respectively(Table3). Agriculture land was found to be the dominant land use classes throughout the study period.

To provide a further calculation in losing and gaining the six LULC classes, land use/cover in Prayagraj district were created in three intervals, 1990-2007, 2007-2017 and 1990-2017 (Table 4).

It was observed that agricultural land, settlement, barren land and salt affected area showed increasing trend whereas forest and water body showed decreasing trend throughout the study period (Table 4). Increase in settlement is attributed to population growth. However, decrease in rainfall, use of excessive fertilizer and waterlogging in this area may causes increase in salt affected area. The main reasons of loss of forest are because of expansion of settlement, developmental activity and expansion of agriculture land.

Table 3: Area Statistics of Different Land Use classes of Different Years

	1990		2007		2017	
Class	Area (ha)	% Area	Area(ha)	% Area	Area (ha)	% Area
Settlements	58868.1	11.29	80476	15.43	86388.1	16.57
Forest	76817.9	14.73	27433.9	5.26	16882.2	3.23
Agriculture	308599	59.20	331485	63.59	334810	64.23
Barren Lands	65431.4	12.55	70271.1	13.48	71775.5	13.76
Salt affected area	6432.21	1.23	6533.82	1.25	6831.72	1.31
Water Bodies	5107.14	0.97	5056.2	0.97	4568.49	0.87
Total Area	521255.75	100	521256.02	100	521256.01	100

Table 4: Comparison between land use and land cover derived from 1990 and 2007 and 2017 images.

class	1990-2007	2007-2017	1990-2017
Settlements	21607.9 ↑	5912.1 ↑	27520 ↑
Forest	49384 ↓	10551.7 ↓	59935.7 ↓
Agriculture	22886 ↑	3325 ↑	26211 ↑
Barren Lands	4839.7 ↑	1504.4 ↑	6344.1 ↑
Salt affected area	101.61 ↑	297.9 ↑	399.51 ↑
Water Bodies	50.94 ↓	487.71 ↓	538.65 ↓
Area	0.27 ↑	0.01 ↓	0.26 ↑

Table 5: Classification accuracy of satellite images

Years	Overall accuracy (%)	Kappa coefficient
1990	84.22	0.8102
2007	85	0.8177
2017	87.67	0.8444

3.2 Fragmentation analysis

The landscape metrics based analysis of LULC maps of 1990, 2007 and 2017 have been used to find class level matrix by means of FRAGSTATS software (Table 6).

It has been observed that number of patches for agriculture has decreased from 6053 to 4046 between 1990 and 2017. It means aggregation of agriculture land takes place during this period. The Largest patch index has also increase from 1990 to 2007 and later it was decrease from 2007 to 2017. The number of patch for settlement has also increase from 14628 to 21201 and PD increased from 1.65per 100 ha to 2.40 per 100 ha between 1990 to 2017. Although number of patches of salt affected area has increase from 1990 to 2007 but it drastically decrease in 2017. Decrease in NP is because some of the salt affected areas get connected. The number of patches of forest has decrease from 16513 to 1011 and PD decrease from 1.86 per 100 ha to 0.11 per 100 ha between 1990 to 2017.

Table 6: Class-Level Landscape Metrics

Date	Type	Pland	NP	PD	LPI (%)	TE(m)	ED(m/ha)	LSI	IJI	MESH
1990	Agriculture	36.2556	6053	0.06853	16.5805	21788220	24.6681	96.2462	63.4382	43548.05
1990	Settlement	6.1783	14628	1.6561	0.4851	13260660	15.0134	141.8556	44.0782	38.1909
1990	Barren land	7.36923	4297	0.4865	1.751	7337460	8.3073	71.8936	75.5153	438.3354
1990	Forest	7.923	16513	1.8696	2.9221	14235780	16.1174	134.5028	56.784	771.5591
1990	Water Body	0.5589	718	0.0813	0.0597	939360	1.0635	33.3817	73.1733	1.2584
1990	Salt Affected Area	0.7155	309	0.035	0.0897	618600	0.7004	19.4528	20.9206	2.2721
2007	Agriculture	38.6844	3824	0.04329	20.605	18359400	20.786	78.5194	58.8922	60540.46
2007	Settlement	8.6523	14995	1.6977	0.9948	1607140	18.1958	145.3386	56.3306	149.298
2007	Barren land	7.8616	5688	0.644	2.1036	7308900	8.2749	69.3312	66.6806	576.944
2007	Forest	2.5119	10604	1.2006	0.2213	6563520	7.431	110.0523	58.2599	9.7166
2007	Water Body	0.5695	184	0.0208	0.2631	680220	0.7701	23.9683	54.4911	6.37037
2007	Salt Affected Area	0.7195	482	0.0546	0.0997	665220	0.7531	20.8402	55.2443	2.1417
2017	Agriculture	39.5951	4046	0.4581	17.8234	23559120	26.673	99.582	46.531	40245.61
2017	Settlement	8.9517	21201	2.4003	1.217	21288840	24.1027	189.2341	35.24287	143.773
2017	Barren land	7.8259	8847	1.0016	2.4807	8325480	9.4259	79.1546	74.3526	777.7247
2017	Forest	0.6951	1011	0.1145	0.4536	857700	0.9711	27.3327	55.5668	4.9042
2017	Water Body	1.3993	7180	0.8129	0.1127	3637560	4.1184	81.7062	59.2445	19.3349
2017	Salt Affected Area	0.5308	82	0.0093	0.2184	586680	0.6642	21.3961	60.0328	2.8534

4. Conclusion

This study analyzed the spatial and temporal LULC changes to landscape fragmentation of Prayagraj district between, 1990 to 2017. The ground truth verification was made to verify the results. Analyses of the result exhibit that agriculture and settlement has increased whereas forest has decreased between, 1990-2017. Increase in population throughout the studied period results in the extent of settlement area. The extend of settlement area contributed the major changes of landscape.

For further understanding of landscape, important landscape indices were used to perform the different changes in landscape structure in the surroundings of study area. This study comes with conclusion that settlement has increasing continually however it is important to be settled smartly in new places.

This type of study is important for Prayagraj district as district is identify as future development of smart city. However the results of this study will be useful and to work as guide for local administered to understand the landscape structure and plan for future development. Also, Result from this study should encourage using geospatial technologies and landscape metrics for planning and development of the region.

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