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Urban Growth Analysis Using Multi-Temporal Remote Sensing Image and Landscape Metrics for Smart City Planning of Lucknow District, India †

Namrata Maity and Varun Narayan Mishra *

Amity Institute of Geoinformatics and Remote Sensing (AIGIRS), Amity University, Sector 125, Noida 201313, India; namrata.maity1@s.amity.edu
* Correspondence: vnmishra@amity.edu

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Abstract: Rapid urbanization causes a high concentration of human population and economic activities that leads to the changes in landscape and spatial growth of the cities. Landscape features play a key role in understanding the land use and land (LULC) dynamics of urban areas. This work aims to analyze and quantify the changes in LULC over 24 years (1999 to 2023) in Lucknow District of India. It focuses on different land use types including built-up area, cropland, water body, vegetation, and fallow land, using satellite imagery. Multi-temporal Landsat satellite data from the years 1999, 2008, 2015, and 2023 were employed to prepare LULC maps including major classes namely built-up area, cropland, water body, vegetation, and fallow land. Several landscape metrics like Number of Patches (NP), Patch Density (PD), Largest Patch Index (LPI), Landscape Shape Index (LSI), Edge Density (ED), and Total Edge (TE) were calculated to analyze spatial patterns and changes of LULC categories. The study revealed significant changes in the landscape of Lucknow District, characterized by variations in the extent and distribution of the land use categories. Key findings include a remarkable increase in built-up area from 9.04% in 1999 to 25.91% in 2023, and a decrease in vegetation from 26.01% in 1999 to 11.71% in 2023. The PD and ED showed an increased fragmentation, especially in built-up areas where PD increased from 9.18 patches/100 ha in 1999 to 11.85 patches/100 ha in 2023. The LPI for built-up areas significantly grew, indicating larger continuous urban regions. The findings of this study emphasize the importance of monitoring landscape changes using multi-temporal remote sensing images over urban landscapes. Analyzing landscape metrics helps to understand the ongoing changes in LULC, providing essential information for effective sustainable land management practices

Keywords: urban growth; landscape metrics; LULC; remote sensing; sustainable development

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1. Introduction

Urbanization is considered as a pivotal feature of modern society, deeply affecting the land use and environmental conditions followed by socioeconomic development of a region [1,2]. Rapid urban growth and associated land use changes are crucial factors leading to landscape changes and spatial expansion of the cities. The urbanization process and rapidly growing cities results in alteration of natural landscape and adverse effects on biodiversity, climate, hydrological cycles, regional habitats, and various ecosystems services [3–6]. The analysis of urban growth and its pattern is also vital for understanding complex interactions between anthropogenic activities and environmental changes from global to local scale.

Increasing urbanization rate and growing population lead to spontaneous and uncontrolled changes in LULC of an area [7]. The changes in LULC prompt the demand for the land conversion from non-urban into urban [8–10]. Therefore, it is crucial to detect such changes and assess their effects on the environment for promoting sustainable urban planning and natural resource management [11,12]. Alternatively, urban growth in compact manner, linked with socio-economic development, energy, and resource productivity signifies SDG 11 [10,12,13]. The complex, inherent dynamic features, and uncertainty of natural landscape require a demonstration of advanced techniques in urban studies and LULC practices.

A significant amount of data is essential for analyzing and quantifying the ongoing changes in LULC of a region. In recent years, the availability of space-borne remote sensing (RS) images and Geographical Information System (GIS) brought more opportunities in the study of changing landscape spatial patterns. It is beneficial to use remotely sensed data in producing temporal LULC maps over a large area and reported in many studies [4,14–16]. Landscape ecology offers valuable insights into the complexity and spatial arrangements prompting a better understanding of processes and transformations in the landscape of an area. Landscapes are varied geographical regions having interacting ecosystems and anthropogenic activities [17,18]. The landscape metrics include a diverse set of quantitative parameters that play a significant role in characterizing spatial composition and structure of landscape elements, specifically regarding the size, shape complexity, connectivity, and fragmentation [19,20]. Improved understanding of the landscape patterns and information about the drivers of changing LULC helps to quantitatively analyze spatial urban growth [4]. Landscape metrics approach helps policy makers and planners to make appropriate decisions toward sustainable urban development [21]. In the last few decades, several landscape metrics have been developed for measuring landscape structure [22,23]. However, highly correlated and redundant metrics cannot be used adequately for a specific landscape analysis [23,24]. So, only selected landscape metrics at class or landscape level is useful to overcome the problem of redundancy.

The objective of present study was to investigate the spatial and temporal changes in LULC with respect to urbanization from year 1999 to 2023 in Lucknow district of Uttar Pradesh state, India. Additionally, landscape metrics were computed at both class and landscape level scales to evaluate the spatial patterns and configurations of urban growth. This study helps in understanding spatial and temporal urban growth patterns to support more well-versed sustainable land management plans.

2. Study Area

Lucknow district is the capital of Uttar Pradesh state, India. It is located between latitudes 26°30′ N and 27°10′ N and longitudes 80°30′ E and 81°13′ E covering a total geographical area of 2525.61 km^2. Lucknow district is distinguished by a predominantly flat topography with lush alluvial plains typical of the Indo-Gangetic area and Gomti River, a tributary of river Ganga. It is the fifth most populated district in Uttar Pradesh (45.8 lakhs), the second most populous urban area (29.02 lakhs), and India’s 11th largest metropolis. The location map of the study area is given by Figure 1.

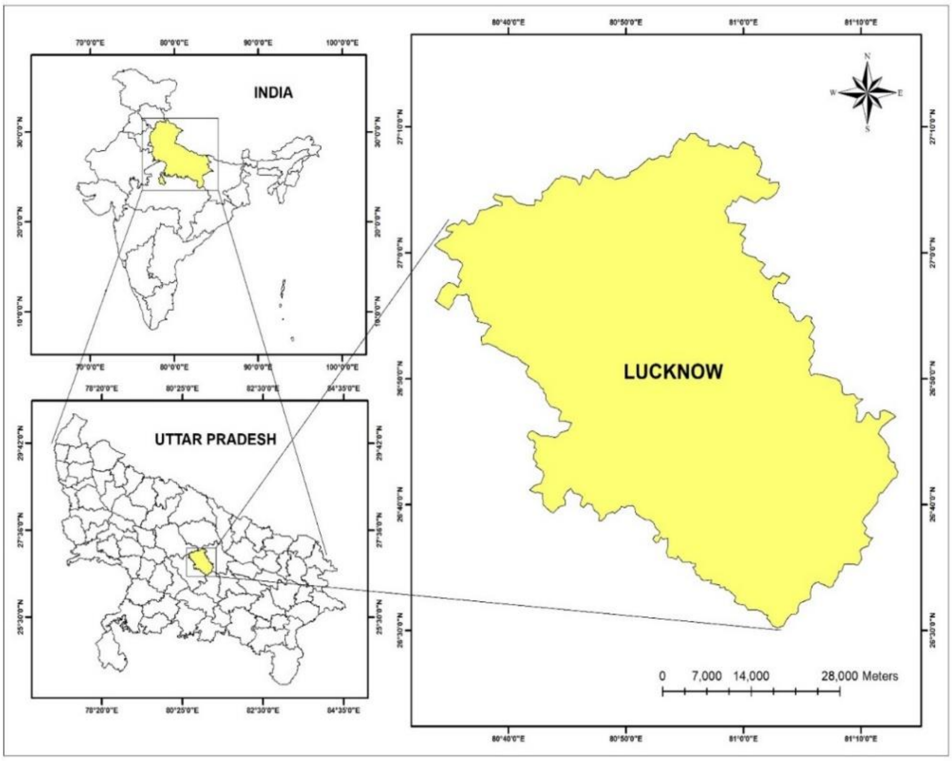

Figure 1. Location map of study area.

3. Materials and Methods

Multi-temporal Landsat images acquired from TM, ETM+, and OLI/TIRS sensors for the period of 1999–2023 were used in this study that is downloaded from the USGS Earth Explorer. The multispectral Landsat images were used for LULC classification and urban growth change analysis in Lucknow district. The complete specification of the images used in this work is given in Table 1. All the succeeding pre-processing and interpretation of multi-temporal Landsat images followed by LULC classification were performed using ArcMap (v 10.8) software.

Table 1. Specifications of satellite images used in this study.

Satellite-Sensor	Date of Acquisition	Spectral Resolution (No. of Bands)	Spatial Resolution (m)
Landsat 7—ETM+	9 November 1999	8	30
Landsat 5—TM	9 November 2008	7	30
Landsat 8—OLI/TIRS	13 November 2015	11	30
	3 November 2023	11	30

3.1. Image Pre-Processing

The co-registration of all the images to the UTM projection system, Zone 44 North, WGS 1984 datum was performed using image-to-image registration method. The ArcMap 10.8 was used to perform intensive pre-processing on the Landsat satellite images including mosaicking, layer stacking, and sub-setting of study area using the district boundary of Lucknow district. An appropriate band combination was chosen to produce false-colour composites (FCCs) for all the images. These FCCs were used further for analysing and creating the training signatures of specific LULC type.

3.2. LULC Classification

It is of significance to decide the number of distinct LULC types for representing the landscape of an area. An accurate LULC classification of satellite image is crucial to analyse the changes and growth pattern of urban area. Five major LULC categories like built-up, water body, vegetation, fallow land, and cropland were identified corresponding to the landscape of Lucknow district. The LULC maps of the years 1999, 2008, 2015, and 2023 were produced by applying supervised classification method on pre-processed Landsat images. The accuracies of LULC maps were assessed by overall accuracy and kappa coefficient. The random points were generated using the stratified random sampling method to examine the accuracy of LULC classified maps.

3.3. Calculation of Landscape Metrices

Landscape metrics were calculated to quantify the changes in the structure of landscape under investigation (Table 2). In this work, FRAGSTATS (v. 4.3) tool was used to measure the ongoing spatial and temporal changes in the landscape patterns within the study region. One of the key benefits of this tool is that the classified data can be used straight away for the landscape fragmentation and analysis [17]. The extent, configuration, and fragmentation of each LULC class can be quantified by using class metrics calculated individually for patch type in the landscape. Different landscape mosaic elements are represented by a variety of metrics, such as composition, shape, complexity, landscape grain size, connectedness, and aggregation [1,17]. Table is showing the selected metrics based on the objective of current study and earlier reported studies. The calculation of metrices was carried out individually for LULC data of years 1999, 2008, 2015, and 2023. The area metrics at class level such as LPI, LSI, TE, ED, PD, NP, and PLAND indicate fragmentation levels for various LULC types and among them NP is exceptionally well in measuring the fragmentation of a given class within it [1,17]. Also, Shannon's Diversity Index (SHDI) and Shannon's Evenness Index (SHEI) have been calculated at landscape level for detecting the diversity and isolation rate within the landscape.

Table 2. Landscape metrics used at class level.

Metrices	Symbol	Description of the Metrices
Number of patches	NP	It is the total number of patches present in a class
Patch Density	PD	It is the ratio between the total patches and the area
Edge Density	ED	Total edge length involving the respective land use/land cover class divided by total area.
Total edge	TE	The total length of all edge segments in the class.
Largest patch index	LPI	The ratio between the biggest patch area and the area under the study.
Landscape shape index	LSI	The average complexity of the entire landscape.
Percentage of Landscape	PLAND	It is the percentage of the landscape that consists of the specific patch type.

4. Results and Discussion

4.1. LULC Maps and Change Analysis

In this study, LULC maps are derived using multi-temporal Landsat images for years 1999, 2008, and 2015, 2023 respectively. The spatial distribution of LULC categories are shown in Figure 2. The overall accuracy of LULC maps for years 999, 2008, and 2015, 2023 are 86.00, 85.00, 86.00, and 88.50%, respectively. The kappa coefficient for respective years is found to be 0.83, 0.82, 0.83, and 0.86.

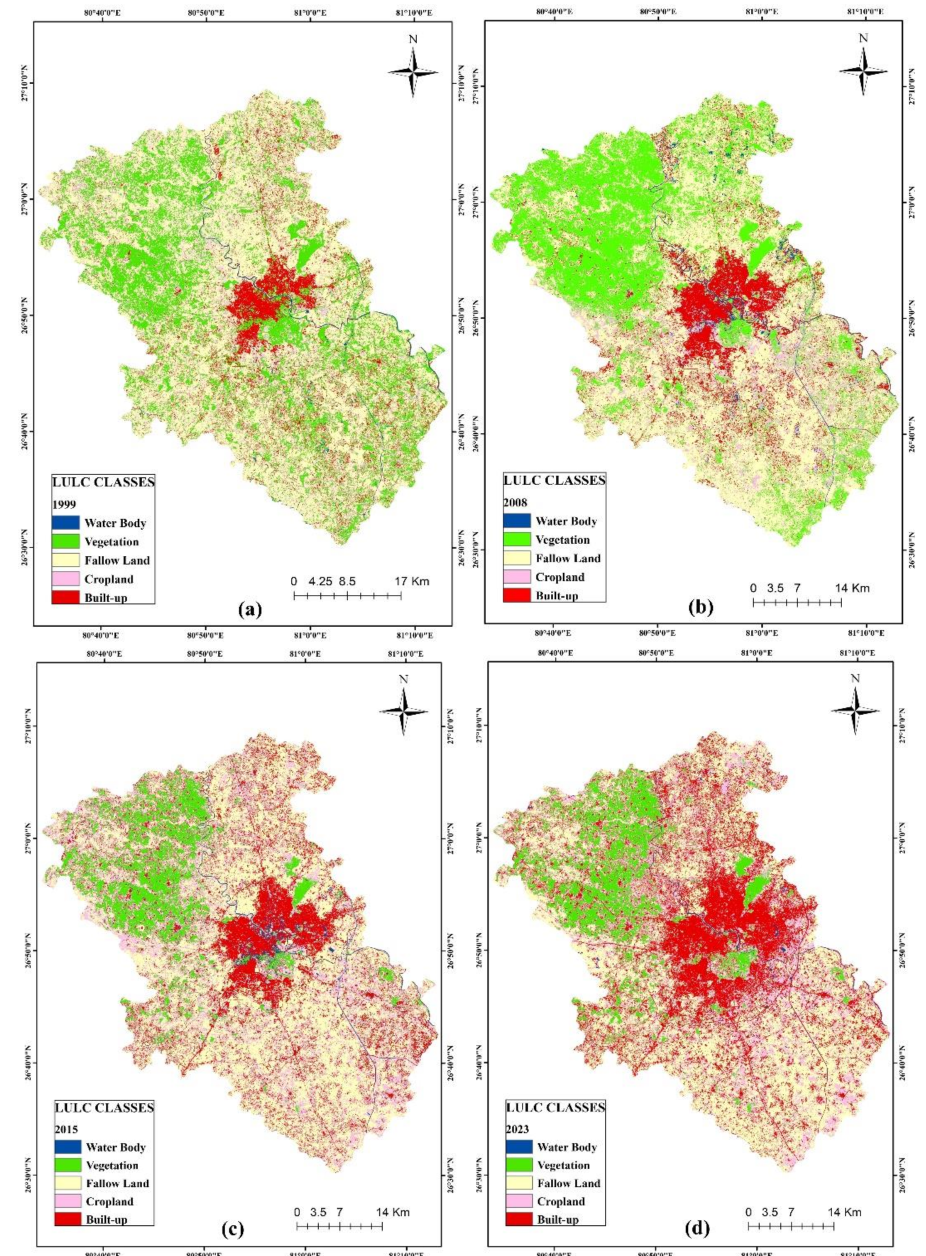

Figure 2. LULC classified maps for years (**a**) 1999, (**b**) 2008, (**c**) 2015 and (**d**) 2023.

Analysis of multi-temporal LULC maps revealed significant urban growth in Lucknow over the specified time frame. The area statistics for LULC classes are given in Table 3. Fallow land is identified as predominant category based on LULC analysis. However, noticeable decline in fallow land from 48.02% to 37.57% over 1999–2023, attributed to the rapid urban expansion of Lucknow. A significant increase in cropland is observed from 16.12% in 1999 to 24.12% in 2023. Post-year 2015, driven by the growing population in the region. Additionally, there has been a marked rise in built-up areas, indicating vigorous urban development. This trend in built-up regions underscores the dynamic nature of Lucknow's landscape, reflecting the city's progress towards infrastructure development and modernization. Multi-date LULC observation revealed the transformation from lush vegetation into fallow lands and cultivated land in the north-west portion of study area juxtaposed with the expanding built-up areas in the core of district. Before year 2015, the vegetated surface decreased due to gradual expansion of urban area in the southern region of Lucknow district. A rapid urbanization trend is witnessed in and around the core of the city following observed shifts in land use patterns implied at evolving agricultural practice in the north-western part. Conversely, the southern sector witnessed a landscape metamorphosis due to urban encroachment, marking a transition from rural to urban land use. This shift was notably influenced by the presence of the Lucknow Planning Area, with its significant allocation to mango orchards and green belts, compelling urban growth to redirect towards the south, north, and east, circumventing this natural barrier.

Table 3. Area statistics of LULC during 1999–2023.

LULC Category	1999		2008		2015		2023	
	Area (km²)	Area (%)	Area (km²)	Area (%)	Area (km²)	Area (%)	Area (km²)	Area (%)
Built-up	228.48	9.05	299.70	12.87	455.13	18.02	654.47	25.91
Vegetation	656.89	26.01	692.38	24.92	300.74	11.91	295.71	11.71
Fallow Land	1212.62	48.01	1211.60	48.97	1121.78	44.42	949.06	37.58
Cropland	407.28	16.13	296.42	11.80	622.95	24.66	609.22	24.12
Water Body	20.34	0.81	25.51	1.45	25.01	0.99	17.06	0.68
Total	2525.61	100	2525.61	100	2525.61	100	2525.61	100

However, there was a decrease in fallow land from 48.02% to 37.57% over time, attributed to the rapid urban expansion of Lucknow. An increase in cropland is observed from 1999 to 2023, especially post-2015, driven by the growing population in the region. There has been a significant increase of built-up areas from 9.05% in the year 1999 to 25.91% in year 2023, indicating active urban development activities. The increasing trend in built-up land during 1999–2023 highlights the dynamic nature of the urban landscape of Lucknow. It reflects the city's progress towards infrastructure development and modernization. The changes among cropland, built-up areas, and fallow land shows the complexity of land use dynamics in the area. A key factor driving this urban expansion in the Lucknow district is the alteration of its municipal boundary, which has been revised three times, progressively encompassing more villages and expanding service coverage. Another contributing factor to the escalating urbanization is the city's transportation network facilitated by three national highways and four state highways.

4.2. Quantification of Landscape Metrices

The landscape fragmentation analysis indicates modest alterations in the Lucknow district, prompting a deeper understanding of the resulting LULC patterns. Landscape metrics analysis, encompassing metrics such as PLAND, NP, LSI, ED, PD, and TE, was employed to discern changes in these metrics and their impact on landscape patterns over four years. Figure 3 illustrates the changes in all landscape metrics over time (1999–2023) for different LULC classes.

The NP shows decline of vegetation cover across the study area, signifying fragmentation of its utilization as shown in Figure 3a. The conversion of small patches of vegetation into built-up and cropland areas resulted in its decline in study area. Conversely, the increase in the NP for built-up areas shows the expansion and development of urban areas in the study region. There was a prominent decline in the utilization of cropland due to the shifting of livelihood agricultural to non-agricultural activities, resulting in a decrease in NP.

The PD analysis shows a substantial change in built-up and cropland categories over time as represented in Figure 3b. A noteworthy increase in PD values of built-up from year 1999 to 2023, representing higher fragmentation. Conversely, PD values of cropland decreased between 1999 to 2023, reflecting a substantial decrease in the patches of cropland and its fragmentation. There is decline in the PD values of vegetation during 1999–2023 that shows its fragmentation. The expansion of built-up areas, leading to ecological discontinuity, contributes to the fragmentation of vegetation and cropland categories. The declining trend in PD values for vegetation cover emphasizes its fragmentation in Lucknow district, reflecting the changing landscape dynamics due to urbanization.

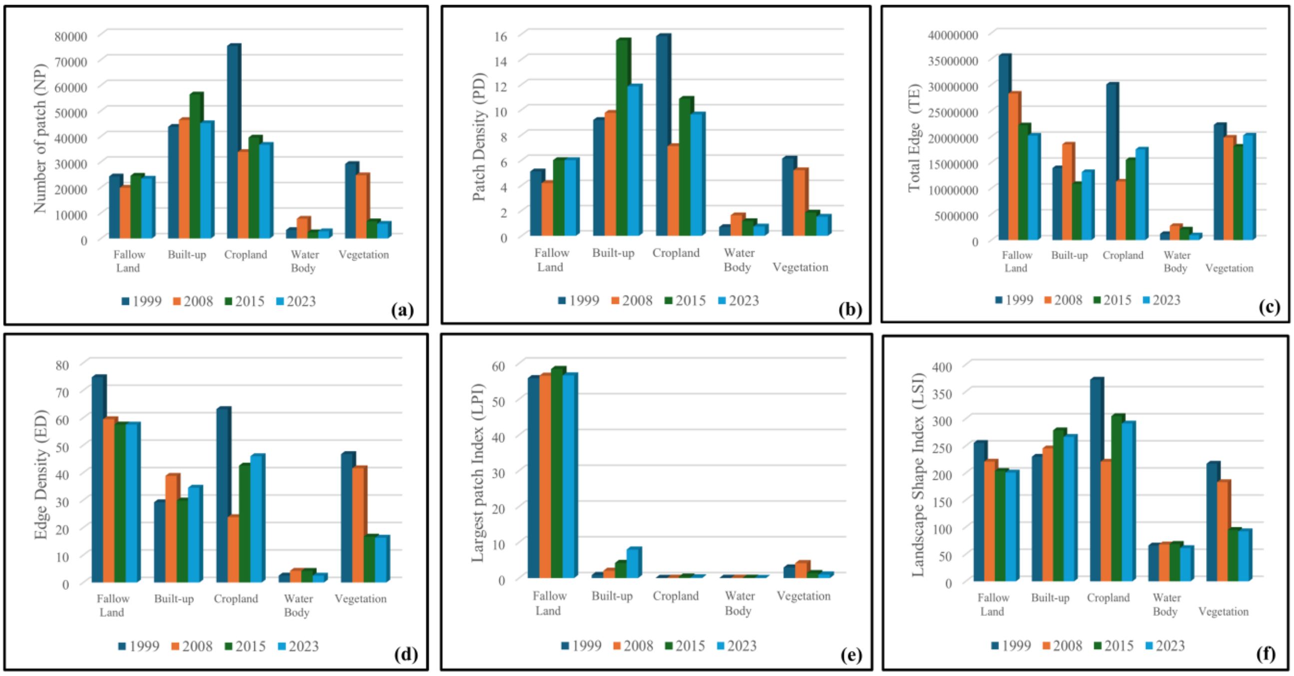

Figure 3. Changes in landscape metrics during 1999–2023.

Figure 3c shows that TE serves as an indicator of the length and proximity of different LULC types, aiding in the assessment of the effectiveness of land use. TE index was utilized to outline the edges of land use such as cropland and vegetation cover, providing insights into their spatial characteristics. It exhibited a decrease over time, particularly after the year 2008 when significant degradation of vegetation cover occurred, the marginal areas of this land cover expanded. The built-up category experienced a prominent increase in TE in year 2008, corresponding to the rapid urban expansion. The decline in TE for cropland can be attributed to its reduction, while in years 2008, 2015 and 2023, it was engulfed by built-up areas. On the other hand, ED value for fallow land decreased rapidly, indicating a more continuous distribution and less fragmentation of this land cover type. The built-up edge increased between 1999 and 2023, as the core city expanded in multiple directions, resembling a ribbon pattern. However, there was a decrease in urban edge between 2008 and 2015, indicating a more directed and orderly growth pattern during that period as shown in Figure 3d.

The LPI at landscape and class levels, signifies the amount of entire landscape comprised of the specific land use under examination. The LPI values were determined for each land use category. Over the period of investigation, the LPI increased for all land uses in the study area and displayed in Figure 3e. However, due to fallow land being the predominant class, only minor changes were observed for the other classes, except for built-up areas. The LPI, particularly for built-up areas, was significantly low in the year 1999, covering only 0.83% of the total area. However, by 2023, it increased by 8%, indicating a substantial expansion of built-up area. This expansion advocates a high level of integration and consolidation of built-up areas within the landscape. The LPI for Cropland experienced a significant increase over the study periods, suggesting a shift towards agricultural land use to meet the demands of the growing population. In 1999, the LPI for Cropland was 0.0337, which surged to 0.3856 in 2015 before declining to 0.1689 in 2023, indicating the rise of built-up areas. Concurrently, the LPI for vegetation cover declined, from 2.9 in 1999 to 0.9 in 2023. Although it rose to 4.14 in 2008, it subsequently dropped to 1.36 in 2015, possibly due to the establishment of parks and increased recognition of the value of green spaces during those years. The LPI for fallow land shows a marginal increase between 1999 and 2023, indicating relatively less fragmentation in this category. This advocates relatively persistent and continuous fallow land throughout the study period.

The LSI serves as an indicator of the ratio of the environment to the landscape class and the overall complexity of the landscape as shown in Figure 3f. The LSI for the vegetation category exhibited a significant descending trend over the evaluation period, dipping from 216.9 units in 1999 to a value of 92.3496 by 2008. This decline indicates a considerable alteration in the vegetation category towards a more fragmented landscape arrangement. Similarly, the LSI for cropland also declined, from 372 units in 1999 to 291 units in 2023. On the contrary, the LSI increased for built-up areas due to increased segmentation and edge diversity. The LSI for built-up increased from 229 units in 1999 to 266 units in 2023, showing increasing diversity within this land use category. The increase in LSI is due to changes in municipal borders and inclusion of more villages during the period of investigation.

Additionally, Figure 4 shows the PLAND that quantifies the class area in four different years. It represents the proportion of the respective patch type in the landscape, providing a relative measure of landscape composition significant in ecological applications. It offers a better evaluation of composition than total class area, especially when comparing landscapes of different sizes. PLAND for fallow land increased from 50.482% in 1999 to 58.617% in 2023, emerging as a dominant patch type. In contrast, the built-up class expanded substantially, from 4.80% in the year 1999 to 17.17% in year 2023. In year 1999, vegetation cover accounted for 13.80% of the landscape, followed by reduction in by 2015 due to transition into built-up areas. This shift suggests that vegetation, water bodies, and other land cover types have reduced due to rapid expansion of built-up areas over time. Additionally, the cropland category exhibited gradual growth from 1999 to 2023, likely driven by the increasing population's demand for agricultural land.

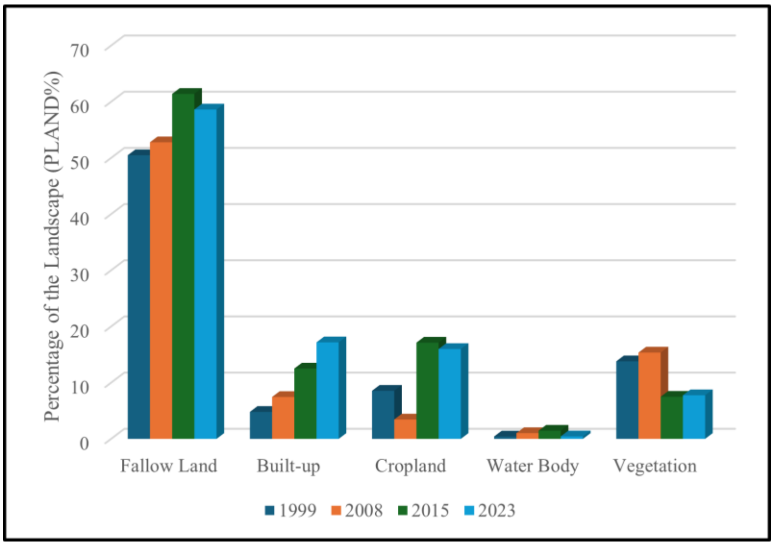

Figure 4. Changes in PLAND during 1999–2023.

The study employs the SHDI to explore point diversity and changes in the area over time. This index provides numerical insights into the diversity of points within a landscape or scene, aiding in comparisons across different landscapes or the same scene at various time points. In this study, landscape-level calculations of the SHDI yielded the values of 1.35, 1.34, 1.11, and 1.35 in years 1999, 2008, 2015, 2023 respectively and represented by Figure 5a. There was a slight increase in SHDI values during 2015–2023 despite a declining trend over the entire period. Initially a decrease in SHDI for landscape can be attributed to fragmentation and lack of integration, subsequently reduction of diversity. A slight increase on the other hand during 2015–2023 shows better integration and diversity within the landscape.

In this study, SHEI is computed to evaluate the dispersion and spatial distribution characteristics of landscape. Its value ranges from 0 (landscape with a single focal point) to 1 (uniform distribution of all points). The SHEI was estimated to be 0.756 in 1999, 0.752 in 2008, 0.69 in 2015, and 0.703 in 2023 and represented by Figure 5b.

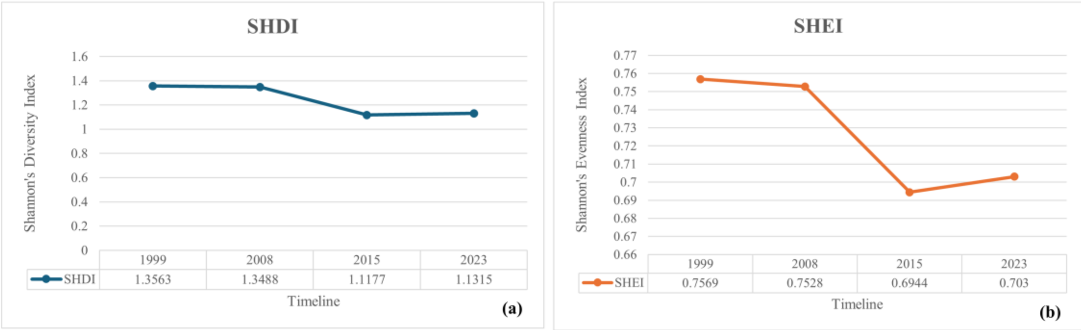

Figure 5. Changes in (**a**) SHDI and (**b**) SHEI during 1999–2023.

The decline observed in the first two time periods suggests that the landscape is becoming more isolated, potentially due to hu man activity. Notably, the significant development of built-up areas has notably impacted the calculated SHEI values, particularly contributing to the decline observed in the earlier time periods.

5. Conclusions

The present study analyzed the spatial and temporal urban growth in Lucknow district of India over a 24-year period through landscape fragmentation. It provides significant insights into urban dynamics and LULC changes, underpinned by meticulous analysis with the help of remote sensing images and landscape metrics. The findings illustrate an intense urbanization pattern leading to an increased built-up area, decreased vegetation cover, and alterations in land use, which correlate with rising population pressures and infrastructural expansions. Such transformations emphasize the need for sustainable urban planning to balance development with environmental conservation. The study not only offers a critical evaluation of urban growth and its ecological implications but also serves as an essential tool for policymakers to envision and implement strategies that promote a balanced ecological footprint, thus contributing to more sustainable urban futures.

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References

1. Smiraglia, D.; Ceccarelli, T.; Bajocco, S.; Perini, L.; Salvati, L. Unraveling Landscape Complexity: Land Use/Land Cover Changes and Landscape Pattern Dynamics (1954–2008) in Contrasting Peri-Urban and Agro-Forest Regions of Northern Italy. *Environ. Manag.* **2015**, *56*, 916–932.
2. Seifollahi-Aghmiuni, S.; Kalantari, Z.; Egidi, G.; Gaburova, L.; Salvati, L. Urbanisation-driven land degradation and socioeconomic challenges in peri-urban areas: Insights from Southern Europe. *Ambio* **2022**, *51*, 1446–1458.

3. Gupta, R.; Sharma, L.K. Efficacy of Spatial Land Change Modeler as a forecasting indicator for anthropogenic change dynamics over five decades: A case study of Shoolpaneshwar Wildlife Sanctuary, Gujarat, India. *Ecol. Indic.* **2020**, *112*, 106171.
4. Arora, A.; Pandey, M.; Mishra, V.N.; Kumar, R.; Rai, P.K.; Costache, R.; Punia, M.; Di, L. Comparative evaluation of geospatial scenario-based land change simulation models using landscape metrics. *Ecol. Indic.* **2021**, *128*, 107810.
5. Cheng, Y.; Kang, Q.; Liu, K.; Cui, P.; Zhao, K.; Li, J.; Ma, X.; Ni, Q. Impact of Urbanization on Ecosystem Service Value from the Perspective of Spatio-Temporal Heterogeneity: A Case Study from the Yellow River Basin. *Land* **2023**, *12*, 1301.
6. Mishra, V.N. Investigation of Land Use/Land Cover Changes in Alaknanda River Basin, Himalaya During 1976–2020. In *Advances in Remote Sensing Technology and the Three Poles*; Pandey, M., Pandey, C., Ray, Y., Arora, A., Jawak, S.D., Shukla, U.K., Eds.; John Wiley & Sons Ltd: Hoboken, NJ, USA, 2023.
7. Yadav, P.K.; Mishra, V.N.; Kumari, M.; Kumar, A.; Kumar, P.; Bhatla, R. Spatially Explicit Simulation and Forecasting of Urban Growth Using Weights of Evidence Based Cellular Automata Model in a Millennium city of India. *Phys. Chem. Earth (Pt A B C)* **2024**, *136*, 103739. https://doi.org/10.1016/j.pce.2024.103739.
8. Yu, W.; Zhang, Y.; Zhou, W.; Wang, W.; Tang, R. Urban expansion in Shenzhen since 1970s: A retrospect of change from a village to a megacity from the space. *Phys. Chem. Earth (Pt A B C)* **2019**, *110*, 21–30.
9. Mishra, V.N.; Prasad, R.; Kumar, P.; Gupta, D.K.; Agarwal, S.; Gangwal, A. Assessment of spatio-temporal changes in land use/land cover over a decade (2000–2014) using earth observation datasets: A case study of Varanasi district, India. *Iran. J. Sci. and Technol.-Trans. Civ. Eng.* **2019**, *43*, 383–401.
10. Mahtta, R.; Fragkias, M.; Güneralp, B.; Mahendra, A.; Reba, M.; Wentz, E.A.; Seto, K.C. Urban land expansion: The role of population and economic growth for 300+ cities. *npj Urban Sustain.* **2022**, *2*, 5.
11. Hasan, S.; Shi, W.; Zhu, X. Impact of land use land cover changes on ecosystem service value—A case study of Guangdong, Hong Kong, and Macao in South China. *PLoS ONE* **2020**, *15*, e0231259.
12. Kalfas, D.; Kalogiannidis, S.; Chatzitheodoridis, F.; Toska, E. Urbanization and Land Use Planning for Achieving the Sustainable Development Goals (SDGs): A Case Study of Greece. *Urban Sci.* **2023**, *7*, 43.
13. Wu, J.; Wu, N. Spatial structure and evolutionary logic of urban agglomerations based on remote sensing data. *Phys. Chem. Earth (Pt A B C)* **2023**, *132*, 103478.
14. Mishra, V.N.; Rai, P.K. A remote sensing aided multi-layer perceptron-Markov chain analysis for land use and land cover change prediction in Patna district (Bihar), India. *Arab. J. Geosci.* **2016**, *9*, 249.
15. Mishra, V.N.; Rai, P.K.; Prasad, R.; Punia, M.; Nistor, M.M. Prediction of spatio-temporal land use/land cover dynamics in rapidly developing Varanasi district of Uttar Pradesh, India, using geospatial approach: A comparison of hybrid models. *Appl. Geomat.* **2018**, *10*, 257–276.
16. Seyam, M.M.H.; Haque, M.R.; Md Mostafizur Rahman, M.M. Identifying the land use land cover (LULC) changes using remote sensing and GIS approach: A case study at Bhaluka in Mymensingh, Bangladesh. *Case Stud. Chem. Environ. Eng.* **2023**, *7*, 100293.
17. Kumar, M.; Denis, D.M.; Singh, S.K.; Szabó, S.; Suryavanshi, S. Landscape metrics for assessment of land cover change and fragmentation of a heterogeneous watershed. *Remote Sens. Appl. Soci. Environ.* **2018**, *10*, 224–233.
18. Enrica, G.; Josep, P.R.; Amanda, J.A.; Garry, P.; Albert, N.; Anna, R.P.; Josep, V.S. Landscape features shape people's perception of ecosystem service supply areas. *Ecosyst. Serv.* **2023**, *64*, 101561.
19. Forman, R.T.T.; Godron, M. *Landscape Ecology*; John Wiley & Sons: New York, NY, USA, 1986.
20. Justeau-Allaire, D.; Ibanez, T.; Vieilledent, G.; Lorca, X.; Birnbaum, P. Refining intra-patch connectivity measures in landscape fragmentation and connectivity indices. *Landsc. Ecol.* **2024**, *39*, 24.
21. Verma, R.; Garg, P.K. Multi-temporal urban growth analysis with expansion indicators in Lucknow constituency by open-source data, India. *J. Urban Manag.* **2022**, *11*, 412–423.
22. McGarigal, K.; Cushman, S.A.; Ene, E. *FRAGSTATS v4: Spatial Pattern Analysis Program for Categorical and Continuous Maps*; University of Massachusetts: Amherst, MA, USA, 2012.
23. Szabó, S.; Novák, T.; Elek, Z. Distance models in ecological network management: A case study of patch connectivity in a grassland network. *J. Nat. Conserv.* **2012**, *20*, 293–300.
24. Singh, S.K.; Basommi, B.P.; Mustak, S.K.; Srivastava, P.K.; Szabo, S. Modelling of land use land cover change using earth observation data-sets of Tons River Basin, Madhya Pradesh, India. *Geocarto Int.* **2018**, *33*, 1202–1222.