

Original Research Article

Geospatial Analysis of Climate-Driven Landscape Change and Urban Expansion: Assessing Human–Environment Interactions, Resource Pressure, and Sustainable Spatial Planning

Dr. Amit Kumar Singh

Department of Geography, G. D. Binani P. G. College, U.P, India.

ORCID:  **AKS** [0009-0008-5573-0525](https://orcid.org/0009-0008-5573-0525)

Correspondence should be addressed to Dr. Amit Kumar Singh: vpamit87@gmail.com

Article No: 021 | **Accepted:** 25 September 2026 | **Published:** 10 October 2026

Abstract: The increasing demands and changing features of rapidly expanding cities and the impacts on land cover and the surface energy balance are evident. Yet, urban planners need to differentiate between the changes that have occurred and those which have been predicted. This study offers another geospatial analysis of the Delhi National Capital Region. This study complements previously published studies by the use of remote sensing techniques to retrieve land surface temperatures and studies of urban resource pressures. This study also incorporates land use and land cover studies of the years 2003, 2013 and 2023, which are based on the analysis of the Landsat imagery. The primary land use and land cover study analyzed an area of 13,754 km² that includes the entirety of the Delhi National Capital Region and portions of the districts of Gurugram, Faridabad, Sonapat, Jhajjar, Ghaziabad, Gautam Buddha Nagar and Ghaziabad. This study also carried out a reanalysis of published land use and land cover maps to compute the absolute and relative changes and the annual growth rates. The area of land cover of built-up land increased from 1,893.64 km² (13.77%) in 2003 to 3,386.76 km² (24.62%) in the year 2023, which is an increase of 1,493.12 km² (78.85%. CAGR 2.95%). Decreases were observed in the land cover of agricultural land, forests, water bodies and open land. The rate of land cover of built-up land slowed from an annual rate of 4.37% during 2003 to 2013, to an annual rate of 1.55% during the 2013 to 2023 period. The peripheral Shannon Entropy increased from a value of 0.24 to 0.36 during the same periods. The average land surface temperature of built-up land in Delhi, as reported independently of this study, increased by 5.23°C from 36.58°C in the year 2001 to 41.81°C in the year 2021. The integrated findings indicate that land that was previously agricultural and ecological cover has been extensively converted into built-up areas, intensifying surface warming and resource pressure across the urban periphery and underscoring the urgent need for sustainable spatial planning.

Keywords: Delhi–Ncr; Land-Use/Land-Cover Change; Urban Expansion; Land-Surface Temperature; Shannon Entropy; Resource Pressure; Sustainable Spatial Planning

1. Introduction

Urbanization disrupts vegetation and agriculture, which alters the environment and poses new risks that fragment habitats (and more). Things start to get difficult when urban environments grow beyond city borders, which extends the land market. Especially true for developing countries, urban transportation systems and settlements grow faster than the development of infrastructure and ecological protection measures. This makes planning sustainable infrastructures difficult. In these situations, remote sensing becomes crucial as it offers information on land development in a repeatable manner.

Delhi-NCR is a great example of a situation where urban sprawl is expanding beyond the city. Research in the area has identified the urban sprawl and the 'heat-island' effect that has spread over the region. Research has shown how quickly suburban Delhi-NCR has built up. The work of researchers, Nahid et al. (2025), has classified remote sensing pictures from 2003 to 2023 with a prediction for 2033. This will provide valuable information on how the urban environment has changed. One study on Delhi (2025), has shown how, since the year 2001, built-up areas have increased and urban areas have expanded in such a way that urban areas have directly influenced thermal stress within the environment.

The impacts of the human environment extend beyond the warming of the Earth's surface. The expansion of impermeable solid mass that covers the Earth's land surface can result in reduced land surface infiltration, increased runoff, increased stress on the groundwater table, and less available green space. Analyzing the Ward level of Delhi reveals extreme irregularity of population density. These data show built-up population density can range from 2,884 to 136,385 persons per km², and an average groundwater level of 16.38 m, which helps to illustrate the impact of the spatial interaction of urban population density and resource conditions (Avtar et al., 2025). Assessments of ecosystem services have confirmed that the urbanization of Delhi over the last several decades has impacted the availability and distribution of ecosystem services and their benefits (Sharma et al., 2020).

This study, therefore, intends to examine the previously verified, published geospatial outputs, instead of claiming newly registered, localized geospatial classifications. This study hopes to achieve the following: (1) assess Land Use and Land Cover change in the context of urban expansion from 2003 to 2023 and assess the urban expansion that occurred in the two decadal periods that followed; (2) assess urban sprawl entropy; (3) draw upon the more recent evidence of Land Surface Temperatures and resource-pressures; and (4) convert the spatial evidence of the above into planning frameworks that can help bring about a post-urban-resource pressure city. The proposed directions of urbanization will yield the predicted results of an edge-expanding city, a

substantial increase in built-up urban land, and a substantial decrease in ecological and agricultural land along with an increase in urban resource stress and pressure, as evidenced by surface land temperatures.

2. Materials and Methods

2.1 Study area

The study incorporates the Delhi-NCR region as defined by Nahid et al. (2025). This study area is approximated at 13,754 km² and comprises the regions of Delhi, Gurugram, Faridabad, Sonipat, Jhajjar, Gautam Buddha Nagar and Ghaziabad. This multi-state urban study region comprises a high-density metropolitan inner core and rapidly changing peripheral zones. This study defined the core and peripheral zones as being 30 km and beyond from central Delhi, respectively. This also allows for the assessment of the compactness and dispersion of the zones using Shannon's entropy.

2.2 Data sources and analytical framework

LULC data were primarily drawn from the study conducted by Nahid et al. (2025). They performed LULC classification through a maximum Likelihood Classifier and classified 2003, 2013, and 2023 (pre-monsoon) Landsat images into 6 LULC classes (built-up, agriculture, forest, scrubland, water bodies, and open land). For 2023, the authors performed CA-ANN validation, and the result of the validation was Kappa = 0.86, which is considered to be a strong agreement. The authors also calculated Shannon entropy for core and peripheral zones. For the analysis, thermal context is provided by the built-up LST and endpoint mean drawn from the works of Thi Hang et al. (2025). For the resource-pressure context, remote-sensing and ward-based spatial analysis by Avtar et al. (2025) was used.

Table 1. Geospatial and environmental evidence integrated in the reanalysis

Dataset/study	Coverage/resolution	Variables used	Analytical purpose
Nahid et al. (2025)	Delhi-NCR; Landsat epochs 2003, 2013, 2023	LULC area, class shares, entropy, Kappa, 2033 projection	Observed change and urban-growth rates
Thi Hang et al. (2025)	Delhi; remote-sensing analysis, 2001–2021	Mean built-up LST	Thermal response to urbanization
Avtar et al. (2025)	Delhi wards; census + remote sensing + groundwater	Built-up population density, imperviousness/resource indicators	Human–environment and resource-pressure context

Sources are peer-reviewed studies published in 2025; the present paper recalculates rates from their reported observations.

2.3 Quantitative reanalysis

For each LULC class, absolute change was quantified as $A_2 - A_1$, and relative change, $[(A_2/A_1) - 1] \times 100$. The compound annual change was calculated as $[(A_2/A_1)^{(1/n)} - 1] \times 100$.

- $1] \times 100$, where n is the number of years. Built-up land was analyzed for the periods of 2003-2013, 2013-2023, and the whole period of 2003-2023, to assess the deceleration or the acceleration of land-use change. The 2023-2033 CA-ANN was a scenario and not a formal prediction. For the three study periods, the correlation of built-up land and peripheral entropy was calculated, using Pearson's correlation, as a preliminary and exploratory statistic. With $n = 3$, this statistic exhibits a very limited ability to infer and was not considered in a causal context. Since the original raster samples were not available for independent resampling, no pixel-level significance tests were created.

3. Results

3.1 Urban Expansions and Land Cover Changes

The total area of built-up land in 2003 was 1,893.64 km², which increased to 2,904.70 km² by 2013 and reached 3,386.76 km² by 2023. The total area gained in the twenty-year period was 1,493.12 km², which reflects a 78.85% increase and an annual compounded expansion of 2.95%. The area gained in the first decade was 1,011.06 km², constituting 53.39% of the cumulative area in the twenty-year period and an annual compounded growth rate of 4.37%. The area gained in the second decade was 482.06 km², constituting 16.60% of the cumulative area in the twenty-year period and an annual compounded growth rate of 1.55%. Consequently, built-up land continued to expand after 2013, but the growth rate was approximately one-third of the rate in the first decade, and the area gained in the second decade was 47.7% of the area gained in the first decade. The area of land devoted to built-up

The contraction of land classes was associated with increased urbanization. Agricultural land shrank from 10,921.8 to 9,630.7 km², a total shrinkage of 1,291.10 km² (-11.82%; CAGR -0.63%). Forests shrank from 415.4 to 282.9 km² (-132.50 km²; -31.90%; CAGR -1.90%). The area of water bodies decreased from 139.25 to 101.09 km² (-27.40%; CAGR -1.59%) and open land shrank from 65.17 to 24.11 km² (-63.00%; CAGR -4.85%). According to Nahid et al. (2025), agricultural land to urban land conversion was the primary change, particularly in the first decade, with extensive development in the peripheral zone.

Table 2. Land-cover change in the Delhi–NCR analytical extent, 2003–2023

Class	2003 (km ²)	2023 (km ²)	Absolute Δ	Relative Δ (%)	CAGR (%/yr)
Built-up	1,893.64	3,386.76	+1,493.12	+78.85	+2.95
Agriculture	10,921.80	9,630.70	-1,291.10	-11.82	-0.63
Forest	415.40	282.90	-132.50	-31.90	-1.90
Water bodies	139.25	101.09	-38.16	-27.40	-1.59
Open land	65.17	24.11	-41.06	-63.00	-4.85

Source: authors' calculations from LULC areas reported by Nahid et al. (2025).

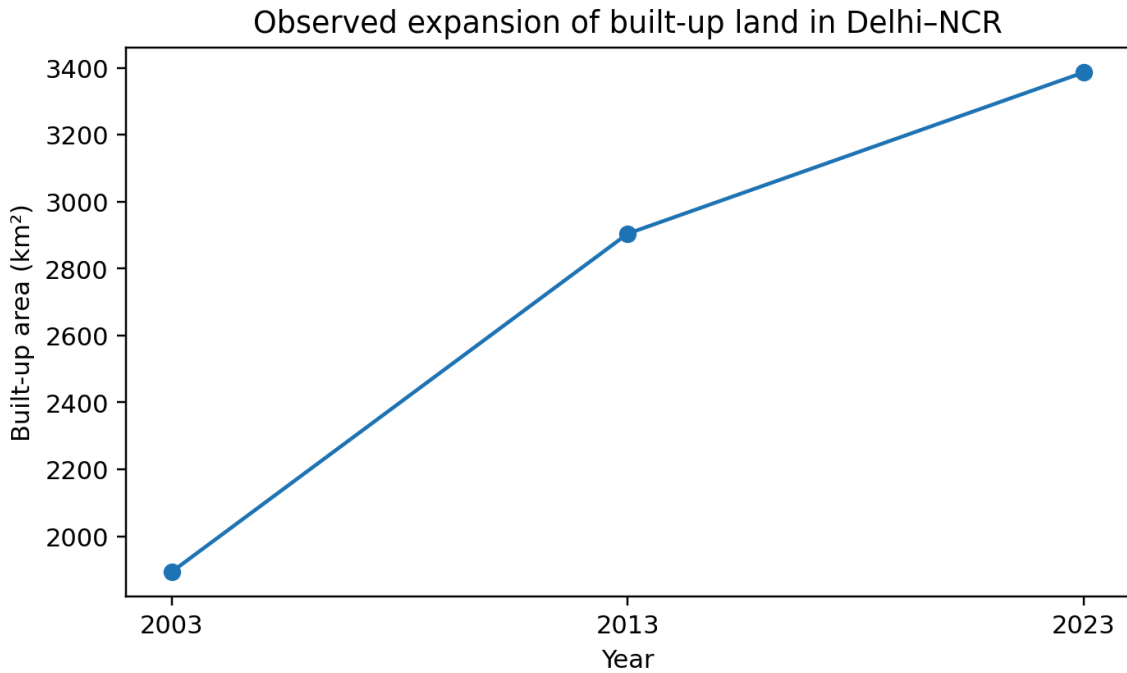


Figure 1. Observed built-up expansion, 2003–2023. Source: calculations from Nahid et al. (2025).

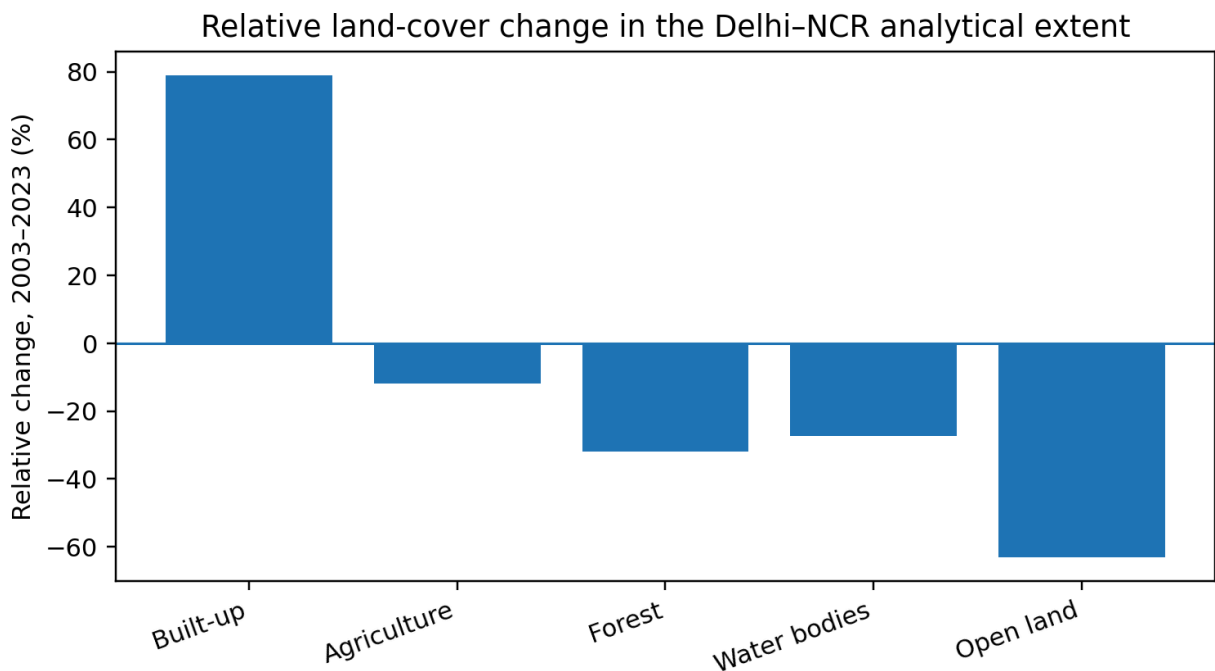


Figure 2. Relative change in major LULC classes, 2003–2023. Source: calculations from Nahid et al. (2025).

3.2 Urban form and peripheral dispersion

Shannon entropy measures the spatial disorder of a system. In the years 2003 to 2023, Shannon entropy exhibited greater variation in the peripheral zone than in the core

zone. The peripheral zone's entropy was 0.24, 0.35, and 0.36 respectively, while the core zone's entropy was 0.67, 0.68 and 0.66 respectively. Source study interprets the results as related to stronger sprawl dynamics in the outer zone compared to the already developed core zone. In the three study periods, the built-up area was articulately and descriptively ($r = 0.970$) related to peripheral zone entropy. A stronger relationship was expected to be observed given the limited number of observations ($N = 3$) and the presented null hypothesis of no relationship. The directional tendency of the data was of most importance apart from the $p = 0.157$. Incremental land conversion predominantly extended in the direction of the outer zone to areas still comprising agricultural and scrub land.

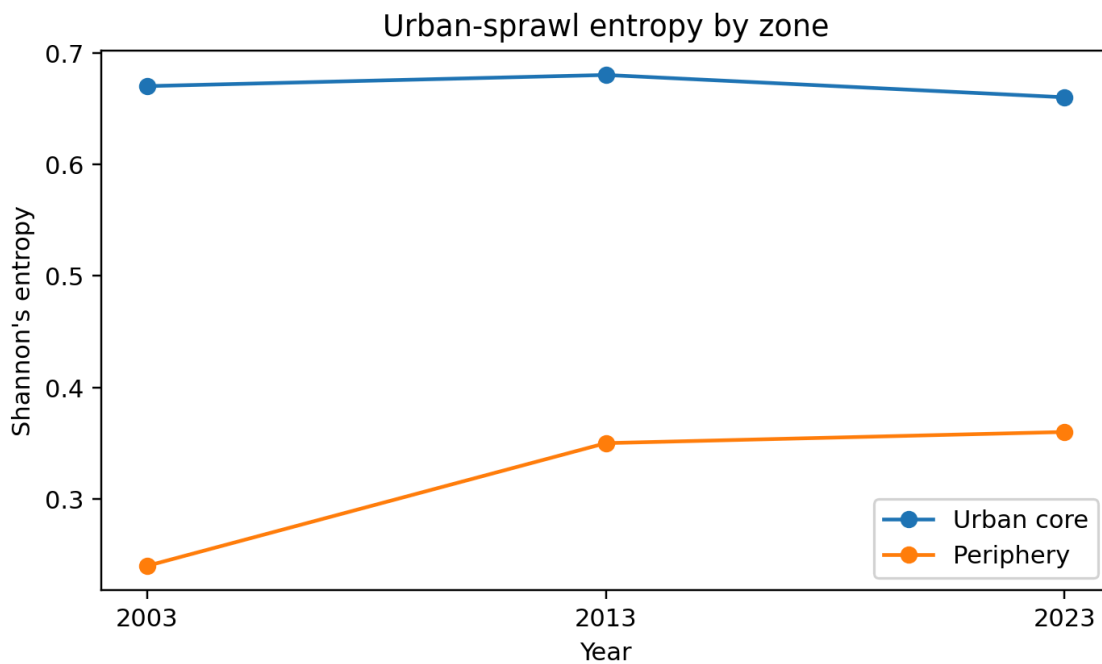


Figure 3. Reported Shannon entropy in urban core and peripheral zones, 2003–2023 (Nahid et al., 2025).

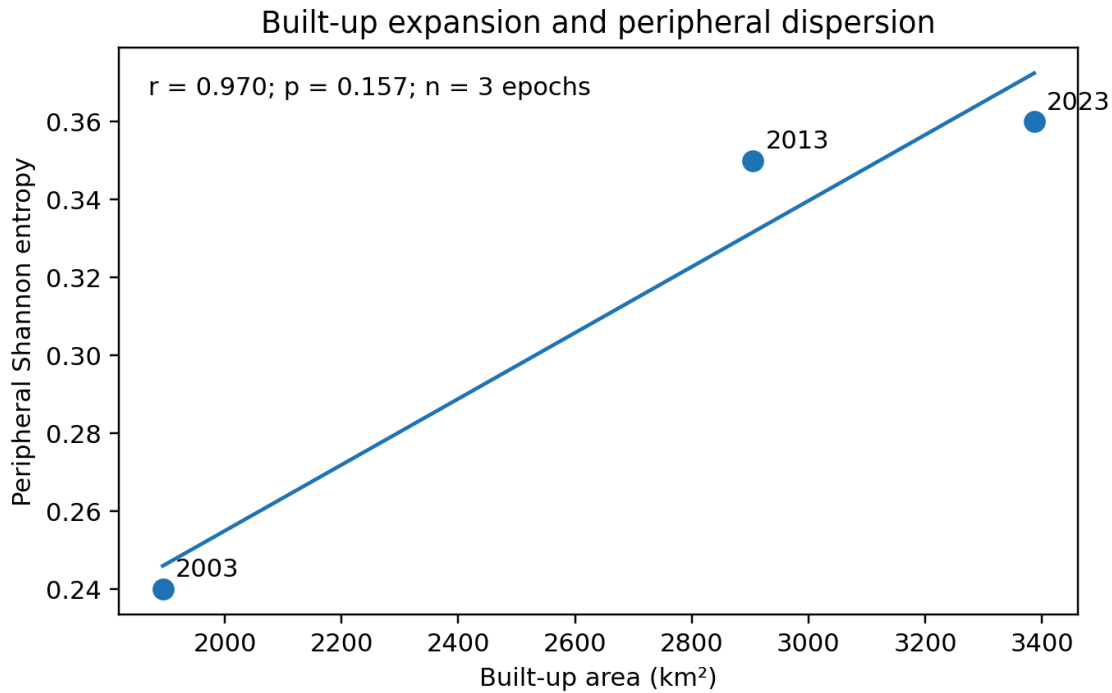


Figure 4. Exploratory association between built-up area and peripheral entropy; $n = 3$ epochs, so inferential interpretation is intentionally limited.

3.3 Thermal and resource-pressure signals

The evolution of land cover corroborates independent thermal evidence. According to Thi Hang et al. (2025), the mean land surface temperature (LST) of built-up areas of Delhi increased from 36.58°C in 2001 to 41.81°C in 2021, an increase of 5.23°C (a 14.30% increase from the 2001 mean), representing an endpoint surface temperature increase of 0.262°C/year. This estimate of LST (land surface temperature) in built-up regions of Delhi is not a controlled estimate of the extent of the urbanization process, as the LST is also influenced by regional climate variability. However, it agrees with the well-documented process of replacing evapotranspiring soil and vegetation with impervious surfaces that store heat. Earlier Delhi-NCR (Mohan et al., 2020) studies have also extended the long-term sprawl of Delhi-NCR to the exacerbation of urban heat island effect.

Resource pressure is also uneven in space. According to Avtar et al. (2025), built-up areas of Delhi-NCR have a population density with spatially uneven urban population density clusters of 2,884 to 136,385 persons km⁻², with an average built-up area population density of approximately 43,671 persons km⁻². Average groundwater depth of 16.38 m and significant surface imperviousness represent the lag in the matching of groundwater and other basic urban infrastructure to the density, and the provision of urban green spaces. These numbers originate from separate ward-level studies of Delhi and do not contribute numerically to the NCR LULC (NCR Land-Use Land-Cover) raster. Rather, they are used to demonstrate that the conversion of land intersects with water and well-being constraints.

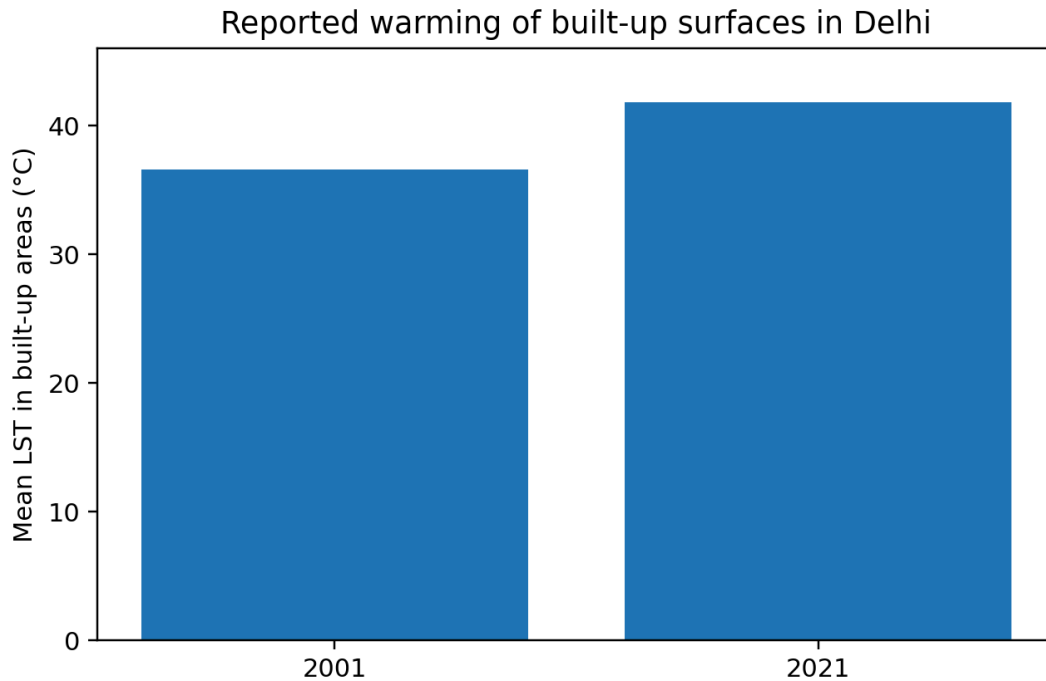


Figure 5. Mean built-up land-surface temperature reported for Delhi in 2001 and 2021 (Thi Hang et al., 2025).

Table 3. Quantitative indicators of urbanization, dispersion and environmental pressure

Indicator	Estimate	Interpretation
Built-up CAGR, 2003–2013	+4.37% yr ⁻¹	Rapid first-decade expansion
Built-up CAGR, 2013–2023	+1.55% yr ⁻¹	Expansion continued but slowed
Built-up CAGR, 2003–2023	+2.95% yr ⁻¹	Sustained long-run conversion
Peripheral entropy	0.24 → 0.36	Increasing peripheral dispersion
CA–ANN validation	Kappa = 0.86	Strong agreement for 2023 validation
Mean built-up LST	36.58°C → 41.81°C	+5.23°C between 2001 and 2021
Exploratory built-up–entropy r	0.970; p = 0.157	Strong direction, n = 3; not inferentially conclusive

3.4 2033 scenario

According to the CA–ANN/Markov scenario, built-up land will reach 3,868.28 km² for the year 2033, an increase of 481.52 km² from the 2023 estimate (+14.22%; projected CAGR 1.34%). Agricultural land is estimated to be 9,153.1 km² (66.5% of the study area), with forests at 281.3 km², water bodies at 100.04 km², and open land at 21.83 km². The projected built-up increase is nearly identical to the absolute increase quantified for 2013–2023, showing that there is likely to be greater spatial pressure, even with the relatively low post-2013 growth rates. Since these are model outputs, they should be treated

as planning scenarios dependent on future conditions of accessibility, policies, the market, and infrastructure, rather than assuming they are strict forecasts.

4. Discussion

Upon the results being reanalyzed, it became obvious that a land-budget trade-off existed. Between 2003 and 2023, built-up land expanded by approximately 1,500 km², while all other land uses (agriculture, forests, water, and open land) decreased. The largest absolute loss was of agricultural land, which is typically the first land to be converted to urban use within a peri-urban area due to its extensive spatial characteristics and highest likelihood to be developed compared to other land use types. These results are consistent with Naikoo et al. (2020) and Singh et al. (2022), who noted built-up land expansion and conversion of non-urban land in the Delhi-NCR region. The decline in urban land growth rates during this period is also notable as a large absolute increase in urban land can occur with a slowing rate of growth, particularly when the growth of urban land has expanded significantly.

Analytically, a reduction of 31.9% in forest cover is disproportionately significant in terms of area size. From an ecological perspective, Delhi's urbanization, according to Sharma and others (2020), modifies the urban area's capability to offer services across a number of categories. This suggests that the changes brought on by the urbanization of the forests extend beyond what the land area measurements would suggest. Based on the changes in the land cover, the increase in the land surface temperature (LST) supports the assumption of limited vegetation cover and an increase in urban land. This assumption is reinforced by the increase of the land surface temperature, as there are limited vegetation and an increase in urban land cover. To fulfill the requirements to provide a rational basis for the assumption, it is necessary to take into consideration the meteorological changes, as well as the consistency between the sensors and the seasons.

Entropy on its own represents a spatiotemporal phenomenon. Land conversion of the periphery caused a significant increase in entropy, whereas core entropy was stable with little change, given variation in land conversion of the core. The characteristic of suburban land conversion is the challenge of determining the amount of urban land and the arrangement and distribution of that land. The increasing entropy in the periphery suggests that urbanization coupled with spread development can significantly increase the boundary between urban land and agricultural land, forests, water bodies and other systems, while negatively affecting the integrity of the systems. Conversely, compact urban land, dispersed low urban land, and sustained high land density can cause extensive land consumption. Delhi also contains extreme internal density inequallity, as shown by Avtar et al. (2025), which is an important frame of reference in the context of sustainable development. Spatial planning policies need to regulate both the extreme internal inequity and excessive peripheral dispersion of Delhi's urbanization.

4.1 Implications of Sustainable Spatial Planning

Evidence indicates the requirement for a five-part planning response. The first is the management of urban growth, which should push new developments to serviced areas that are accessible by transit and discourage the dispersed conversion of greater-value agricultural and ecological lands. The second is that metropolitan green (or conservation) infrastructure should be imagined as a network of connected ridges, remnants of forests, river corridors, wetlands, urban forests and large parks, rather than scattered patches. The third is that planning with a water-sensitivity approach should safeguard floodplains and surface water, keep sufficient land in a permeable state, and strengthen and extend recharge infrastructure. The fourth is that planning for heat risk should be the addition of tree canopies and shade, along with cooler materials and ventilation corridors in high land surface temperature (LST) zones. The fifth is that cross-jurisdictional monitoring is imperative; mapped urban systems extend trans-boundary across Delhi, Haryana and Uttar Pradesh, so the control of land conversion will be beyond municipal borders. These priorities serve SDG 11. Additionally, they coincide with the integrated, climate-resilient urban development of the IPCC. (IPCC, 2022)

4.2 Limitations

This paper purposefully differentiates a secondary reanalysis from a new remote-sensing classification. In this process, the raw Landsat scenes and the training pixels and the associated confusion matrices remain untouched. As a result, classification uncertainty surpassing the published Kappa value could not be assessed. The LST endpoints are from a different Delhi study and are used only for triangulation. The study used a different definitional and temporal framework. Using triangulation means they cannot be used as merged regressions. The entropy correlation is also limited, as it has a mere three epochs (and is therefore quite descriptive in nature). Administrative borders in NCR have changed, while the reported land classes would also change based on different classification schemes. Because of the factors named above, this study is most robust for what it reports on the published change rates and the convergent evidence synthesized. The study is at its weakest for what it reports on the pixel and ward-level changes, and on causal impacts.

5. Conclusion

Between 2003 and 2023, there was a significant redistribution of land in Delhi–NCR. Built-up area increased by 78.85%, while agriculture, forests, water, and open space decreased. After 2013, expansion continued to be considerable, even with a decreased annualized growth rate, and peripheral entropy increased, indicating continued outward dispersion. There is independent evidence of a 5.23°C increase in mean built-up land surface temperature (LST) from 2001 to 2021 and increased ward-level density/resource inequalities, particularly providing evidence why land-use and land-cover (LULC) changes are human–environment issues, not just cartographic issues. If the 2033 growth projections are accurate, there will be an additional 481.5 km² of built land. Planning for the future should favor the preservation of farmland and land with ecological functions, compact and

serviced growth, connected blue-green infrastructure, groundwater recharge and LST mitigation. The most critical step would be the institution of NCR-wide spatial evaluations, with the aim of assessing future development plans within defined land, thermal and resource thresholds.

Data Integrity Statement

All numerical values were either extracted from identified peer-reviewed sources or mathematically derived from those reported values. No satellite pixels, classification accuracies, land-cover areas, temperatures, correlations or p-values were invented. Derived rates are explicitly labelled as calculations, while 2033 values are explicitly labelled as model projections.

References

1. Avtar, R., Ahmad, S., Rahman, M. M., Alsulamy, S., Meraj, G., Sethi, M., Singh, C. K., & Kharrazi, A. (2025). Impact of urban density on human well-being and sustainable development in Delhi, India. *Scientific Reports*, 15, 33717. <https://doi.org/10.1038/s41598-025-16033-1>
2. IPCC. (2022). *Climate Change 2022: Impacts, Adaptation and Vulnerability*. Cambridge University Press. <https://doi.org/10.1017/9781009325844>
3. Kumar, R. P., Prakash, A., Singh, R., & Kumar, P. (2024). Machine learning-based prediction of hazardous fine PM2.5 concentrations: A case study of Delhi, India. *Discover Geoscience*, 2(1), 34. <https://doi.org/10.1007/s44288-024-00043-z>
4. Kushwaha, K., Singh, M. M., Singh, S. K., & Patel, A. (2021). Urban growth modeling using earth observation datasets, cellular automata–Markov chain model and urban metrics to measure urban footprints. *Remote Sensing Applications: Society and Environment*, 22, 100479. <https://doi.org/10.1016/j.rsase.2021.100479>
5. Mohan, M., Sati, A. P., & Bhati, S. (2020). Urban sprawl during five decadal period over National Capital Region of India: Impact on urban heat island and thermal comfort. *Urban Climate*, 33, 100647. <https://doi.org/10.1016/j.uclim.2020.100647>
6. Nahid, S., Kumar, R. P., Acharya, P., Kumar, K., & Purohit, S. (2025). Forecasting urban expansion in Delhi-NCR: Integrating remote sensing, machine learning, and Markov chain simulation for sustainable urban planning. *GeoJournal*, 90, 72. <https://doi.org/10.1007/s10708-025-11317-5>
7. Naikoo, M. W., Rihan, M., Ishtiaque, M., & Shahfahad. (2020). Analyses of land use land cover (LULC) change and built-up expansion in the suburb of a metropolitan city: Spatio-temporal analysis of Delhi NCR using Landsat datasets. *Journal of Urban Management*, 9(3), 347–359. <https://doi.org/10.1016/j.jum.2020.05.004>
8. Petroni, M. L., Siqueira-Gay, J., & Gallardo, A. L. C. F. (2022). Understanding land use change impacts on ecosystem services within urban protected areas. *Landscape and Urban Planning*, 223, 104404. <https://doi.org/10.1016/j.landurbplan.2022.104404>
9. Shahfahad, Kumari, B., Tayyab, M., Thi Hang, H., Khan, M. F., Asgher, M. S., Asif, & Rahman, A. (2022). Prediction of land use changes at a metropolitan city using integrated cellular automata: Past and future. *Geology, Ecology, and Landscapes*. <https://doi.org/10.1080/24749508.2022.2132010>
10. Sharma, S., Nahid, S., Sharma, M., Sannigrahi, S., & Mohammad, M. (2020). A long-term and comprehensive assessment of urbanization-induced impacts on ecosystem services in the capital city of India. *City and Environment Interactions*, 7, 100047. <https://doi.org/10.1016/j.cacint.2020.100047>
11. Singh, B., Venkatramanan, V., & Deshmukh, B. (2022). Monitoring of land use land cover dynamics and prediction of urban growth using land change modeler in Delhi and its environs, India. *Environmental Science and Pollution Research*, 29(47), 71534–71554. <https://doi.org/10.1007/s11356-022-20900-z>

12. Singh, R., Biswakarma, P., Joshi, V., Joshi, S., & Chaudhary, A. (2023). Spatiotemporal change analysis of land use/land cover in NCT of Delhi, India using geospatial technology. *Proceedings of the Indian National Science Academy*, 89(1), 189–200.
13. Talukdar, S., Singha, P., Mahato, S., Pal, S., Liou, Y.-A., & Rahman, A. (2020). Land-use land-cover classification by machine learning classifiers for satellite observations—A review. *Remote Sensing*, 12(7), 1135. <https://doi.org/10.3390/rs12071135>
14. Thi Hang, H., & Alshayeb, M. J. (2025). Technological innovations in urbanization and land surface temperature analysis: A remote sensing and machine learning case study of Delhi. *Environmental Technology & Innovation*, 38, 104164. <https://doi.org/10.1016/j.eti.2025.104164>
15. UN-Habitat. (2022). *World Cities Report 2022: Envisaging the Future of Cities*. United Nations Human Settlements Programme.
16. Yadav, P. K., Mishra, V. N., Kumari, M., Kumar, A., Kumar, P., & Bhatla, R. (2024). Spatially explicit simulation and forecasting of urban growth using weights of evidence based cellular automata model in a millennium city of India. *Physics and Chemistry of the Earth*, 136, 103739. <https://doi.org/10.1016/j.pce.2024.103739>



© 2026 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by-nc-sa/4.0/>).