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Geospatial Deconstruction and Predictive Modeling of Urban Morphogenesis in India's Tier-2 Cities: A Multi-Decadal Remote Sensing-Based Entropy Analysis

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Abstract

A geospatial analysis of urban morphogenesis in India's Tier-2 cities is essential as these cities face rapid expansion driven by population growth, infrastructure development, and economic pressures. This study investigates the spatial patterns, growth processes, and projected urban trajectories in three representative Tier-2 cities—Nashik, Gandhinagar, and Thiruvananthapuram using a multi-decadal analytical framework. The research employs satellite-based Land Use Land Cover (LULC) data from 1995 to 2025, supervised image classification, Shannon's Entropy Index, and Built-up Density metrics to assess spatio-temporal urban expansion. Urban growth simulations for 2035 are conducted using the MOLUSCE plugin in QGIS, supported by Artificial Neural Networks and Cellular Automata modeling. A cardinal zoning-based directional analysis reveals significant spatial variation across the three cities. Nashik exhibits dispersed urban sprawl, driven by the expansion of industrial corridors and the Samruddhi Expressway. Gandhinagar demonstrates relatively stable and concentric growth, influenced by its planned urban design and proximity to Ahmedabad. Thiruvananthapuram shows compact, high-density growth constrained by coastal and topographic barriers. Projected LULC scenarios for 2035 indicate substantial built-up expansion, particularly in Nashik, accompanied by the loss of green spaces and vegetation. The findings emphasize the urgent need for region-specific, data-driven planning to address the risks of unregulated sprawl, ecological loss, and inefficient land use. This study offers a geospatially integrated, comparative framework to support urban planners and policymakers in shaping sustainable, balanced growth trajectories for India's rapidly urbanizing Tier-2 cities. The research underlines the importance of integrating ecological preservation within future urban development strategies.

1. Introduction

Urbanization has emerged as one of the most defining phenomena of the twenty-first century, dramatically transforming both developed and developing regions of the world. As of 2014, more than 54% of the global population resided in urban areas, with projections suggesting this figure will reach approximately 6.3 billion by 2050 (United Nations, 2014). A staggering 90% of this projected growth is expected to occur in developing regions such as Asia and Africa, where the pace of urban transformation is both rapid and spatially extensive (United Nations, 2014). While urbanization in developed regions like North America (82%) and Europe (73%) has largely stabilized, nations in the Global South continue to experience aggressive spatial and demographic shifts driven by industrialization, migration, and infrastructural expansion (UN-Habitat, 2016). The ongoing urban transformation in India reflects broader global trends, with the nation's urban population projected to increase from 290 million in 2001 to approximately 590 million by 2030 (McKinsey Global Institute, 2010). A simultaneous expansion in the number of million-plus cities is anticipated, rising from 42 in 2021 to 68 by 2030 (Directorate of Census Operations Maharashtra, 2011). The urban landscape is evolving not only as a demographic epicenter but also as a crucial economic hub, with projections indicating that urban India will generate nearly 70% of the country's GDP and account for the majority of new employment opportunities by 2030 (MoHUA, 2015). However, the spatial diffusion of urbanization is uneven, increasingly radiating beyond traditional metropolitan centers toward Tier-2 and Tier-3 cities, thereby redefining the contours of urban development across the nation. In India, urban areas are officially classified as either statutory towns or census towns. Statutory towns include those recognized under state legislation such as municipal corporations, municipalities, and cantonment boards and census towns are determined by specific demographic criteria, including a minimum population of 5,000; a population density of at least 400 persons per square kilometer; and more than 75% of the male main working population engaged in non-agricultural activities(Directorate of Census Operations Maharashtra, 2011). The Reserve Bank of India categorizes these cities for the purpose of banking infrastructure development, while the Sixth Central Pay Commission (2008) utilizes them for determining house rent allowance classifications(Reserve Bank of India, 2005; Sixth Central Pay Commission, 2008). Furthermore, national urban programs such as the Smart Cities Mission and Atal Mission for Rejuvenation and Urban Transformation (AMRUT) have prioritized many of these cities for targeted infrastructural and governance enhancements(MoHUA, 2015). Despite these definitions, urban expansion frequently transcends administrative boundaries, resulting in peripheral growth and the engulfment of adjoining rural settlements. This phenomenon is commonly termed as urban sprawl and is characterized by the dispersed and low-density development of land at the urban fringe, often in the absence of structured planning and infrastructure provisioning(Bhatta, 2010b, 2010a; Sudhira et al., 2004). The saturation of megacities such as Mumbai and Delhi have catalyzed the emergence of Tier-2 cities as the principal frontiers for spatial expansion. This evolution signifies a fundamental shift in urban growth dynamics, from concentrated metropolitan regions toward more dispersed and mid-sized urban centers. The observed trajectory necessitates a targeted investigation into the patterns, processes, and drivers of urbanization specific to Tier-2 cities, where planning challenges like limited institutional capacity, inadequate spatial data infrastructure, uncoordinated land use changes, and escalating environmental degradation coexist alongside opportunities for promoting sustainable and resilient urban development. The drivers underpinning urban sprawl in Tier-2 cities are inherently multi-faceted. (Bhatta, 2010b, 2010a) delineates several interconnected factors, including rural-to-urban migration, economic liberalization, expansion of state-led infrastructure projects, and the proliferation of real estate markets, as primary catalysts of this phenomenon. Additionally, Tier-2 cities offer strategic advantages such as lower land costs, the growth of emerging service sectors, and improved quality of life, rendering them increasingly attractive to both industrial investments and population inflows(McKinsey Global Institute, 2010). Nevertheless, the rapid and often unregulated nature of this expansion engenders significant concerns related to environmental sustainability, infrastructural strain, and socio-spatial inequality. Agricultural lands and ecologically sensitive zones are frequently subjected to urban conversion without comprehensive impact assessments, resulting in the erosion of critical environmental buffers and heightened vulnerability to climate-induced hazards(Sudhira et al., 2004).

In the present research, the application of Geographic Information System (GIS)-based methodologies has become indispensable for analyzing and managing urban sprawl. The integration of satellite imagery with spatial metrics enables the precise detection and quantification of land use and land cover (LULC) changes over temporal scales. The utilization of remote sensing technologies has been extensively demonstrated in monitoring built-up area expansion, delineating directional growth patterns, and computing urban form metrics such as Shannon's Entropy Index(Herold et al., 2003; Jat et al., 2008). A growing emphasis on predictive modeling techniques, including Cellular Automata–Markov (CA-Markov) chains and Modules for Land Use Change Simulations (MOLUSCE), has provided valuable foresight into future urban growth trajectories, thereby assisting policymakers in devising spatially informed and proactive urban planning strategies(Deep & Saklani, 2014).

The aim of this research is to analyze and compare urban sprawl in three representative Tier-2 cities in India—Nashik (Maharashtra), Gandhinagar (Gujarat), and Thiruvananthapuram (Kerala) using geospatial methodologies. These cities have been selected based on their unique urban trajectories, administrative significance, economic profiles, and geographic settings. The study employs multi-temporal satellite imagery, supervised classification techniques, entropy-based urban form analysis, and future LULC projections to derive comprehensive insights into urban expansion patterns. The present study contributes to bridging the empirical and policy gaps in urban research, given the critical role Tier-2 cities are expected to play in India's urban future. It offers a replicable methodological framework for assessing urban sprawl in emerging cities by emphasizing spatial metrics and predictive modeling. Moreover, it addresses the pressing need for localized, data-driven strategies that can balance developmental imperatives with environmental sustainability.

2. Literature Review

The literature reviewed in this study was identified through a comprehensive search strategy using databases such as Scopus, SpringerLink, ScienceDirect, Elsevier, and Google Scholar. The search employed Boolean combinations of terms including "urban sprawl," "Tier-2 cities," "GIS in urban planning," "LULC change," "urban growth modeling," and "Shannon's entropy." The inclusion criteria focused on peer-reviewed articles published between 2000 and 2024 that emphasized spatial or quantitative methodologies with a particular focus on developing country contexts, while studies limited to Tier-1 cities or lacking methodological robustness were excluded. The initial corpus of 1,319 scholarly articles addressing urban development, simulation, and management was refined to a shortlist of approximately 200 studies which were selected for thematic analysis. The categorization of these studies aligned with four dominant research themes: Land Use and Land Cover (LULC) Analysis, Measurement of Urban Sprawl, Drivers and Impacts of Urban Growth, and Predictive Urban Modeling Techniques as shown in table 1.

An extensive number of studies (126) directly examined LULC data to explore urban sprawl patterns, while 98 studies engaged with predictive modeling approaches. The scarcity of research explicitly addressing Land Use and Cover Change (LUCC) was evident, with only 10 studies highlighting a gap in in-depth analysis in this area. The significance of GIS as a planning and evaluation tool was further underscored by 782 articles employing the Analytical Hierarchy Process (AHP) for urban land use planning and site suitability assessments. The application of remote sensing and regional spatial analysis in 41 studies demonstrated the potential of these technologies to delineate urban sprawl; however, they often fell short of addressing the risks associated with uncontrolled expansion, emphasizing the need for more strategic GIS-based interventions. The growing reliance on GIS and remote sensing technologies reflects the urgency of managing rapid urban growth, particularly in developing regions, where unchecked sprawl threatens effective land management, environmental sustainability, and socioeconomic resilience. The reviewed literature affirms the utility of geospatial tools in evaluating urbanization trends and supports the need for interdisciplinary approaches to ensure informed planning and sustainable urban development.

Theme	**Description**	**Research Papers Reviewed**
Land Use/Land Cover (LULC) Analysis	Utilizing remote sensing to analyze LULC changes is a foundational tool for understanding urban expansion. Researchers can track spatial changes and urbanization over time by categorizing satellite images into types like built-up areas, vegetation, water bodies, and agricultural	(Al-Dousari et al., 2023; Atef et al., 2023; Kanav et al., 2024; Oyedele et al., 2023; Selmy et al., 2023)

Measuring Urban Sprawl	Metrics like Shannon's entropy and landscape metrics provide insights into the structure of urban sprawl, helping to assess spatial patterns, fragmentation, and dispersion, which are key to understanding the intensity and extent of sprawl.	(Al Mazroa et al., 2024; Deo et al., 2024; Jamali et al., 2023; Mansour et al., 2023)
Drivers and Impacts of Urban Growth	Identifying the key drivers, such as population growth, economic factors, and policy decisions, sheds light on urban sprawl's causes. Recognizing these drivers is essential for managing and mitigating the environmental and societal impacts of rapid urbanization.	(Elangovan & Krishnaraaju, 2023; Öncel & Levend, 2023; Wang et al., 2018)
Urban Growth Modeling and Prediction	Predictive models, such as Cellular Automata (CA)-Markov, MOLUSCE, and regression-based analyses, allow researchers to forecast urban growth patterns. These models utilize historical data and identify growth drivers to anticipate future urban expansion and guide proactive planning.	(Aziz et al., 2024; Somvanshi et al., 2020; Wang et al., 2018; Wicaksono et al., 2023)

Table 1: Thematic Classification of Reviewed Literature

3. Data and Methods

This study adopts a geospatial analytical framework to investigate and compare urban sprawl in three representative Tier-2 Indian cities: Nashik (Maharashtra), Gandhinagar (Gujarat), and Thiruvananthapuram (Kerala) over a multi-decadal temporal span (1995–2025) as shown in figure 1. The methodology integrates remote sensing, spatial statistics, and predictive modeling to assess historical land use and land cover (LULC) transitions, quantify built-up growth dynamics, and simulate future urban expansion scenarios. The approach is structured into five core components: satellite data acquisition and preprocessing, supervised classification, spatiotemporal analysis of urban expansion, population-based density estimation, and land use forecasting using machine learning-based models.

3.1 Satellite Data Acquisition and Pre-processing

Multi-temporal remote sensing datasets were procured from the United States Geological Survey (USGS) Earth Explorer platform. Four time periods—1995, 2005, 2015, and 2021—were selected to represent key inflection points in India's urban development trajectory. These intervals allowed for the analysis of long-term changes in urban morphology. To ensure consistency in spatial resolution and spectral quality, imagery was sourced from Landsat 5 Thematic Mapper (TM) for the years 1995 and 2005, and Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) for 2015 and 2021, respectively. A strict filtering criterion was applied, restricting selection to scenes with less than 15% cloud cover to minimize atmospheric interference. The administrative boundaries of the study areas were delineated using Census 2011 urban agglomeration shapefiles and further verified through digitized municipal boundary overlays. All satellite images were clipped to these extents for uniformity. Radiometric correction and band stacking were applied to generate true and false color composites, and all images were reprojected to a consistent spatial reference system (WGS 84, UTM Zone).

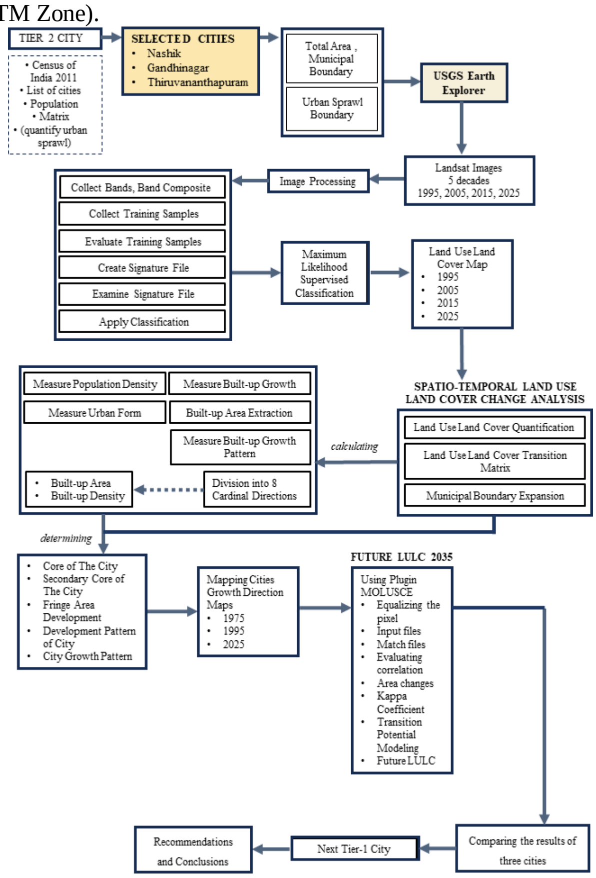

Figure 1: Methodological Framework for Geospatial Analysis of Urban Sprawl

3.2 Supervised Image Classification

LULC classification was performed using the Maximum Likelihood Classification (MLC) algorithm in ArcGIS Pro 3.0. MLC, a Bayesian probabilistic classifier, was selected for its proven effectiveness in multi-spectral image classification in urban environments. Training samples for land use categories—built-up, vegetation (dense/sparse), water bodies, barren land, and fallow land—were generated using the Region of Interest (ROI) tool. Class separability was assessed using the Transformed Divergence Index, ensuring the minimization of classification error. Post-classification, raster outputs were subjected to a series of smoothing operations to reduce speckle noise (i.e., salt-and-pepper effect). Classification accuracy was evaluated through confusion matrices using high-resolution Google Earth imagery as reference data. The Kappa coefficient was employed to determine the reliability of the classification results, with values exceeding 0.85 indicating high classification agreement.

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3.3 Quantification of Built-Up Area and Urban Growth The temporal expansion of the built-up area was quantified by extracting the built-up class from each classified raster and computing the area in square kilometers through raster-to-vector

transformation using Maximum Likelihood Classification (MLC)

and Zonal Statistics. The rate of built-up growth between successive years was computed using the formula:

$$\textit{Build-up growth} = A_{t_2} - A_{t_1}$$

where A_{t_1} and A_{t_2} denote the built-up area at the initial and subsequent time points, respectively. This facilitated the assessment of urban growth magnitude and velocity across the selected cities.

3.4 Directional Growth and Built-Up Density Analysis

To elucidate the spatial directionality of urban sprawl, each city was divided into eight directional sectors (N–NE, NE–E, E–SE, SE–S, S–SW, SW–W, W–NW, NW–N) radiating from the centroid of the 1995 built-up footprint. Zonal statistics were applied to determine the extent of built-up area in each sector. Built-up Density (BD) was calculated using the following expression:

$$BDi = \frac{B_i}{TA_i}$$

where BDi represents the built-up density in zone i, B_i represents total built-up area (sq. km) in zone I, and TA_i represents total area (sq. km) of zone. This metric enabled spatial comparison of density variation and growth bias across different zones, thereby revealing patterns of concentric, radial, or leapfrogging urban expansion.

3.5 Population Data Integration and Urban Density Estimation

Population data for 1991, 2001, and 2011 were acquired from the Census of India. Population values for intermediate and non-census years were interpolated using the Compound Annual Growth Rate (CAGR) method, which assumes exponential growth:

$$CAGR = \left(\frac{Pt}{P_0}\right)^{\frac{1}{t}} - 1$$

Where P_0 refers to base year population, Pt refers to population at time t, and t refers to number of years between P_0 and Pt. Population density (PD) was then computed using built-up area as the denominator:

$$PD = \frac{P_i}{TA_i}$$

Where

P_i refers to total urban population during the year I and TAi Total built-up area (in sq. km) during the year i. This approach provides a more accurate reflection of urban population distribution than using total administrative area.

3.6 Spatial Form Assessment Using Shannon's Entropy The morphological structure of urban sprawl was quantitatively evaluated using **Shannon's Entropy Index**, which measures the degree of spatial dispersion of the built-up area. The entropy index is expressed as:

$$H_n = -\sum_{L=1}^{n} P_i \log(P_i)$$

where H_n represents Shannon's entropy index for n zones (n=8) and PP_i refers to proportion of built-up area in zone i. The proportion Pi is derived using the formula:

$$P_i = \frac{x_i}{\sum_{i=1}^{n} x_i}$$

where x_i refers to built-up area in zone i and $\sum$Xi refers to total built-up area in the entire city. Entropy values approaching zero indicate compact and concentrated growth, while higher values denote dispersed, fragmented expansion. By comparing entropy values across different years, temporal trends in the compactness or diffuseness of urban form were determined.

3.7 LULC Change Simulation Using MOLUSCE

To simulate future urban growth, the MOLUSCE (Modules for Land Use Change Simulations) plugin in QGIS was employed. Historical LULC maps from 1995, 2005, 2015, and 2025 were used as training data. MOLUSCE supports several modeling algorithms; in this study as shown in table 2. Artificial Neural Networks (ANNs) were chosen for their capability to learn complex transition patterns. Transition potential maps were generated based on topographic and proximity variables (e.g., slope, distance to roads and rivers). Additionally, Cellular Automata (CA) were utilized to simulate spatial dynamics and neighborhood influences, maintaining spatial continuity in growth projections. The model output was validated using the Kappa coefficient, comparing simulated and actual LULC for the nearest known year. The resultant 2035 LULC projection map facilitated the identification of future urban hotspots and high-risk areas for sprawl-induced land degradation. The following table shows the details of each steps that were followed to simulate 2035 LULC using MOLUSCE plugin.

Component	What it does	Importance
Evaluating Correlation	Determines relationship strength between inputs	Higher correlation = more accurate model
Area Changes	Quantifies changes across classes	Detects dominant land transformation
Transition Matrix	Shows probabilities of LULC conversions	Essential for simulating realistic transitions
Transition Potential	Predicts where changes are likely to happen using ANN	Enables spatial accuracy
Cellular Automata	Applies neighbourhood rules to simulate change spread	Capture spatial dependencies
Validation	Compares predicted and actual results using Kappa coefficient	Ensures model reliability

Table 2: Methodological Steps for LULC Modeling Using MOLUSCE in QGIS

4. Results

This section presents the spatiotemporal and quantitative analysis of urban sprawl in Nashik, Gandhinagar, and Thiruvananthapuram using satellite imagery, GIS-based classification, spatial metrics, and modeling. The results are organized thematically across six domains: land use and land cover (LULC) change, built-up area growth, population density trends, directional urban growth patterns, entropy-based urban form analysis, and predictive modeling using MOLUSCE for 2035.

4.1 Land Use and Land Cover Change Analysis (1995–2025)

The study period's LULC analysis provides important information about each city's rate and trend of urban change. The four land classifications were built-up area, forest/vegetation, barren terrain, and water bodies. While changes in bare land and water bodies were relatively small, the data show a significant rise in built-up areas in all three cities together with a discernible decrease in vegetative cover.

4.1.1 Gandhinagar

To assess the spatio-temporal dynamics of urban expansion in Gandhinagar, Land Use Land Cover (LULC) maps for the years 1995, 2005, 2015, and 2025 were prepared using multi-temporal Landsat satellite imagery and processed through supervised classification employing the Maximum Likelihood Classification (MLC) method in ArcGIS.

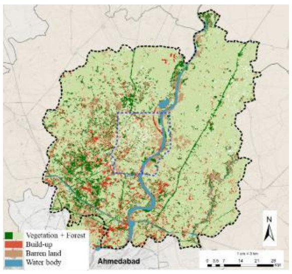

Figure 2: LULC 1995

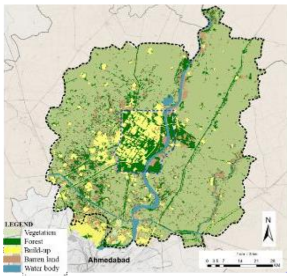

Figure 3: LULC 2005

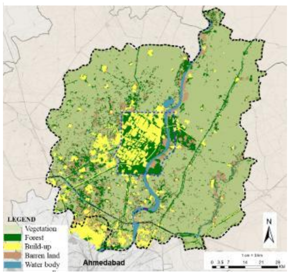

Figure 4: LULC 2015

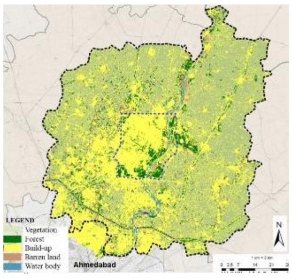

Figure 5: LULC 2025

The classified maps, presented in figures 2 to 5, visually depict the evolving urban landscape of Gandhinagar over the three-decade period. As shown in table 3, four major land categories were identified through the analysis: built-up land, vegetation/forest, barren land, and water bodies. In 1995, the region was predominantly vegetated, with green cover occupying approximately 72% of the total area, while built-up land accounted for only 18%, indicating early-stage urban development. By 2005, signs of urbanization became apparent, with fragmented built-up forms expanding along transportation corridors and a noticeable reduction in dense forest cover. In 2015, built-up areas increased significantly to 28%, primarily at the urban fringes, accompanied by continued fragmentation of vegetation.

Land Use/Cover Type (Gandhinagar)	***1995***	***2005***	***2015***	***2025***
Vegetation/Forest	72%	76.29%	60%	49%
Built-up Area	7%	18%	28%	42%
Barren Land	18%	7%	5%	5%
Water Bodies	3%	3.79%	3%	3%

Table 3: Land Use Land Cover Change - Gandhinagar

The projected map for 2025 indicates a further rise in built-up land to 42%, largely driven by peripheral expansion, resulting in a sharp decline in vegetation and forest cover. The percentage distribution of each land use and land cover category over the study years is detailed in Table 4, underscoring the urgent need for integrated land use planning to balance developmental pressures with ecological sustainability.

4.1.2 Thiruvananthapuram

The Land Use Land Cover (LULC) maps for Thiruvananthapuram for the years 2005, 2015, and 2025 are presented in figures 6 to 8, offering a visual representation of the city's spatial transformation over two decades. The percentage distribution of each land use category during this period is detailed in table 4, highlighting notable shifts in land utilization. The analysis reveals a steady increase in built-up areas from 12% in 2005 to an estimated 30% by 2025, predominantly expanding along the coastal belt, southern corridors, and major transportation routes.

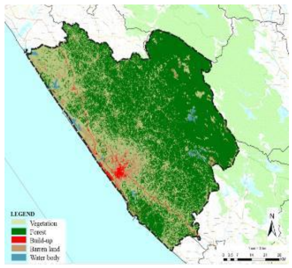

Figure 6: LULC 2005

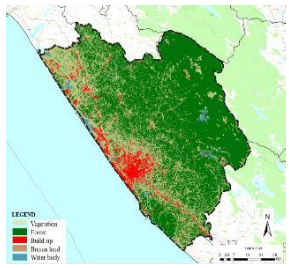

Figure 7: LULC 2015

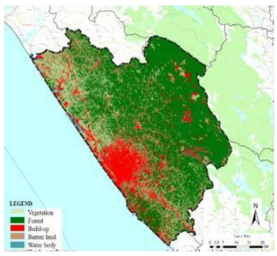

Figure 8: LULC 2025

Land Use/Cover Type (Thiruvananthapuram)	***2005***	***2015***	***2025***
Vegetation/Forest	78%	72%	60%
Built-up Area	12%	20%	30%
Barren Land	7%	5%	6%
Water Bodies	3%	3%	2%

Table 4: Land Use Land Cover Change - Thiruvananthapuram

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This growth reflects a combination of urban densification and peripheral sprawl, driven by demographic pressures and infrastructure development. Concurrently, forest cover has shown a substantial decline—from 78% in 2005 to just 48% by 2025—indicating severe ecological disruption and widespread urban encroachment. Vegetation areas have also diminished significantly, while barren land has remained relatively constant. Water bodies, meanwhile, have maintained a consistent presence, occupying approximately 3% of the region's area throughout the study period. These patterns underscore an unsustainable trajectory of land conversion, emphasizing the critical need for integrated urban planning, the conservation of ecological corridors, and the enforcement of regulatory mechanisms to mitigate the environmental consequences of unchecked urban expansion.

4.1.3 Nashik

Nashik's LULC evolution between 1995 and 2025 as shown in figure 9 to 12 presents a clear pattern of fast urban growth. In 1995, 25% of the land was covered by built-up areas, predominantly concentrated along the central river corridor, and 35% was barren land, with 18% of vegetation, representing the pre-expansion status. By 2005, land with built-up areas had grown to 38%, indicating transitional growth along transportation axes, accompanied by a drop in barren land (25%) and forest cover (8%), and an increase in vegetation to 27%. By 2015, built-up areas further increased to 41%, indicating more urban sprawl, whereas vegetation was stable, and barren land reduced to 23%. Forest cover decreased to 7%, while water bodies also remained stable at 3% as shown in table 5.

The anticipated 2025 map reveals urbanized zones reaching 47%, with wasteland decreasing to 21% and vegetation reducing to 22%, reflecting increasing pressure on green zones. Forest cover went down slightly to 6%, and water bodies remained unchanged at 2–3%. This change reflects the need for urgent planning for sustainable land use to balance growth while maintaining Nashik's environmental integrity.

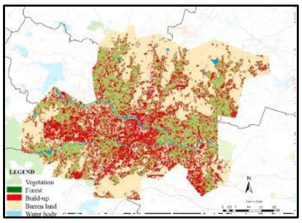


Figure 9: LULC 1995

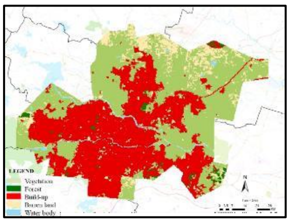


Figure 10: LULC 2005

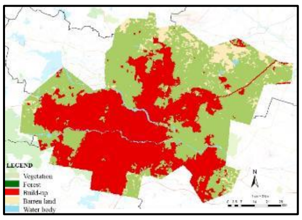


Figure 11: LULC 2015

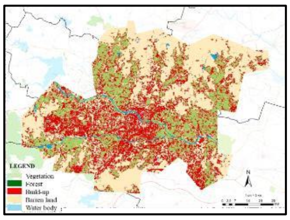


Figure 12: LULC 2025

Land Use/Cover Type (Nashik)	*1995*	*2005*	*2015*	*2025*
Vegetation/Forest	20%	35%	34%	27%
Built-up Area	25%	38%	41%	45%
Barren Land	35%	25%	23%	22%
Water Bodies	3%	3%	3%	3%

Table 5:Land Use Land Cover Change - Nashik

4.2 Spatio-Demographic Trends and Urban Expansion

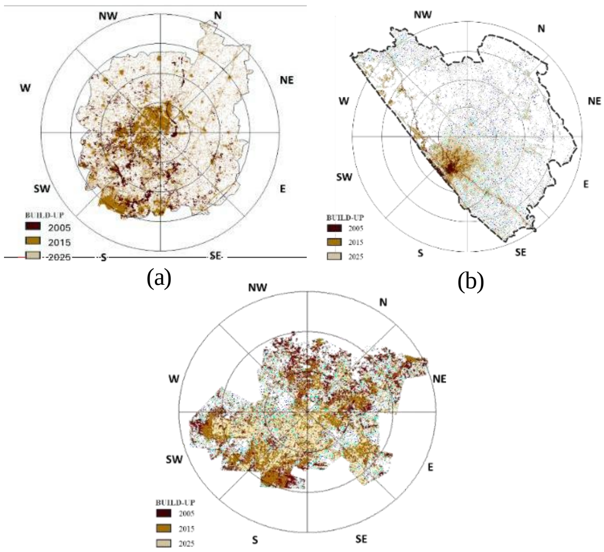
Urban morphogenesis in Tier-2 Indian cities is intricately shaped by demographic growth and spatial land conversion. Gandhinagar's population is projected to nearly triple from 4.14 million in 1995 to 11.17 million by 2035. The built-up area correspondingly expands from 34.2 sq.km to 107.8 sq.km, marking a 215% increase. Interestingly, despite this spatial expansion, population density declines slightly—from 121,052 persons/sq.km in 1995 to 103,661 persons/sq.km in 2035—suggesting a relative spatial dispersal of urban development and possibly the success of planned peripheral urbanization.

In contrast, Thiruvananthapuram exhibits a steadier growth pattern. Its population increases from 998,000 in 1995 to 4.59 million in 2035, while the built-up area grows from 65 sq.km to 240 sq.km (a 269% rise). Population density stabilizes around 17,000 persons/sq.km, highlighting a balanced densification process, likely due to constraints imposed by its topography and coastal geography, as well as planned urban containment zones.

Nashik shows a highly dynamic urban expansion, with its population surging from 886,000 in 1995 to 3.99 million by 2035. The built-up area more than triples, from 85 sq.km to 315 sq.km. While this expansion initially causes a drop in density (from 10,423 persons/sq.km in 1995 to 7,682 in 2025), it starts climbing again post-2025, reaching 12,675 persons/sq.km in 2035. This inflection indicates that Nashik is transitioning from sprawl to intensification, possibly due to infrastructure upgrades and vertical growth in the urban core.

Cities	*1995-2025*	*2026-2037*
Gandhinagar	3.02	2.59
Thiruvananthapuram	3.51	3.77
Nashik	3.37	3.19

Table 6: Average Annual Growth Rate of Built-up Area (%) in Tier-2 Cities (1995–2025 and 2026–2035)



(a) (b) (c)

Figure 13: Growth Direction Map (a) Gandhinagar (b) Thiruvananthapuram (c) Nashik

The average annual growth rate of built-up area from 1995 to 2025 and 2026 to 2035 reveals distinct temporal trends in urban spatial growth rate during both periods, increasing from 3.51% (1995–2025) to 3.77% (2026–2035), indicating a sustained and even accelerating pattern of land cover transformation. Nashik and Gandhinagar followed with initial growth rates of 3.37% and 3.02%**,** respectively, between 1995 and 2025. However, in the subsequent decade (2026–2035), Gandhinagar exhibited a noticeable decline in built-up expansion to 2.59%**,** suggesting a potential saturation of developable land or a shift toward densification policies. In contrast, Nashik maintained a moderate built-up growth rate of 3.19%**,** consistent with its ongoing peripheral expansion. These findings reflect both the pace and intensity of urban morphogenesis, offering critical insights into the spatiotemporal dynamics of land use conversion in emerging Indian urban centers.

4.3 Directional Growth and Built-Up Density Analysis

The directional patterns of built-up expansion were evaluated through the application of cardinal zoning methods and GIS-based radial analysis, as represented in figure 13 and table 8.

4.4 Spatial Form Assessment Using Shannon's Entropy

Shannon's Entropy Index computation for 1995 to 2035 exhibits clear patterns of Nashik, Gandhinagar, and Thiruvananthapuram urban spatial development. Nashik demonstrates an overall rise in entropy values from 1.87 in 1995 to 2.00 in 2035, representing a step-by-step progression toward a more scattered urban structure. This indicates that the city is seeing more urban sprawl, with developed zones radiating out instead of growing denser in already established zones. Gandhinagar, however, shows very little change, with entropy rates remaining close to static at a value of about 2.06 to 2.07. This shows a controlled and even pattern of urban growth, most likely the result of conscious planning and managed expansion. Likewise, Thiruvananthapuram has a

consistently high entropy value (around 2.06–2.07) across the decades, indicating a mature and stable urban form. The absence of considerable change indicates that urban expansion in expansion across the three Tier-2 cities studied. As shown in table 6, Thiruvananthapuram recorded the highest average annual Thiruvananthapuram is taking place through internal densification instead of outward growth. While Nashik is growing spatially, Gandhinagar and Thiruvananthapuram exhibit compact and well-planned urban forms with minimal sprawl.

4.5 LULC Change Simulation Using MOLUSCE

A comprehensive Land Use and Land Cover (LULC) assessment for Gandhinagar, Thiruvananthapuram, and Nashik from 1995 to 2035 will reveal significant spatial transformation driven by rapid urbanization and increasing anthropogenic pressures. The LULC projection, as illustrated in figure 14 to 16 and table 9, will highlight major conversions across land use categories and major drives of these changes along with environmental implications over the four-decade period.

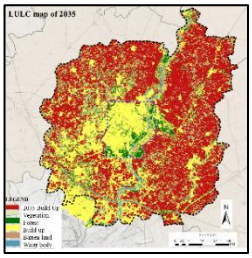


Figure 14: LULC 2035 - Ahmedabad

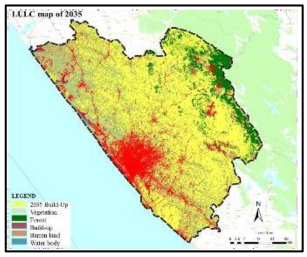


Figure 15: LULC 203 5-Thiruvananthapuram

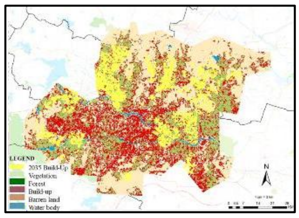


Figure 16: LULC 2035 - Nashik

City	*Dominant Growth Directions*	*% Growth (Max)*	*Reasons for Growth in Those Directions*	*Constraints in Low-Growth Areas*	*Projected BD (2027–2035)*
Gandhinagar	E–SE, S–SW, NE–E	39%–42%	Proximity to Ahmedabad-Gandhinagar corridor; Smart City projects; residential and institutional demand; highway access	NW–N, W–NW, SW–W: Planning constraints, natural barriers, limited infrastructure	E–SE > 0.78; NE–E & S–SW > 0.70
	SE–S (Moderate)	~37%	Radial densification and Smart City focus	–	–
Thiruvananthapuram	S–SW, NW–N	S–SW: 16.91%; NW–N: 16.51%	Growth along NH-66 corridor; IT parks; flat terrain; institutional development	N–NE, NW–N: Topographic constraints, ecological zones, regulatory controls	Leapfrog & linear growth; BD oriented toward S and SE
	SE–S, E–SE, SW–W	15–16%	Corridor-led development, population pressure	Eastern zones moderate due to terrain and planning	–
Nashik	NE–E, S–SW	NE–E: 32.3%; S–SW: 31.34%	Industrial hubs; proximity to major highways; peri-urban land availability	NW–N, W–NW, N–NE: Terrain limitations, zoning restrictions, low infrastructure	SE–S strongest future growth axis
	SE–S, E–SE	~20%	Fringe urban expansion; radial connectivity	–	–

Table 7: Directional Urban Growth Characteristics and Built-up Density Projections (2027–2035)

City	*Built-up Area Change*	*Vegetation Loss*	*Forest Loss*	*Barren Land Trend*	*Water Bodies Trend*	*Major Drivers*	*Environmental Implications*
Gandhinagar	18% → 55% (+37 pp)	57.07% → 28% (−29.07 pp)	19.22% → 7% (−12.22 pp)	Stable ~7%	3.79% → 3% (−0.79 pp)	Proximity to Ahmedabad, GIFT City, IIT-Gn, industrial corridors	Urban heat island, biodiversity loss, infiltration decline
Thiruvananthapuram	18% → 35% (+17 pp)	38% → 24% (−14 pp)	32% → 22% (−10 pp)	6% → 16% (+10 pp)	Stable ~3%	Growth in Technopark, IIST, residential expansion in S-C & NW	Edge degradation, peri-urban sprawl, ecological fragmentation
Nashik	7% → 50% (+43 pp)	57.07% → 26% (−31.07 pp)	19.22% → 9% (−10.22 pp)	18% → 12% (−6 pp)	Stable ~3%	Industrial zones, Samruddhi Expressway, logistics hubs	Peri-urban transformation, environmental stress, reduced green cover

Table 8: Projected LULC Changes and Environmental Implications in Tier-2 Cities (1995/2005–2035)

5. Discussion

The comparative geospatial evaluation of Nashik, Gandhinagar, and Thiruvananthapuram reveals distinct urban morphogenetic patterns that are deeply influenced by geography, infrastructure, planning paradigms, and institutional priorities. Nashik, with the highest projected increase in built-up area (from 7% in 1995 to 50% in 2035), demonstrates a rapid and dispersed urban growth trajectory. This transformation is driven primarily by industrial investments, connectivity enhancements such as the Samruddhi Expressway, and logistic expansion, placing the city on a high-intensity urban sprawl trajectory. The entropy analysis further validates this spatial diffusion, with values rising from 1.87 to 2.00—indicating increasing urban fragmentation. Gandhinagar, despite experiencing a 37 percentage point increase in built-up area, exhibits a planned and relatively concentric expansion model. Its entropy values remain nearly constant, reflecting the success of regulated spatial development supported by Smart City initiatives, regional integration with Ahmedabad, and controlled peripheral growth. The directional growth, concentrated in E–SE and S–SW corridors, is consistent with regional planning efforts and institutional clusters such as GIFT City and IIT-Gandhinagar. Thiruvananthapuram presents a hybrid model of compact core densification and corridor-led outward growth. Built-up area rises from 18% to 35% between 2005 and 2035, mainly in the southern and coastal sectors, constrained by hilly terrain and ecological buffers. Despite being geographically limited, the city shows sustained entropy levels (~2.06), reflecting a balance between expansion and densification.
In terms of environmental impacts, all three cities face significant loss of green infrastructure. Nashik and Gandhinagar exhibit sharp declines in vegetation and forest cover, while Thiruvananthapuram suffers from ecological fragmentation and edge degradation. However, Nashik's scale of transformation, especially the conversion of open and vegetated lands into urban fabric, is more intense—raising concerns over heat island effects, biodiversity loss, and peri-urban vulnerability.Urban density trends further differentiate the cities. Gandhinagar and Thiruvananthapuram maintain relatively stable or decreasing population densities despite increasing population, suggesting managed spatial dispersion. In contrast, Nashik reverses its trend post-2025, shifting from sprawl to core densification, indicating a potential pivot in planning direction.

6. Conclusion

The geospatial and predictive analysis confirms that Nashik is poised to emerge as the most dynamically transforming Tier-2 city by 2035, owing to its rapid spatial expansion, strategic location, and infrastructural investments. Among the three cities studied, Nashik's built-up area shows the highest growth rate and most substantial land cover transition, aligning with national economic and logistic priorities. Its shift toward higher entropy and eventual re-densification marks it as a city transitioning through key urban development phases. Gandhinagar, while expanding steadily, retains its character as a regulated administrative and institutional hub with minimal entropy change and balanced land conversion. Thiruvananthapuram, constrained by geography, continues on a compact and controlled urbanization path, with growth largely limited to corridors and edge settlements. The findings underscore the critical need for data-driven planning, ecological conservation, and growth management strategies to address the divergent urban futures of India's Tier-2 cities. For Nashik, especially, the forecasted transformation necessitates urgent attention to sustainability, infrastructure provisioning, and spatial equity to avoid the pitfalls of unregulated sprawl. The study also highlights the value of geospatial analytics in proactively guiding urban policy, offering a replicable framework for anticipating and managing urban growth across emerging Indian cities.

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