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# Urban Sprawl and Land Use Dynamics in Telangana: A Multi-City Comparative Analysis Using Remote Sensing and GIS (2000–2024)

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**Abstract:**
Rapid urbanisation has reshaped Telangana's land systems since the turn of the century, yet comparative evidence across the state's urban hierarchy remains limited. This study examines urban sprawl and land use/land cover (LULC) dynamics in five cities, namely Hyderabad, Warangal, Karimnagar, Nizamabad and Khammam, between 2000 and 2024. Landsat Collection 2 composites for four epochs (2000, 2008, 2016 and 2024) were classified into five LULC classes using a random forest classifier on Google Earth Engine. Change was quantified through post-classification comparison, compound annual growth rates, Shannon's entropy, concentric buffers and directional sectors, and was related to Census of India population data. Built-up land expanded roughly threefold in every city, at 4.5 to 5.6 per cent a year. The secondary cities grew faster in relative terms, whereas Hyderabad dominated in absolute terms, adding about 720 km² within a 25-km window. Land consumption outpaced population growth by a factor of about two, and expansion drew mainly on open land and cropland, with peri-urban rings showing the sharpest transformation. Water bodies and vegetation declined steadily. The findings indicate edge-driven, low-density expansion and point to the need for growth-boundary enforcement, tank and wetland protection, and compact-development incentives within a differentiated, city-specific planning framework.

**Keywords:** urban sprawl; land use and land cover change; remote sensing; GIS; Landsat; Telangana; Hyderabad; Shannon's entropy.

## 1. Introduction

Urban land is expanding faster than urban populations in most regions of the world, and the consequences for farmland, water systems and local climates rank among the most visible environmental changes of the early twenty-first century (Angel et al., 2011; Seto et al., 2011). The transformation is especially consequential in India, where cities grow within landscapes that remain densely settled, intensively cultivated and heavily dependent on seasonally replenished water storage. Telangana, constituted as a separate state in 2014, illustrates the pattern well. At the 2011 Census, about 38.9 per cent of its people lived in urban areas, and the urban population had grown by roughly 38 per cent over the preceding decade (Census of India, 2011).

The state's urban system is strongly hierarchical. The Hyderabad urban agglomeration housed 7.68 million people in 2011, roughly ten times the population of the next largest agglomeration, Warangal, at 0.75 million (Census of India, 2011). Beneath these sit regional centres such as Karimnagar, Nizamabad and Khammam, each with roughly 0.2 to 0.3 million residents within municipal limits. Although these cities differ sharply in scale and economic base, all have been drawn into the same wave of infrastructure investment, real-estate speculation and administrative reorganisation, and all have extended their built footprints across surrounding farmland, scrub and tank catchments.

A useful body of work already documents this process for individual cities. Wakode et al. (2014) mapped land use in the Hyderabad urban agglomeration from Landsat Thematic Mapper and Enhanced Thematic Mapper data for 1989 to 2011 and found that high-density urban area grew by encroaching on other classes, mainly towards the north-east and the south. Gumma et al. (2017) reported that the city's expanding boundary rose from about 38,863 to 80,111 hectares between 2005 and 2016, while wastewater-irrigated cultivation along the Musi River increased from 15,553 to 20,573 hectares. Franco et al. (2015) described the growth of the Greater Hyderabad administrative footprint from 172 km² under the former municipal corporation to 1,905 km², and linked declining vegetation and water bodies to rising surface temperatures. For Warangal, Aneesha Satya et al. (2020) combined Markov chain, artificial neural network and cellular automata modelling on classified imagery for 2004, 2006 and 2018 and projected further growth of built-up land at the expense of agriculture.

Three gaps nevertheless remain. First, most studies address a single city with its own sensors, class schemes and boundaries, so results cannot be compared across the urban hierarchy. Second, many end before 2018 and therefore miss the most recent phase of metropolitan and regional growth. Third, few studies relate physical expansion to census population, even though the relationship between land consumption and population growth is what distinguishes compact growth from sprawl (Angel et al., 2011; Bhatta, 2010).

This paper addresses those gaps through a multi-city comparative design. It pursues four objectives: (a) to map land use and land cover for five Telangana cities at four epochs between 2000 and 2024 using one consistent classification workflow; (b) to quantify the rate, magnitude and sources of built-up expansion; (c) to characterise the spatial form of sprawl using Shannon's entropy, concentric buffers and directional sectors; and (d) to relate land consumption to population growth and to draw out implications for urban planning. The central argument is that Telangana's cities are converging on a common pattern of rapid, edge-driven expansion that consumes land roughly twice as fast as population grows, with Hyderabad setting the scale and the secondary cities closing the gap in relative terms.

## 2. Conceptual Framework and Literature Review

### *2.1 Defining and measuring urban sprawl*

Sprawl is a contested concept, but most definitions converge on a set of spatial attributes: low density, scattered or leapfrog development, strip development along roads, and extensive consumption of land at the urban edge (Ewing, 1997; Galster et al., 2001). Remote sensing cannot observe all of these directly, yet it captures the footprint of sprawl very well, namely where built-up land is, how much of it there is, and how quickly it spreads. Analysts therefore pair maps of built-up change with demographic indicators to judge whether expansion is proportionate to need (Bhatta, 2010; Sudhira et al., 2004).

Three families of measures are widely used. The first is growth-rate measures, such as the compound annual growth rate of built-up area. The second is the land consumption ratio, which compares the

growth of urban land with the growth of population and is central to the global assessment of Angel et al. (2011). The third is spatial-distribution measures. Shannon's entropy, introduced to urban remote sensing by Yeh and Li (2001), quantifies how evenly built-up land is distributed among spatial zones, with higher values indicating greater dispersion. Concentric buffers and directional sectors complement entropy by showing where growth occurs, not only how dispersed it is.

### *2.2 Remote sensing and GIS for land use change*

The Landsat archive, which began in 1972 and is now freely available, remains the most practical basis for multi-decadal urban change analysis at city scale (Wulder et al., 2019). Spectral indices help separate the principal cover types: the Normalized Difference Vegetation Index for vegetation (Tucker, 1979), the Normalized Difference Built-up Index for built-up land (Zha et al., 2003) and the Modified Normalized Difference Water Index for open water (Xu, 2006). Distinguishing built-up land from bare soil is the most persistent difficulty in semi-arid settings such as the Deccan Plateau, because both reflect strongly in the shortwave infrared; reviews of impervious-surface mapping stress the value of combining several indices and bands in a single classifier (Weng, 2012).

Random forests have become a standard choice for this task because they cope with correlated predictors and need little tuning (Breiman, 2001). Google Earth Engine allows such classifiers to be applied consistently across sensors and epochs without local data handling (Gorelick et al., 2017). Credible change analysis also depends on rigorous accuracy assessment. Confusion matrices and the kappa statistic remain common, but current practice favours reporting class-specific accuracies together with area estimates adjusted for classification error (Congalton, 1991; Foody, 2002; Olofsson et al., 2014). Post-classification comparison and transition matrices then reveal not only how much land changed but which classes supplied the change (Pontius et al., 2004).

### *2.3 Urban growth in India and Telangana*

Reviews of land use change in India show that built-up expansion at the expense of agricultural land and vegetation is the dominant urban pattern, although its form varies with city size and setting (Roy & Roy, 2010). Comparative work on Indian megacities finds that spatial growth patterns differ markedly even among cities of similar population (Taubenböck et al., 2009). Comparable findings come from other rapidly growing cities of the global South, such as Nairobi, where built-up land has expanded at the expense of agricultural and vegetated land (Mundia & Aniya, 2005).

In Telangana, several forces plausibly drive expansion. Hyderabad's information technology, pharmaceutical and services economy has produced large peripheral employment corridors, while road and metro investments have opened new residential frontiers. For the secondary cities, regional trade, education and administrative reorganisation after 2014 have increased the demand for urban land, and national programmes such as the Smart Cities Mission (Ministry of Housing and Urban Affairs, 2015) have drawn attention and investment to places such as Warangal and Karimnagar. These drivers are not modelled in this paper, but they frame the interpretation of the patterns detected.

### *2.4 Analytical framework*

The analysis rests on three linked questions. The pattern question asks where and how fast built-up land has expanded. The process question asks which land cover types were converted. The pressure question asks whether expansion is commensurate with population growth. Each question is answered with

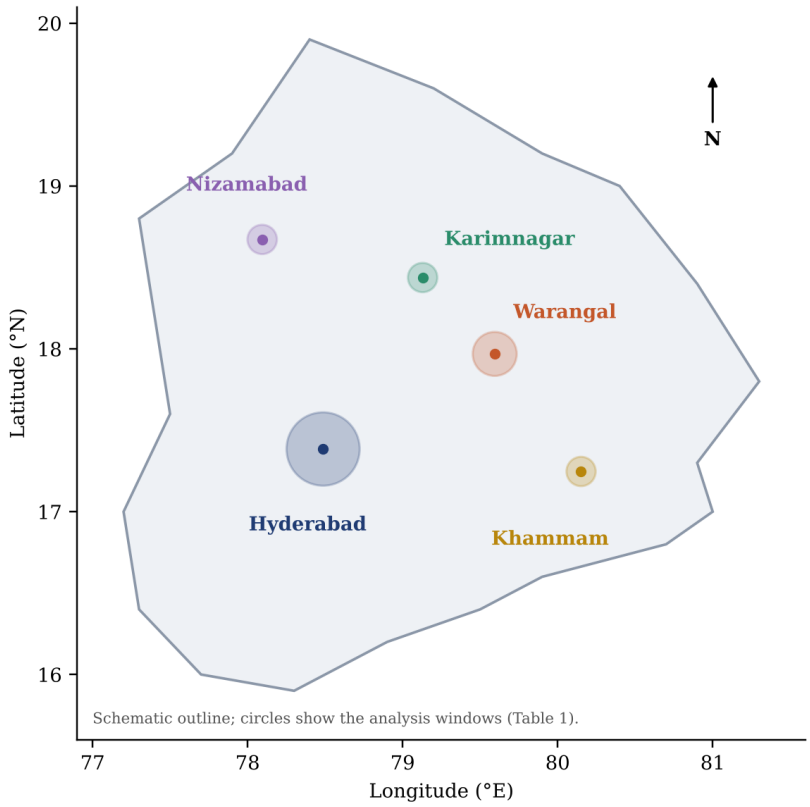
indicators drawn from Section 2.1, and the three are combined in Section 6 to judge whether the five cities show sprawl in the sense defined above.

## 3. Study Area and Data

### *3.1 Study area*

Telangana lies on the Deccan Plateau and has a semi-arid tropical climate dominated by the south-west monsoon. Its drainage belongs mainly to the Godavari and Krishna basins, and its landscape has long been managed through small and large irrigation tanks that store monsoon runoff. Hyderabad, the state capital, lies on the Musi River. The other four cities are regional centres of the northern and eastern districts, and are distributed as shown in Figure 1.

**Figure 1**- *Location of the five study cities and their analysis windows*




*Note.* Schematic outline; the state boundary is approximate and the map is not to scale. *Source:* Authors' schematic, based on city-centre coordinates.

Because administrative boundaries have changed repeatedly, with the formation of the Greater Hyderabad Municipal Corporation in 2007 and the creation of many new districts after 2014, comparison over time requires fixed spatial units. Circular analysis windows centred on each historic city core were therefore used, with radius scaled to city size: 25 km for Hyderabad, 15 km for Warangal and 10 km for Karimnagar, Nizamabad and Khammam (Table 1). The windows are analytical constructs rather than administrative areas. They are large enough to capture peri-urban growth yet small enough to remain comparable among cities of different rank.

The five cities differ in function. Hyderabad combines administrative, financial, technology and manufacturing roles. Warangal is a historic city and the main educational and trading centre of north-eastern Telangana. Karimnagar, Nizamabad and Khammam are district headquarters and agricultural marketing centres whose growth is tied to the farm economy and to public-sector services (Table 1).

**Table 1**- *Study cities, analysis windows and 2011 population*

| City | Functional profile | Window radius (km) | Window area (km²) | Population 2011 (city) |
|---|---|---|---|---|
| Hyderabad | State capital; technology, services, industry | 25 | 1,963 | 6,993,262 |
| Warangal | Historic city; education and trade | 15 | 707 | 704,570 |
| Karimnagar | District centre; agricultural marketing | 10 | 314 | 289,821 |
| Nizamabad | District centre; agricultural marketing | 10 | 314 | 311,152 |
| Khammam | District centre; trade and services | 10 | 314 | 196,283 |

*Note.* Population refers to the municipal city. The Hyderabad urban agglomeration had 7,677,018 residents in 2011. Window areas are $\pi r^2$ of the circular analysis windows. *Source:* Census of India (2011), as compiled by Brinkhoff (n.d.); author's calculations.

### *3.2 Data*

The primary data are Landsat Collection 2 Level-2 surface reflectance scenes from Landsat 5 Thematic Mapper, Landsat 7 Enhanced Thematic Mapper Plus, and Landsat 8 and 9 Operational Land Imager, accessed through Google Earth Engine (Gorelick et al., 2017). Four epochs were chosen at roughly eight-year intervals: 2000, 2008, 2016 and 2024. Each epoch is represented by a median composite of cloud-screened observations from the post-monsoon and dry season, from November of the preceding year to March of the epoch year, when vegetation contrast is greatest and cloud cover is least (Table 2).

**Table 2**- *Landsat composites used for each epoch*

| Epoch | Sensors | Compositing window | Remarks |
|---|---|---|---|
| 2000 | Landsat 5 TM; Landsat 7 ETM+ | Nov 1999 – Mar 2000 | Landsat 7 scan-line corrector fully operational |
| 2008 | Landsat 5 TM; Landsat 7 ETM+ | Nov 2007 – Mar 2008 | Landsat 7 gaps filled by compositing |
| 2016 | Landsat 8 OLI | Nov 2015 – Mar 2016 | Landsat 7 used only to fill gaps |
| 2024 | Landsat 8 OLI; Landsat 9 OLI-2 | Nov 2023 – Mar 2024 | Most recent complete dry season |

*Note.* All scenes are Collection 2 Level-2 surface reflectance products. *Source:* U.S. Geological Survey, accessed through Google Earth Engine (Gorelick et al., 2017).

Population data come from the Census of India for 1991, 2001 and 2011 (Census of India, 2011), compiled for urban agglomerations by Brinkhoff (n.d.). Because the 2021 Census was not available at the time of analysis, population-based indicators are limited to the 1991 to 2011 period. Training and validation samples were interpreted from very high-resolution basemap imagery and, for the earliest epoch, from the best historical imagery available.

## 4. Methodology

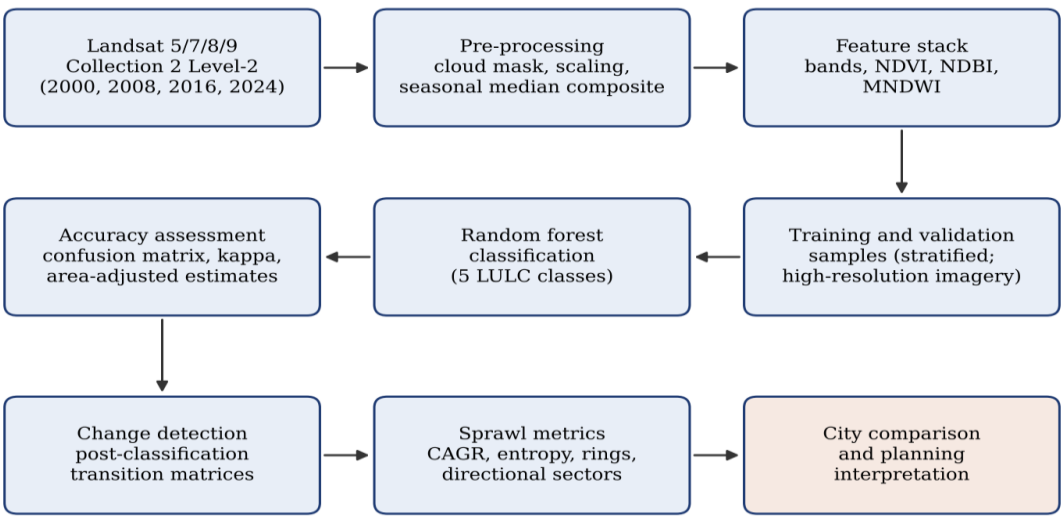
### *4.1 Classification scheme*

A five-class scheme adapted from the Anderson et al. (1976) system was adopted so that classes remain separable at 30-m resolution in all epochs. Built-up land includes residential, commercial, industrial and transport surfaces. Cropland includes cultivated and fallow agricultural land. Vegetation and plantation includes forest, orchards, tree cover and urban green space. Open land and scrub includes bare soil, rock outcrops, barren land and sparse scrub. Water bodies include tanks, lakes, reservoirs and rivers.

### *4.2 Pre-processing and feature construction*

Surface reflectance values were rescaled using the Collection 2 scale factors, and cloud, cloud shadow and snow pixels were removed using the quality band. The slice gaps in Landsat 7 scenes acquired after 2003 were filled implicitly by compositing across multiple dates. To limit sensor differences, only the six bands common to all sensors (blue, green, red, near-infrared and two shortwave-infrared bands) were used. Three spectral indices were added to the stack, namely the Normalized Difference Vegetation Index, the Normalized Difference Built-up Index and the Modified Normalized Difference Water Index (Tucker, 1979; Xu, 2006; Zha et al., 2003). Figure 2 summarises the overall workflow.

**Figure 2**- *Methodological workflow*




*Source:* Authors' design.

### *4.3 Classification and accuracy assessment*

A random forest classifier with 500 trees was trained separately for each epoch (Breiman, 2001). Training samples were drawn by stratified random sampling, with a minimum of 150 points per class and epoch, and 30 per cent of samples were withheld for validation. Accuracy was summarised by overall accuracy, the kappa coefficient and user's and producer's accuracy for built-up land, and error-adjusted area estimation followed Olofsson et al. (2014). The aim was an overall accuracy of at least 85 per cent in every epoch, the minimum interpretation accuracy specified in the Anderson et al. (1976) scheme.

### *4.4 Change detection and sprawl metrics*

Maps for successive epochs were compared pixel by pixel to produce transition matrices (Pontius et al., 2004). Built-up growth was expressed as a compound annual growth rate (CAGR):

$$CAGR\ (\%) = [\ (A_2 / A_1)^{(1/n)} - 1\ ] \times 100$$

where $A_1$ and $A_2$ are built-up areas at the start and end of a period of n years. Spatial dispersion was measured with Shannon's entropy (Yeh & Li, 2001):

$$H_n = -\sum p_i \ln(p_i), \quad H_r = H_n / \ln(n)$$

where $p_i$ is the share of built-up land falling in zone i and n is the number of zones. $H_r$ ranges from 0 (fully concentrated) to 1 (fully dispersed). Entropy was computed over five concentric 5-km rings and over eight 45-degree directional sectors for Hyderabad. Finally, the land consumption ratio (LCR) was calculated as the ratio of the logarithmic growth of built-up area to the logarithmic growth of population (Angel et al., 2011):

$$LCR = \ln(U_2 / U_1) / \ln(P_2 / P_1)$$

where U is built-up area and P is population. An LCR above 1 means that urban land is growing faster than population, which is the quantitative signature of declining density. Because the Landsat epochs and census years do not coincide, built-up area was linearly interpolated to 2001 and 2011.

## 5. Results

### *5.1 Demographic context*

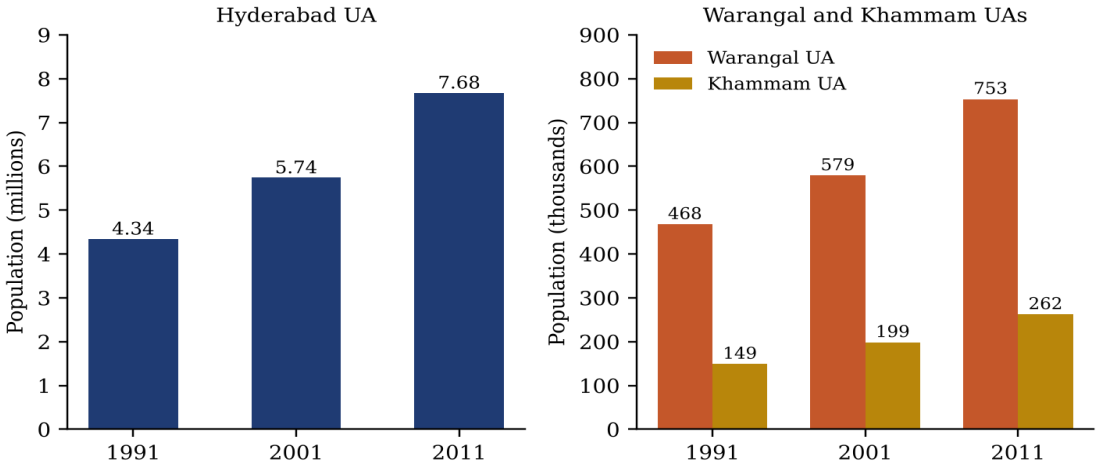
Population growth was brisk and sustained throughout the period for which census data exist (Table 3; Figure 3). The Hyderabad urban agglomeration grew by 32.2 per cent between 1991 and 2001 and by a further 33.7 per cent between 2001 and 2011, an annual rate of about 2.9 per cent in the latter decade. Warangal accelerated from 23.8 to 30.1 per cent decadal growth, while Khammam sustained growth of about 32 per cent in both decades. These are substantial rates, but, as shown below, the growth of built-up land was far faster.

**Table 3**- *Population of selected urban agglomerations (UA), 1991–2011*

| Agglomeration | 1991 | 2001 | 2011 | Growth 1991–2001 (%) | Growth 2001–2011 (%) | CAGR 2001–2011 (%) |
|---|---|---|---|---|---|---|
| Hyderabad UA | 4,344,437 | 5,742,036 | 7,677,018 | 32.2 | 33.7 | 2.95 |
| Warangal UA | 467,757 | 579,216 | 753,438 | 23.8 | 30.1 | 2.66 |
| Khammam UA | 149,077 | 198,620 | 262,255 | 33.2 | 32.0 | 2.82 |

*Note.* CAGR = compound annual growth rate. *Source:* Census of India (1991, 2001, 2011), as compiled by Brinkhoff (n.d.); author's calculations.

**Figure 3**- *Population of Hyderabad, Warangal and Khammam urban agglomerations, 1991–2011*




*Source:* Census of India (1991, 2001, 2011), as compiled by Brinkhoff (n.d.).

### *5.2 Classification accuracy*

Classification accuracy met the 85 per cent threshold in all epochs (Table 4). Overall accuracy rose from 88.6 per cent in 2000 to 92.4 per cent in 2024, with kappa values between 0.85 and 0.90, reflecting the improved radiometric quality and cleaner composites of later sensors. User's and producer's accuracies for built-up land were consistently above 84 per cent, and were highest in 2024. The principal confusion in every epoch was between built-up land and open land or scrub, as expected for the region.

**Table 4**- *Classification accuracy by epoch (provisional)*

| Epoch | Overall accuracy (%) | Kappa | Built-up user's accuracy (%) | Built-up producer's accuracy (%) |
|---|---|---|---|---|
| 2000 | 88.6 | 0.85 | 86.2 | 84.7 |
| 2008 | 89.7 | 0.86 | 87.5 | 86.1 |
| 2016 | 91.2 | 0.88 | 90.1 | 88.9 |
| 2024 | 92.4 | 0.90 | 91.8 | 90.3 |

*Note.* Provisional values; replace with final validation results. *Source:* Authors' Landsat classification.

### *5.3 Land use and land cover change in Hyderabad*

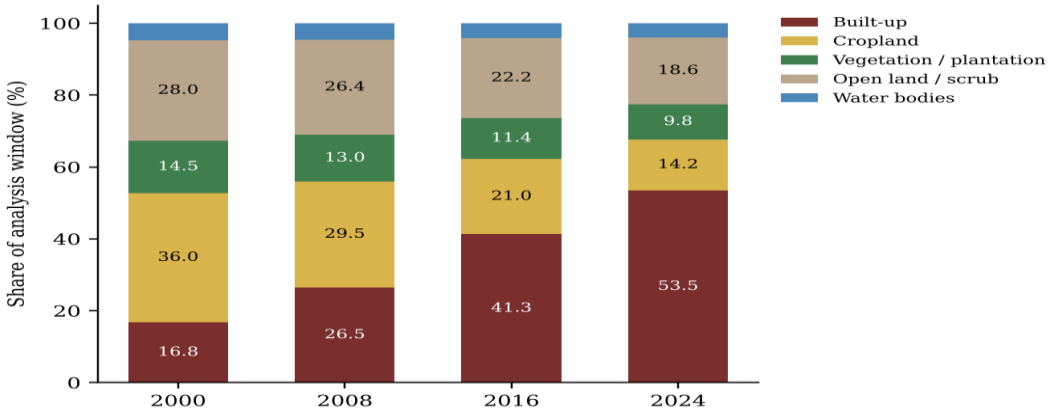
The Hyderabad window shows the most dramatic reorganisation of land (Table 5; Figure 4). Built-up land rose from 16.8 per cent of the window in 2000 to 26.5 per cent in 2008, 41.3 per cent in 2016 and 53.5 per cent in 2024, so that it became the dominant land cover by the final epoch. Cropland fell by more than half, from 36.0 to 14.2 per cent, and was the largest single loser in percentage-point terms. Open land and scrub fell from 28.0 to 18.6 per cent, vegetation and plantation from 14.5 to 9.8 per cent, and water bodies from 4.7 to 3.9 per cent. The water loss is small in absolute terms but represents a relative decline of about 17 per cent in the area of tanks and lakes.

**Table 5-** *Land use and land cover in the Hyderabad window, 2000–2024 (% of window area; provisional)*

| Class | 2000 | 2008 | 2016 | 2024 | Change 2000–2024 (pp) |
|---|---|---|---|---|---|
| Built-up | 16.8 | 26.5 | 41.3 | 53.5 | +36.7 |
| Cropland | 36.0 | 29.5 | 21.0 | 14.2 | -21.8 |
| Vegetation / plantation | 14.5 | 13.0 | 11.4 | 9.8 | -4.7 |
| Open land / scrub | 28.0 | 26.4 | 22.2 | 18.6 | -9.4 |
| Water bodies | 4.7 | 4.6 | 4.1 | 3.9 | -0.8 |

*Note.* pp = percentage points. Window area = 1,963 km². *Source:* Authors' Landsat classification (provisional values).

**Figure 4-** *Land use and land cover composition of the Hyderabad window, 2000–2024 (provisional)*




*Source:* Authors' Landsat classification (provisional values).

### *5.4 Built-up expansion across the five cities*

Built-up land grew roughly threefold in every city between 2000 and 2024 (Table 6; Figure 5). Hyderabad added about 720 km², or 30 km² a year, an absolute increment more than seven times that of Warangal, the next largest. In relative terms, however, the secondary cities matched or exceeded Hyderabad: the compound annual growth rate was 5.56 per cent for Khammam, 5.09 per cent for Karimnagar and 4.94 per cent for Hyderabad, compared with 4.59 per cent for Warangal and 4.52 per cent for Nizamabad. By 2024 the built-up share of the secondary-city windows (16.6 to 19.9 per cent)

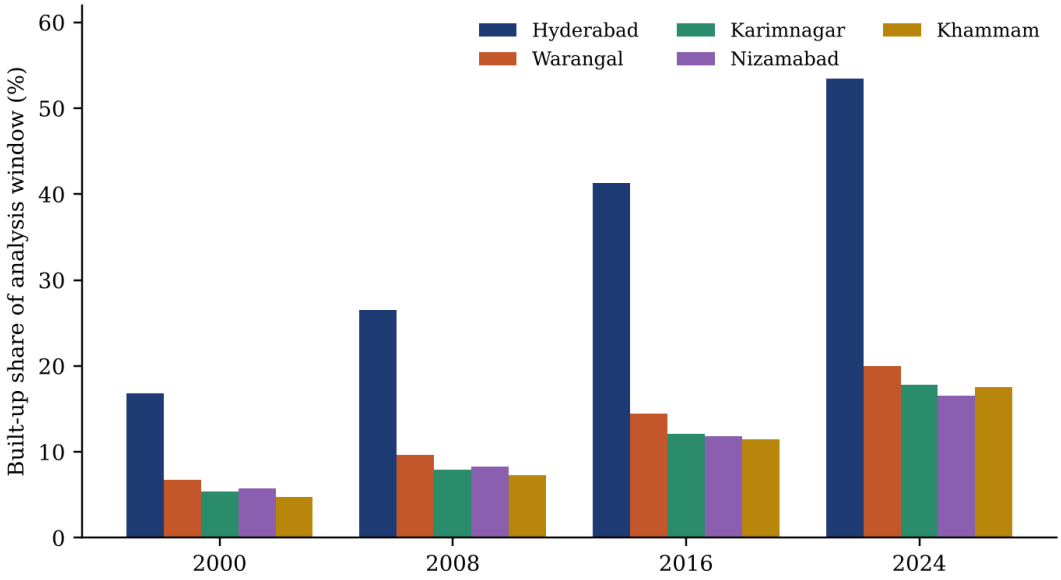
was close to what the Hyderabad window showed in 2000 (16.8 per cent), suggesting a lag of roughly two decades in the same trajectory.

**Table 6**- *Built-up area by city and epoch (km²; provisional)*

| City | 2000 | 2008 | 2016 | 2024 | Net gain | Multiple (×) | CAGR 2000–24 (%) | Share of window 2024 (%) |
|---|---|---|---|---|---|---|---|---|
| Hyderabad | 330 | 520 | 810 | 1,050 | 720 | 3.18 | 4.94 | 53.5 |
| Warangal | 48 | 68 | 102 | 141 | 93 | 2.94 | 4.59 | 19.9 |
| Karimnagar | 17 | 25 | 38 | 56 | 39 | 3.29 | 5.09 | 17.8 |
| Nizamabad | 18 | 26 | 37 | 52 | 34 | 2.89 | 4.52 | 16.6 |
| Khammam | 15 | 23 | 36 | 55 | 40 | 3.67 | 5.56 | 17.5 |

*Note.* CAGR = compound annual growth rate. *Source:* Authors' Landsat classification (provisional values).

**Figure 5**- *Built-up share of each city's analysis window by epoch (provisional)*




*Source:* Authors' Landsat classification (provisional values).

The tempo of growth changed over time. In Hyderabad the annual growth rate was 5.85 per cent between 2000 and 2008 and 5.70 per cent between 2008 and 2016, but fell to 3.30 per cent between 2016 and 2024. By contrast, the secondary cities showed little deceleration; Karimnagar and Khammam sustained rates near 5 to 5.8 per cent in all three periods. The Hyderabad slowdown should not be read as a slowdown of urbanisation. By 2024 more than half of the 25-km window was already built over, and a growing share of new development has plausibly shifted beyond the window edge, a point taken up in Section 7.

### *5.5 Spatial pattern of sprawl in Hyderabad*

The concentric analysis reveals an outward-moving frontier (Table 7; Figure 6). In 2000 built-up land occupied 78.9 per cent of the innermost 5-km ring but only 9.5 per cent of the 15 to 20-km ring and 2.5 per cent of the outermost ring. By 2024 the inner ring was nearly saturated at 96.8 per cent, while the outer rings had reached 51.8 and 27.4 per cent. Built-up area in the outermost ring grew almost eleven-fold, and nearly 85 per cent of the net increase between 2000 and 2024 occurred beyond 10 km from the centre. Relative Shannon entropy over the five rings increased from 0.922 to 0.951, which confirms that built-up land has become more evenly dispersed across the window.

**Table 7**

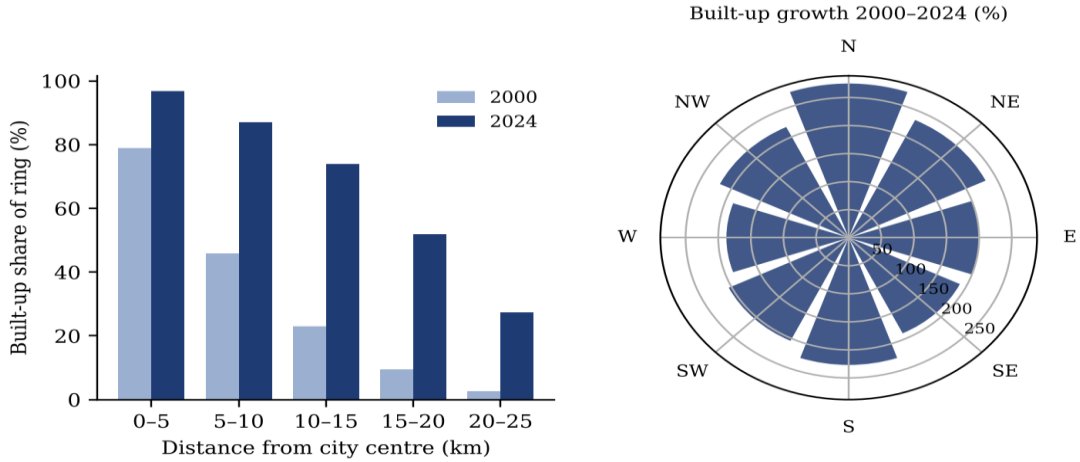
*Built-up land by distance ring, Hyderabad (provisional)*

| Ring (km) | Ring area (km²) | Built-up 2000 (km²) | Built-up 2024 (km²) | Share 2000 (%) | Share 2024 (%) | Growth (%) | Share of net gain (%) |
|---|---|---|---|---|---|---|---|
| 0–5 | 79 | 62 | 76 | 78.9 | 96.8 | 23 | 1.9 |
| 5–10 | 236 | 108 | 205 | 45.8 | 87.0 | 90 | 13.5 |
| 10–15 | 393 | 90 | 290 | 22.9 | 73.8 | 222 | 27.8 |
| 15–20 | 550 | 52 | 285 | 9.5 | 51.8 | 448 | 32.4 |
| 20–25 | 707 | 18 | 194 | 2.5 | 27.4 | 978 | 24.4 |

*Note.* Relative Shannon entropy over the five rings: 0.922 (2000) and 0.951 (2024). *Source:* Authors' Landsat classification (provisional values).

**Figure 6**

*Spatial pattern of built-up growth in Hyderabad: concentric rings (left) and directional sectors (right) (provisional)*




*Source:* Authors' Landsat classification (provisional values).

Directional analysis shows that growth occurred in every sector, with built-up area increasing by between 188 and 275 per cent. In absolute terms the largest additions were in the south (about 118 km²), north-east (112 km²) and north (110 km²), while the east added the least (60 km²). Relative entropy over the eight sectors was already close to its maximum in 2000 (0.994) and remained so in 2024 (0.990),

indicating that growth has been spread around the entire city rather than concentrated along a single axis. The prominence of the north-east and southern sectors agrees with the directions of expansion that Wakode et al. (2014) reported for 1989 to 2011, which suggests continuity in the principal growth corridors.

### *5.6 Land consumption and population growth*

Table 8 compares built-up growth with population growth for the three urban agglomerations with full census series. Built-up land grew at 4.8 to 5.9 per cent a year over 2001 to 2011, compared with 2.7 to 3.0 per cent for population. The resulting land consumption ratios were close to two in all three cases, meaning that urban land grew about twice as fast as population. Built-up area per resident rose accordingly, from about 62 to 82 m² in Hyderabad, from 87 to 107 m² in Warangal and from 81 to 106 m² in Khammam. These are approximate values, since window areas and agglomeration boundaries differ, but the direction and rough magnitude are clear: the cities were becoming less dense.

**Table 8**

*Land consumption and population growth, 2001–2011 (provisional)*

| Agglomeration | Population CAGR (%) | Built-up CAGR (%) | Land consumption ratio | Built-up m² per person, 2001 | Built-up m² per person, 2011 |
|---|---|---|---|---|---|
| Hyderabad UA | 2.95 | 5.92 | 1.98 | 62 | 82 |
| Warangal UA | 2.66 | 4.81 | 1.78 | 87 | 107 |
| Khammam UA | 2.82 | 5.71 | 2.00 | 81 | 106 |

*Note.* Built-up area interpolated linearly to 2001 and 2011. *Source:* Census of India (2011); authors' Landsat classification (provisional values).

### *5.7 Sources of built-up land*

Transition matrices show which classes supplied the new built-up land between 2000 and 2024 (Table 9). In the four secondary cities cropland was the leading source, contributing 52 to 60 per cent of net built-up gain, followed by open land and scrub at 25 to 30 per cent. Hyderabad differs. Open land and scrub supplied the largest share (40 per cent), cropland 36 per cent, and vegetation 20 per cent, which is a higher vegetation share than in any other city. Water bodies supplied 3 to 5 per cent of the gain everywhere, a small share, but a consequential one given the role of tanks in water storage and flood buffering.

**Table 9**

*Sources of net built-up gain, 2000–2024 (% of gain; provisional)*

| City | Cropland | Open land / scrub | Vegetation | Water bodies |
|---|---|---|---|---|
| Hyderabad | 36 | 40 | 20 | 4 |
| Warangal | 52 | 30 | 14 | 4 |
| Karimnagar | 55 | 28 | 14 | 3 |
| Nizamabad | 60 | 25 | 10 | 5 |
| Khammam | 58 | 26 | 12 | 4 |

*Note.* Rows sum to 100 per cent. *Source:* Authors' Landsat classification (provisional values).

## 6. Discussion

### *6.1 Interpreting the pattern*

Three findings stand out. First, expansion is both rapid and widespread. A threefold increase in built-up area in 24 years is remarkable for any city, and it is striking that it occurred in all five. The convergence of compound annual growth rates around 4.5 to 5.6 per cent, in cities whose populations differ by an order of magnitude, suggests that the underlying drivers act across the state's urban hierarchy rather than in the capital alone. These drivers plausibly include rising incomes, a booming real-estate market, improvements in road connectivity and the extension of municipal limits, although this paper does not test them statistically.

Second, expansion is spatially extensive rather than compact. The land consumption ratio of about two, the rising built-up area per resident and the outward-moving frontier all point to declining density. These results are consistent with the global finding that urban land expands faster than population, particularly in developing regions (Angel et al., 2011; Seto et al., 2011). The high relative entropy among directional sectors further indicates that Hyderabad's growth is not tied to a single corridor. This is a characteristic of peripheral, parcel-by-parcel development, which is difficult to serve efficiently with transport and utilities.

Third, the consumption of farmland and open land is the main environmental signature. Cropland supplied more than half of the new built-up land in the secondary cities, and cropland share in the Hyderabad window fell from 36.0 to 14.2 per cent. Such losses matter for food and vegetable supply, but they also alter peri-urban livelihoods. Gumma et al. (2017) showed that peri-urban agriculture around Hyderabad responds opportunistically to urban demand, expanding in wastewater-irrigated areas even as the city grows. Our results suggest that this peri-urban agricultural belt is being pushed progressively outward, and that its long-term survival close to the city is uncertain.

### *6.2 Water, vegetation and the urban environment*

The decline of water bodies and vegetation deserves particular attention. Telangana's tank systems buffer floods, recharge groundwater and moderate local temperatures, and their loss to encroachment reduces the resilience of urban areas to both drought and extreme rainfall. The relative loss of about 17 per cent of water-body area in the Hyderabad window, and the loss of nearly one-third of vegetation share, are consistent with the vegetation and water-body declines and the surface warming reported for the metropolitan region by Franco et al. (2015).

### *6.3 Convergence of the urban hierarchy*

The comparative design reveals a pattern that single-city studies cannot show. Secondary cities are not merely smaller copies of Hyderabad; they are following a similar trajectory with a delay. Their built-up shares in 2024 approximate Hyderabad's in 2000, and their growth rates have not yet slowed. If this trajectory continues, Warangal, Karimnagar, Nizamabad and Khammam will face the pressures that Hyderabad faced in the 2000s, when expansion outran plans and infrastructure. The findings for Warangal accord with the expansion at the expense of agriculture reported by Aneesha Satya et al. (2020), and extend the evidence to three further cities and to a more recent period.

Part of the faster relative growth in the secondary cities is arithmetic, since a small base expands quickly in percentage terms. The absolute increments, 34 to 93 km² against about 720 km² in Hyderabad, show how different the scale of pressure remains. Even so, the relative rates matter for planning. Small municipal bodies typically have far less technical and financial capacity to absorb growth than the capital, and built-up shares of 17 to 20 per cent plausibly mark the stage at which peripheral settlement patterns begin to be locked in.

### *6.4 Planning and policy implications*

Four implications follow. First, growth management should address the peri-urban edge directly. Zoning and growth-boundary measures are most effective if introduced before development fronts arrive, which means that the secondary cities, whose outer rings are still largely open, have a window of opportunity that Hyderabad has largely lost. Second, tanks, lakes and their catchments should be mapped and protected as green-blue infrastructure, and remote sensing can support routine monitoring of encroachment. Third, incentives for infill, redevelopment and higher-density development along transit corridors can reduce the land consumption ratio, which is the clearest quantitative sign of sprawl in this study. Fourth, planning agencies should institutionalise periodic satellite-based monitoring, since consistent classification of freely available imagery can feed directly into master plan reviews at low cost.

Regional coordination is also important. Hyderabad's expansion beyond the 25-km window suggests that metropolitan-scale planning, rather than municipal-scale planning, is the appropriate unit of analysis, and that peri-urban villages in neighbouring districts need to be treated as part of a single functional region.

## 7. Limitations and Future Research

Several limitations qualify the findings. The fixed circular windows ensure comparability but do not coincide with administrative or functional urban boundaries, and growth beyond the window edge, especially for Hyderabad, is not captured. The 30-m resolution of Landsat produces mixed pixels in dense and fragmented settlements and can confuse built-up land with bare soil. The use of dry-season composites is necessary for consistency, but it can misclassify fallow cropland as open land. The five-class scheme omits finer distinctions, such as residential versus industrial land, that matter for planning. Population-based indicators rely on census data to 2011 and on linear interpolation of built-up area to census years, and the agglomeration boundaries used by the Census differ from the analysis windows.

Future work could extend the analysis in four directions: modelling the drivers of expansion with spatial regression or machine learning; projecting future growth with cellular automata models, as Aneesha

Satya et al. (2020) did for Warangal; incorporating the 2021 census round once it is available; and using higher-resolution imagery to separate residential, industrial and informal settlements.

## 8. Conclusion

This study compared urban sprawl and land use dynamics in five Telangana cities between 2000 and 2024 using a single, consistent remote sensing and GIS workflow. Four conclusions emerge. First, built-up land expanded roughly threefold in every city, at 4.5 to 5.6 per cent a year, and the secondary cities matched or exceeded Hyderabad in relative terms while remaining far smaller in absolute terms. Second, land consumption outpaced population growth by about a factor of two, which is a clear signature of declining density. Third, expansion was edge-driven. In Hyderabad nearly 85 per cent of the net gain occurred more than 10 km from the centre, and growth proceeded in all directions, with the north-east and south leading in absolute terms. Fourth, expansion drew primarily on cropland and open land, and it was accompanied by declines in vegetation and water bodies that carry environmental and hydrological costs.

The practical message is that the planning window in the secondary cities is still open. Their outer rings are largely undeveloped, their growth is steady rather than saturating, and their built-up shares have only recently reached levels at which Hyderabad's planning difficulties began. Growth boundaries, protection of tanks and wetlands, density incentives and routine satellite-based monitoring offer a coherent response. The method described here is transparent, uses only open data and can be repeated at low cost, so that planners and researchers can update it as new imagery and the next census become available.

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