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Simulating Future Urban Growth in Telangana's Secondary Cities: A CA-Markov and Machine Learning Approach Integrating Transport Corridor Influence (2024–2050)

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Abstract:
Rapid urbanisation is reshaping Telangana's secondary cities, yet projections of their future form are scarce and seldom consider how transport corridors steer land conversion. This study simulates built-up expansion in Warangal, Karimnagar, Nizamabad and Khammam from 2024 to 2050 by coupling a random forest suitability model with a cellular automaton–Markov (CA-Markov) allocation procedure under three infrastructure scenarios. Land use maps for 2000, 2010 and 2020 were classified from Landsat imagery (overall accuracy 89.4–93.1 per cent). Combined built-up area rose from 107.2 to 262.1 km², a compound annual growth of 4.57 per cent, mostly at the expense of cropland. Thirteen spatial drivers were used to train the suitability model; the three transport-corridor variables jointly contributed 31.1 per cent of predictor importance. Validation against the observed 2020 map gave a kappa of 0.88 and a figure of merit of 25.7 per cent, outperforming a conventional CA-Markov baseline. Three scenarios project built-up area of 497.8 to 674.3 km² by 2050, with 24 to 44 per cent of new growth falling within one kilometre of major highways. The findings identify corridor investment as the main lever shaping urban form and support corridor-sensitive planning that protects irrigated cropland, tanks and other water bodies.

Keywords: urban growth simulation; CA-Markov; random forest; transport corridors; secondary cities; Telangana; land use change.

1. Introduction

Urbanisation in India is moving beyond its metropolitan cores. Between the 2001 and 2011 censuses the country's urban population grew from about 286 million to 377 million, and a growing share of this increase was absorbed by small and medium-sized towns and by the peripheries of existing cities rather than by the largest metropolises (Bhagat, 2011; Kundu, 2011; Registrar General & Census Commissioner, India, 2011). Global assessments project that most urban land expansion in the coming

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decades will occur in Asia, and that it will outpace urban population growth because densities are falling (Angel et al., 2011; Seto et al., 2012). For South Asia, the World Bank has argued that unmanaged spatial expansion, rather than urbanisation itself, is the source of the region's most serious land, infrastructure and environmental costs (Ellis & Roberts, 2016).

Telangana illustrates this shift clearly. It is among the most urbanised large states in India, with roughly 39 per cent of its population living in urban areas in 2011, and its urban system has long been dominated by Hyderabad (Registrar General & Census Commissioner, India, 2011). Since the state's formation in 2014, however, public investment has increasingly targeted a second tier of cities, including Warangal, Karimnagar, Nizamabad and Khammam, through national highway upgrades, bypasses and ring roads, urban missions such as the Atal Mission for Rejuvenation and Urban Transformation (AMRUT), and industrial and educational facilities intended to deflect growth from the capital (Ministry of Urban Development, 2015; Planning Department, Government of Telangana, 2021). These cities are administrative, commercial and educational hubs for agrarian hinterlands, and their expansion draws directly on irrigated cropland, tank systems and peri-urban commons.

Transport corridors are central to how such expansion unfolds. Evidence from the United States, China and India shows that highways and radial roads push population and economic activity outwards and reshape the location of industry (Baum-Snow, 2007; Duranton & Turner, 2012; Ghani et al., 2016). In Indian secondary cities, ribbon development along national highway frontages and land conversion at bypass junctions are visible to any traveller, yet they are rarely built into spatial forecasts. Most simulation studies in India treat roads as one distance layer among many, weigh them subjectively, or omit variation in corridor investment altogether, which limits their value for planners deciding whether, and where, to build the next link.

Land-change simulation offers a way to examine such choices before they are made. Cellular automata (CA) models, which grow urban land according to neighbourhood and suitability rules, and Markov chains, which supply the quantity of change from observed transitions, have been combined in the widely used CA-Markov approach (Eastman, 2012; Arsanjani et al., 2013; Aburas et al., 2016). Machine learning methods, notably random forests, now allow the suitability surface to be estimated empirically from observed change rather than assigned by expert weights (Kamusoko & Gamba, 2015; Gounaridis et al., 2018). Integrating the two combines the quantity discipline of Markov analysis with data-driven spatial allocation, and it makes the influence of corridors measurable.

Despite this progress, three gaps remain. First, little published simulation work addresses Telangana's secondary cities as a group, although their trajectories matter for the state's urban strategy. Second, corridor influence is seldom isolated or tested through explicit infrastructure scenarios. Third, validation often relies on kappa alone, which can overstate model skill when most cells do not change (Pontius & Millones, 2011).

This paper addresses these gaps with four objectives: (1) to map and quantify land use and land cover change in four cities between 2000 and 2020; (2) to estimate, with a random forest, the relative importance of biophysical, demographic and transport drivers of built-up expansion; (3) to simulate built-up growth from 2024 to 2050 under three scenarios; and (4) to measure how much of the projected growth is attributable to proximity to major road corridors. We hypothesise that corridor-distance

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variables rank among the strongest predictors of conversion (H1), and that the share of growth within the corridor zone rises where infrastructure investment accelerates and falls under compact-growth management (H2).

Section 2 reviews related work, Section 3 describes the study area and data, Section 4 sets out the methods, Section 5 presents the results, and Sections 6 to 8 discuss implications, limitations and conclusions.

2. Literature Review

2.1 Urban growth and land-change models

Spatial simulation of urban growth has a long lineage. Tobler's (1970) cellular simulation of the Detroit region established the idea that urban change can be modelled as a local process on a grid. Clarke et al. (1997) extended it with the self-modifying SLEUTH model, in which growth coefficients are calibrated against historical urban extents, while Li and Yeh (2002) replaced hand-set transition rules with a neural network trained on observed data. Alongside CA models, regression-based and hybrid frameworks such as CLUE-S (Verburg et al., 2002) and the Land Transformation Model (Pijanowski et al., 2002) allocate demand for land across suitability surfaces. Reviews by Verburg et al. (2004) and Batty (2013) conclude that no single structure dominates; the choice depends on whether the question concerns the quantity, the location or the process of change.

2.2 CA-Markov and its limitations

CA-Markov couples a Markov chain, which estimates how much land moves between classes over a period, with a CA filter that allocates that change in space according to contiguity and suitability (Eastman, 2012). Its appeal lies in modest data needs and implementation in common GIS software. Applications range from Patna, where a multilayer perceptron was linked to a Markov chain (Mishra & Rai, 2016), to numerous city and watershed studies reviewed by Aburas et al. (2016). Mondal et al. (2016) showed that CA-Markov predictions can be tested with statistical independence tests as well as agreement statistics.

The approach has well-known weaknesses. Markov projections assume that transition probabilities are stationary, so structural changes such as new infrastructure are not represented. Suitability surfaces are often built by multi-criteria evaluation, in which analysts assign weights to drivers, introducing subjectivity that is hard to defend or reproduce (Aburas et al., 2016). Finally, the standard CA contiguity filter rewards compact growth around existing built-up land and can underrepresent leapfrog development along roads.

2.3 Machine learning for suitability estimation

Random forests aggregate many decision trees trained on bootstrap samples and random predictor subsets, which gives robust classification, measures of variable importance and few tuning requirements (Breiman, 2001; Hastie et al., 2009). Remote sensing reviews report that random forests perform well with heterogeneous predictors and moderate training sets (Belgiu & Drăguţ, 2016). In land-change modelling, Kamusoko and Gamba (2015) combined random forests with a CA to simulate urban growth,

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and Gounaridis et al. (2018) used a similar logic to compare economic and planning scenarios for Athens. Rienow and Goetzke (2015) enhanced SLEUTH with support vector machines, and Liu et al. (2017) embedded artificial neural network suitability in the FLUS model. These studies agree that data-driven suitability improves allocation accuracy relative to expert weighting, but few report how the contribution of specific infrastructure variables changes across scenarios.

2.4 Transport corridors and urban form

The theoretical expectation that transport infrastructure shapes urban land use is well supported empirically. Baum-Snow (2007) found that each new highway passing through a central city reduced its population by about 18 per cent, and Duranton and Turner (2012) showed that interstate highways increased employment growth in US metropolitan areas. In India, Ghani et al. (2016) found that the Golden Quadrilateral highway programme shifted the location and performance of manufacturing along the upgraded corridor, particularly in districts that were non-nodal. Remote sensing studies of Indian cities show that expansion is often directed along radial roads and railway lines (Taubenböck et al., 2009; Ramachandra et al., 2015). These findings imply that corridor effects are both strong and policy-contingent, which argues for treating them as explicit scenario levers rather than as background distance layers.

2.5 Evidence from Indian cities and the research gap

Indian applications have concentrated on metropolitan regions and a few well-studied cities. Bhatta (2009) quantified growth around Kolkata using remote sensing, Bhatta et al. (2010) proposed sprawl measures, Sudhira et al. (2004) modelled sprawl in the Mangalore–Udupi region, and Sahana et al. (2018) analysed spatial patterns of growth in the Kolkata agglomeration. Ramachandra et al. (2015) documented the spatiotemporal patterns of Bengaluru's urbanisation. Secondary cities in the Deccan interior, where corridor investment is a major component of state policy, are much less studied, and simulation work that integrates machine-learning suitability with explicit infrastructure scenarios is rarer still. The present study responds to that gap.

3. Study Area and Data

3.1 Study area

Telangana lies on the Deccan Plateau and has a semi-arid tropical climate, with annual rainfall of roughly 800–1,000 mm delivered mostly by the south-west monsoon. Red and black soils support a cropping system that depends heavily on tanks, canals and, increasingly, groundwater. The four study cities, Warangal, Karimnagar, Nizamabad and Khammam, are the principal urban centres of the northern and eastern parts of the state outside the Hyderabad region. They were selected because each is a district-level service hub, each is served by a different combination of national highway, state highway and railway corridors, and together they span the range of size and growth conditions typical of the state's second tier (Table 1).

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For each city, a window of 25 km × 25 km (625 km²) was centred on the urban core, giving a combined analysis area of 2,500 km². The windows contain the municipal area and its rural–urban fringe, where most conversion of cropland takes place.

Table 1

Characteristics of the four study cities

City	Population, 2011 (millions, approx.)	Principal corridors	Main urban functions
Warangal	0.62	National highway NH-163; Kazipet–Warangal rail junction	Commerce, education, textiles
Karimnagar	0.26	NH-563 towards Warangal; state highways	Agricultural trade, stone industry, education
Nizamabad	0.31	NH-44; Secunderabad–Manmad rail line	Agricultural market, trade
Khammam	0.31	National and state highway links towards Suryapet and Vijayawada; Kazipet–Vijayawada rail line	Agricultural market, trade

Note. Population from Registrar General and Census Commissioner, India (2011), rounded; municipal boundaries differ across census years.

3.2 Data sources and pre-processing

Land use and land cover were derived from cloud-free, dry-season (February–April) Landsat scenes for 2000 (Landsat 7 ETM+), 2010 (Landsat 5 TM) and 2020 (Landsat 8 OLI) at 30 m resolution (Roy et al., 2014; Wulder et al., 2019). Dry-season images were chosen because they separate bare soil, fallow land and built surfaces from green crops more reliably than monsoon scenes, which are cloudy. All scenes were atmospherically corrected, co-registered to a root-mean-square error below half a pixel and projected to UTM zone 44N. Elevation and slope were taken from the Shuttle Radar Topography Mission (Farr et al., 2007). Road and railway networks were extracted from OpenStreetMap (Haklay & Weber, 2008) and checked against high-resolution imagery. Population density combined Census 2011 ward-level data with the WorldPop gridded surface for 2020 (Tatem, 2017). Table 2 lists all layers.

Table 2

Data layers used in the study

Layer	Source	Resolution/date	Use
Landsat 7 ETM+, Landsat 5 TM, Landsat 8 OLI	USGS	30 m; 2000, 2010, 2020	LULC classification
Digital elevation model	SRTM	30 m	Elevation, slope

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Layer	Source	Resolution/date	Use
National, state and district roads	OpenStreetMap	Vector; 2020	Corridor distances
Railway lines and stations	Digitised from imagery and rail maps	Vector; 2020	Corridor distance
Population density	Census 2011; WorldPop	Ward; 100 m	Demographic driver
Soil type	National soil survey maps, digitised	1:250,000	Biophysical driver
Water bodies	MNDWI from Landsat	30 m	Distance to water
Industrial and institutional sites	Digitised from imagery	Vector; 2020	Distance to activity nodes

3.3 Land use classes and driver variables

Five classes were mapped: built-up land, cropland, fallow and scrubland, forest and plantation, and water bodies. Spectral indices supported discrimination: the normalised difference built-up index (Zha et al., 2003) and the modified normalised difference water index (Xu, 2006), together with the normalised difference vegetation index.

Thirteen spatial drivers were prepared for the suitability model: distances to the existing built-up edge, to the city centre, to national highways, to state highways, to major district roads, to the nearest railway line or station, to water bodies and to industrial and institutional sites; population density; slope; elevation; baseline NDVI; and soil type. Distances to the built-up edge and the city centre capture contiguity and centrality; the national highway, state highway and railway layers are the transport-corridor variables whose joint influence is examined throughout this paper.

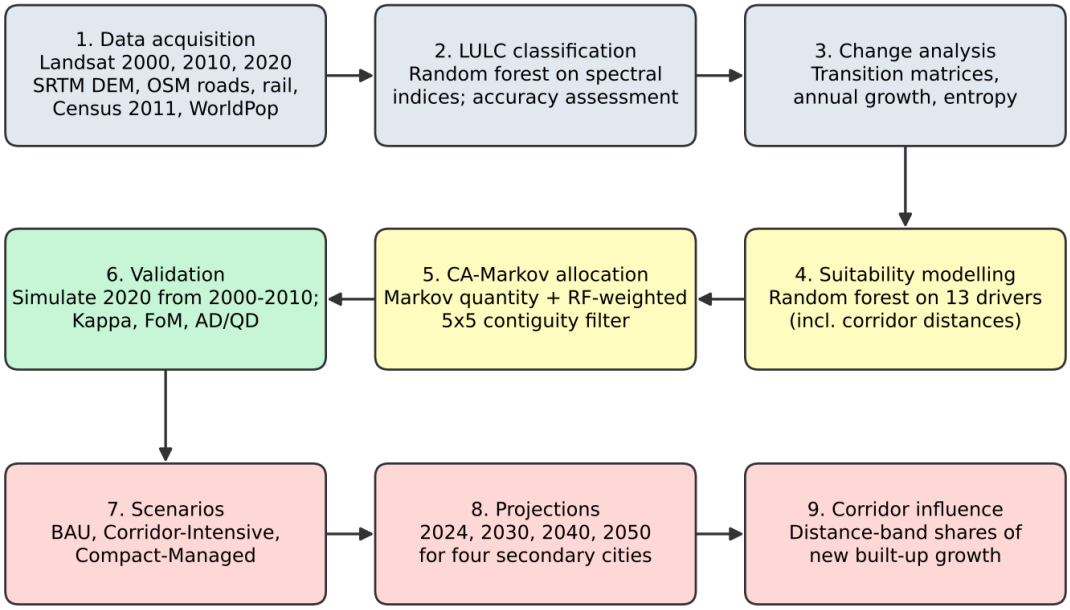
4. Methodology

The analysis followed nine steps, summarised in Figure 1: data preparation, classification, change analysis, suitability modelling, CA-Markov allocation, validation, scenario definition, projection and corridor-influence analysis.

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Figure 1

Methodological workflow of the integrated CA-Markov and machine learning framework



4.1 Land use and land cover classification

Each scene was classified with a random forest classifier using the spectral bands, the three indices and a 3 × 3 local variance texture layer. Training and test samples were collected by visual interpretation of high-resolution imagery and topographic maps: 750 stratified points per year (150 per class), split 70:30 into training and testing sets. Accuracy was assessed with confusion matrices, overall accuracy, producer's and user's accuracy, and Cohen's kappa (Cohen, 1960; Congalton, 1991; Foody, 2002). Kappa values were interpreted using the conventional benchmarks of Landis and Koch (1977).

4.2 Change analysis

Transitions among classes were tabulated by cross-tabulating maps for 2000–2010 and 2010–2020, and persistence was distinguished from change following Pontius et al. (2004). City-level growth in built-up area was summarised by the compound annual growth rate:

$$r = \left(\frac{A_{t_2}}{A_{t_1}}\right)^{\frac{1}{t_2 - t_1}} - 1$$

where A is built-up area in km² at times t_1 and t_2.

4.3 Random forest suitability model

The suitability model estimates the probability that a non-built-up cell converts to built-up use given its location and attributes. For each city, 10,000 cells that converted and 10,000 that remained non-urban were sampled at random and described by the thirteen drivers. A random forest of 500 trees was trained

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with four predictors tried at each split and a minimum node size of five, using scikit-learn (Pedregosa et al., 2011). Seventy per cent of samples were used for training and thirty per cent for testing; model skill was summarised by out-of-bag accuracy and the area under the receiver operating characteristic curve (Pontius & Schneider, 2001). Variable importance was calculated as the mean decrease in accuracy under permutation and rescaled to sum to 100 per cent (Breiman, 2001; Hastie et al., 2009). The fitted forest was applied to every eligible cell to produce a suitability surface between 0 and 1.

4.3.1 Calibration periods

Two calibrations were run. For validation, the model was trained on 2000–2010 transitions and used to simulate 2020. For projection, it was retrained on 2010–2020 transitions, which better reflect current infrastructure and policy conditions.

4.4 CA-Markov allocation

The quantity of change was obtained from Markov chain analysis of the 2010–2020 transition probability matrix, extrapolated forward in time (Eastman, 2012):

$$S_{t+1} = P.S_t$$

where S is the vector of class areas and P the transition probability matrix. Spatial allocation then proceeded iteratively. In each iteration, cells were ranked by a weighted combination of the random forest suitability and a 5 × 5 contiguity filter, and the highest-ranked cells were converted until the Markov demand for that iteration was met. Existing built-up land, reserved forest and water bodies were treated as constraints. This design follows the logic of RF-CA hybrids (Kamusoko & Gamba, 2015) while retaining the quantity control of conventional CA-Markov.

4.5 Scenarios

Three scenarios were defined (Table 3). The Business-as-Usual (BAU) scenario applies the 2010–2020 transition matrix and the corridor network as it stood in 2020. The Corridor-Intensive scenario adds planned and proposed road links, including bypasses and ring roads around the cities, and raises the demand for new built-up land to reflect induced development. The Compact-Managed scenario keeps corridors unchanged but restricts conversion of irrigated cropland and tank buffers and lowers new land demand through higher densities, a design informed by scenario studies in other regions (Gounaridis et al., 2018).

Table 3

Scenario definitions

Scenario	Quantity of new built-up land (relative to BAU)	Corridor network	Spatial constraints
Business-as-Usual (BAU)	Baseline	2020 network	Existing reserved forest and water bodies

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Scenario	Quantity of new built-up land (relative to BAU)	Corridor network	Spatial constraints
Corridor-Intensive (CI)	+28% by 2050	2020 network plus proposed bypasses, ring roads and four-laning	As BAU
Compact-Managed (CM)	−27% by 2050	2020 network	BAU constraints plus protection of irrigated cropland and 100 m tank buffers; contiguity weight raised

4.6 Validation

The model calibrated on 2000–2010 was used to simulate 2020, and the output was compared with the classified 2020 map. Because kappa can be inflated by persistent cells, three further measures were used: kappa for location, the figure of merit (FoM), which is the intersection of observed and simulated change divided by their union, and the decomposition of disagreement into quantity and allocation components (Pontius et al., 2008; Pontius & Millones, 2011). Two benchmarks were run under identical conditions: a conventional CA-Markov model with multi-criteria suitability weights, and a random forest allocation without the contiguity filter.

4.7 Corridor-influence analysis

To measure corridor influence directly, the road network of national and state highways was buffered into four distance bands (0–1 km, 1–3 km, 3–5 km and more than 5 km). The share of new built-up area falling in each band was computed for the observed 2000–2020 period and for each 2020–2050 scenario, and divided by the band's share of the analysis area to obtain a concentration ratio. A ratio above one indicates that growth is concentrated near the corridor relative to a uniform distribution.

5. Results

5.1 Classification accuracy

Overall accuracy of the land use and land cover maps rose from 89.4 per cent in 2000 to 93.1 per cent in 2020, and kappa ranged from 0.86 to 0.91, which falls in the almost-perfect range of Landis and Koch (1977; Table 4). Built-up land was mapped with user's accuracy of 87.6–94.0 per cent. Most errors in the earlier maps arose between built-up land and bare fallow plots, which have similar spectral responses in the dry season.

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Table 4

Accuracy of land use and land cover classification

Year	Sensor	Overall accuracy (%)	Kappa	Built-up user's accuracy (%)	Built-up producer's accuracy (%)
2000	Landsat 7 ETM+	89.4	0.86	87.6	85.9
2010	Landsat 5 TM	91.2	0.88	90.1	88.4
2020	Landsat 8 OLI	93.1	0.91	94.0	92.2

5.2 Land use and land cover change, 2000–2020

Built-up land in the four windows expanded from 107.2 km² in 2000 to 170.2 km² in 2010 and 262.1 km² in 2020 (Table 5), lifting its share of the analysis area from 4.3 to 10.5 per cent. The compound annual growth rate was 4.73 per cent in 2000–2010 and 4.41 per cent in 2010–2020, or 4.57 per cent over the full period. Cropland lost 147.2 km² (10.5 per cent of its 2000 area), fallow and scrubland lost 71.5 km², and forest and plantation declined slightly by 13.6 km². Water bodies increased by 77.4 km², reflecting reservoir and tank expansion and restoration in the surrounding irrigation systems.

Table 5

Land use and land cover areas in the four study windows combined (km²)

Class	2000	2010	2020	Change, 2000–2020
Built-up	107.2	170.2	262.1	+154.9
Cropland	1,402.5	1,349.8	1,255.3	−147.2
Fallow and scrubland	560.3	526.4	488.8	−71.5
Forest and plantation	331.0	324.6	317.4	−13.6
Water bodies	99.0	129.0	176.4	+77.4
Total	2,500.0	2,500.0	2,500.0	0.0

Cropland supplied 59.4 per cent (92.0 km²) of all land converted to built-up use between 2000 and 2020, fallow and scrubland 33.0 per cent (51.1 km²), forest and plantation 4.2 per cent (6.5 km²) and water bodies 3.4 per cent (5.3 km²). The last figure, small in area, indicates encroachment on tank beds and foreshore land, which matters for flood regulation and local water security.

All four cities grew at more than 4 per cent a year (Table 6). Warangal added the most land (53.8 km²) but Karimnagar grew fastest (5.18 per cent a year), expanding to 2.7 times its 2000 area. Khammam was the slowest at 4.33 per cent.

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Table 6

Built-up area by city and compound annual growth rate

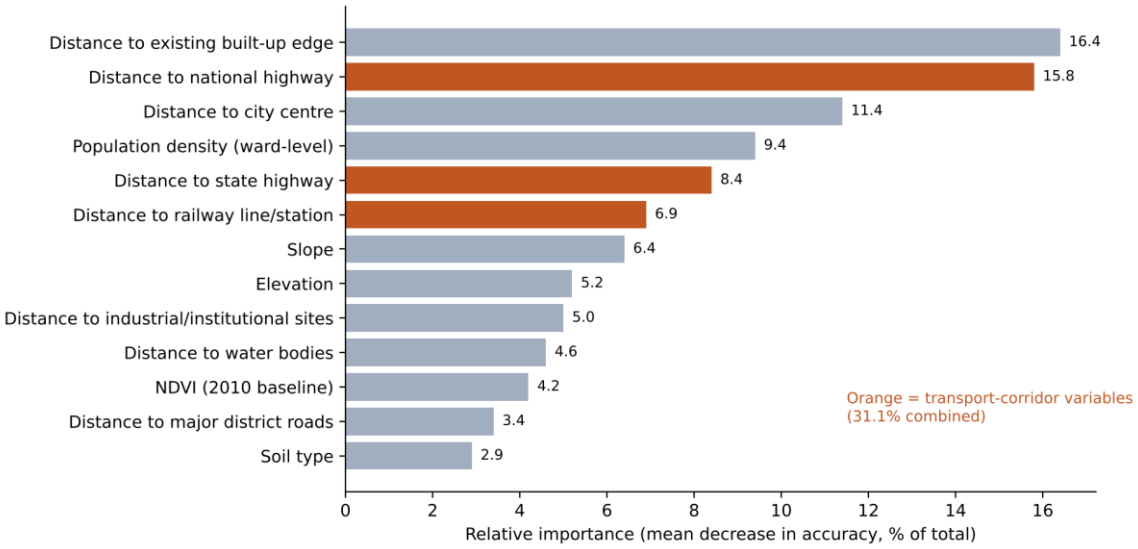
City	2000 (km²)	2010 (km²)	2020 (km²)	Net gain, 2000–2020 (km²)	Annual growth, 2000–2020 (%)
Warangal	38.6	59.8	92.4	53.8	4.46
Karimnagar	21.4	35.1	58.7	37.3	5.18
Nizamabad	25.9	40.6	61.3	35.4	4.40
Khammam	21.3	34.7	49.7	28.4	4.33
All cities	107.2	170.2	262.1	154.9	4.57

5.3 Drivers of built-up expansion

The random forest suitability model achieved an out-of-bag accuracy of 85.7 per cent and an area under the ROC curve of 0.92 on the held-out test sample. Figure 2 ranks the thirteen drivers by permutation importance. Distance to the existing built-up edge was the strongest predictor (16.4 per cent), which confirms that growth is mainly incremental, followed by distance to national highways (15.8 per cent) and distance to the city centre (11.4 per cent). Together the three transport-corridor variables (national highway, state highway and railway) accounted for 31.1 per cent of importance, more than any other group of drivers, and the national highway variable alone ranked second overall. Hypothesis H1 is therefore supported. Biophysical variables such as slope, elevation and soil type mattered less, which is consistent with the gentle relief of the Deccan plateau around these cities.

Figure 2

Random forest importance of spatial drivers of conversion to built-up land



Note. Importance is the mean decrease in accuracy under permutation, rescaled to sum to 100 per cent. Highlighted bars are national highway, state highway and railway distances (31.1 per cent combined).

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5.4 Model validation

The hybrid model calibrated on 2000–2010 reproduced the 2020 map well (Table 7). Pooled kappa was 0.88, kappa for location 0.90 and the figure of merit 25.7 per cent. The figure of merit is lower than kappa because it considers only cells that changed or were predicted to change, a more demanding test, and values of this magnitude are typical for built-up change models (Pontius et al., 2008). Allocation disagreement (3.4 per cent of the map) exceeded quantity disagreement (1.0 per cent), so the Markov step estimated the volume of change reliably while location remained the main source of error. Performance was slightly lower in Khammam (FoM 23.9 per cent), where growth was more dispersed.

The hybrid model outperformed both benchmarks. Relative to conventional CA-Markov with multi-criteria weights, kappa rose by 0.05 and the figure of merit by 6.5 percentage points; relative to the random forest without the contiguity filter, the gains were 0.03 and 3.7 points. Both components therefore contribute: the machine-learning suitability improves location, and the CA filter improves spatial coherence.

Table 7

Validation of the simulated 2020 built-up map against the classified 2020 map

Model and area	Kappa	Kappa location	Figure of merit (%)	Quantity disagreement (%)	Allocation disagreement (%)
Hybrid RF + CA-Markov: Warangal	0.89	0.91	27.4	0.8	3.1
Hybrid RF + CA-Markov: Karimnagar	0.87	0.89	25.1	1.1	3.6
Hybrid RF + CA-Markov: Nizamabad	0.88	0.90	26.3	0.9	3.3
Hybrid RF + CA-Markov: Khammam	0.86	0.88	23.9	1.2	3.9
Hybrid RF + CA-Markov: all cities	0.88	0.90	25.7	1.0	3.4
Benchmark: CA-Markov with MCE weights, all cities	0.83	0.86	19.2	1.4	4.9
Benchmark: RF without contiguity filter, all cities	0.85	0.87	22.0	1.1	4.3

5.5 Projected growth, 2024–2050

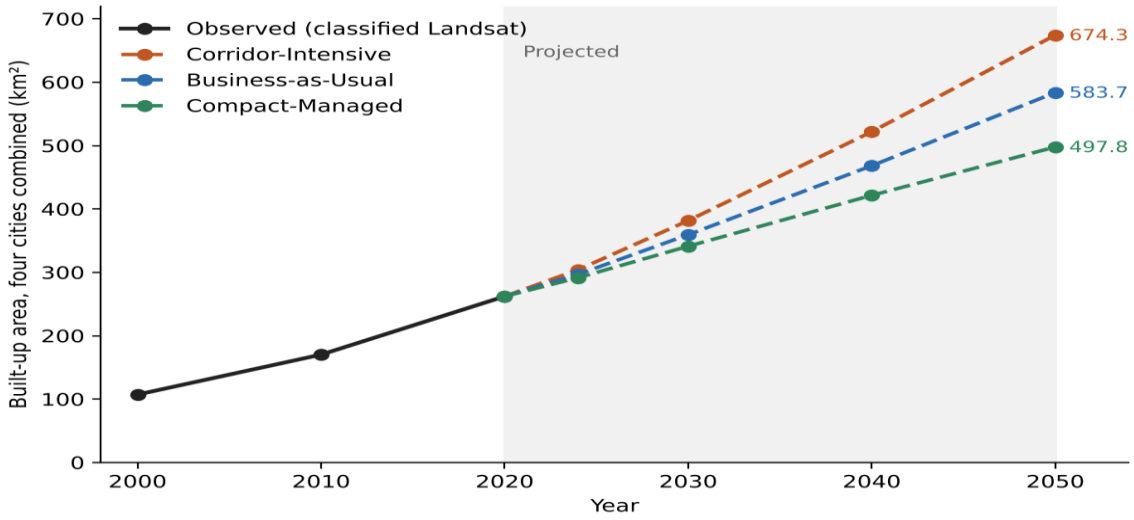
Under all scenarios built-up land continues to expand, but the paths diverge steadily after 2030 (Figure 3). By 2030 combined built-up area reaches 341.2 km² in the Compact-Managed scenario, 359.4 km² under BAU and 381.6 km² under Corridor-Intensive. By 2050 the figures are 497.8, 583.7 and 674.3 km², equal to 19.9, 23.3 and 27.0 per cent of the analysis area and to 1.90, 2.23 and 2.57 times the 2020

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extent. The gap between the Corridor-Intensive and Compact-Managed scenarios in 2050 is 176.5 km², roughly two-thirds of the entire built-up area that exists today.

Figure 3

Observed and projected combined built-up area under three scenarios, 2000–2050



Note. Observed values are from classified Landsat maps; projections are CA-Markov outputs for the four cities combined.

Warangal remains the largest city in every scenario, reaching 172.6–243.9 km² (Table 8). Karimnagar records the highest growth multiple in each scenario, from 1.97 times its 2020 area under Compact-Managed to 2.81 times under Corridor-Intensive, consistent with its fast historical growth rate. Cropland loss differs sharply: converted cropland between 2020 and 2050 is about 186.5 km² under BAU (14.9 per cent of 2020 cropland), 247.3 km² under Corridor-Intensive (19.7 per cent) and 96.6 km² under Compact-Managed (7.7 per cent), where the protection of irrigated land redirects growth to fallow land and scrub.

Table 8

Observed (2020) and projected (2050) built-up area by city and scenario (km²)

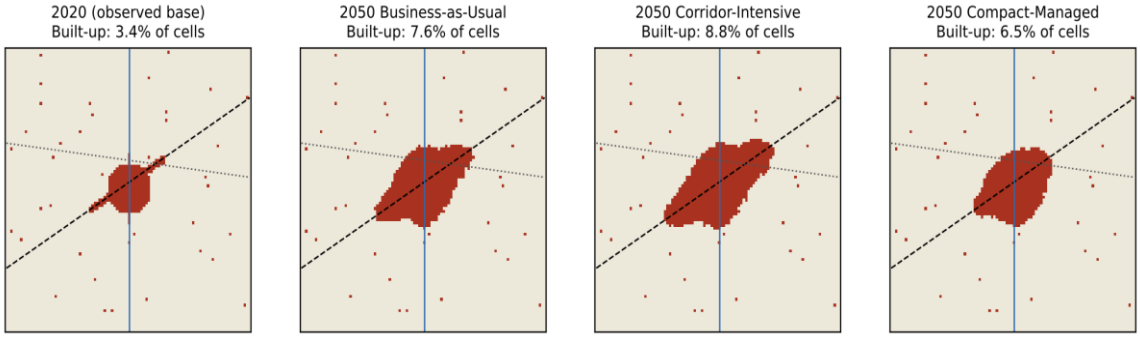
City	2020 observed	2050 BAU	2050 Corridor-Intensive	2050 Compact-Managed
Warangal	92.4	205.0	243.9	172.6
Karimnagar	58.7	140.5	165.0	115.9
Nizamabad	61.3	128.5	143.4	109.5
Khammam	49.7	109.7	122.0	99.8
All cities	262.1	583.7	674.3	497.8

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Figure 4 illustrates how the three scenarios allocate growth spatially, using a schematic city served by a national highway, a railway and a state highway. Under BAU the built-up area extends along the highway in both directions, under Corridor-Intensive the linear spread is longer and denser, and under Compact-Managed growth consolidates around the existing core and the highway–railway intersection.

Figure 4

Schematic spatial allocation under the three scenarios for a representative corridor-served city



Note. Schematic illustration on a 100 × 100 cell grid. Dashed black line: national highway; dotted grey line: railway; blue line: state highway.

5.6 Corridor influence on the location of growth

Corridor proximity strongly shapes where new development occurs (Table 9). During 2000–2020, 34.2 per cent of new built-up land lay within one kilometre of a national or state highway, although this band covers only 9.6 per cent of the analysis area, a concentration ratio of 3.6. The ratio rises to 3.8 under BAU and 4.5 under Corridor-Intensive, where 43.5 per cent of new growth is within the first kilometre. Under Compact-Managed it falls to 2.5, with 24.3 per cent of new growth in the first kilometre and 20.6 per cent beyond five kilometres, against 9.2 per cent in the Corridor-Intensive case. Hypothesis H2 is supported: corridor investment increases highway-adjacent growth, whereas compact management disperses growth towards the core and the fringe.

Table 9

Share of new built-up land by distance from national and state highways (%)

Distance band	Share of analysis area	Observed 2000–2020	BAU 2020–2050	Corridor-Intensive 2020–2050	Compact-Managed 2020–2050
0–1 km	9.6	34.2	36.1	43.5	24.3
1–3 km	17.8	31.5	32.4	33.1	30.2
3–5 km	14.6	18.9	17.8	14.2	24.9
More than 5 km	58.0	15.4	13.7	9.2	20.6
Concentration ratio, 0–1 km		3.6	3.8	4.5	2.5

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6. Discussion

6.1 Corridors as the main lever on urban form

The central finding is that transport corridors act as a persistent organising force for urban growth in Telangana's secondary cities and that their influence is policy-sensitive. Three results point the same way. The three corridor variables jointly carry nearly a third of the suitability model's explanatory power; roughly a third of all new built-up land since 2000 has been located within one kilometre of a major highway, in a band covering less than a tenth of the area; and this concentration is amplified or damped when the scenarios alter corridor investment. The concentration ratio under BAU (3.8) is only slightly above the historical value (3.6), which shows that corridor-oriented growth is path-dependent: without a change in policy, the existing pattern simply continues.

These results are consistent with the wider literature. Highways redistribute people and activity within urban regions (Baum-Snow, 2007; Duranton & Turner, 2012), and in India the Golden Quadrilateral programme measurably changed where manufacturing located along upgraded roads (Ghani et al., 2016). Remote sensing studies of larger Indian cities also describe radial and linear expansion along arterial roads and rail lines (Taubenböck et al., 2009; Ramachandra et al., 2015). The contribution of the present analysis is to quantify this effect for a group of smaller cities and to show how much of it depends on investment choices: moving from compact management to corridor-intensive investment shifts the highway-adjacent share of new growth from 24.3 to 43.5 per cent.

6.2 Differences among cities

The four cities follow the same logic but not the same trajectory. Warangal, with the largest base and the most diverse corridor network, remains the largest in all scenarios. Karimnagar's growth multiple is the highest in each scenario, reflecting a rapid historical rate from a small base. Nizamabad shows the lowest multiple under Compact-Managed (1.79), plausibly because a single dominant highway and rail axis leaves less room for dispersed growth once constraints are applied, while Khammam, where historical growth was more scattered, shows the lowest validation score. These differences suggest that corridor geometry, as well as corridor investment, conditions how a city grows, and that city-specific scenarios are preferable to a single state-wide assumption.

6.3 Cropland, water and the cost of the corridor pattern

The land-use consequences are significant. Even BAU converts about 15 per cent of the 2020 cropland in the windows by 2050, and the Corridor-Intensive scenario raises this to nearly 20 per cent. The Compact-Managed scenario nearly halves the loss to 7.7 per cent by protecting irrigated land and tank buffers. The historical conversion of water bodies and their margins, though small in area (3.4 per cent of all new built-up land), points to an additional risk to flood regulation and groundwater recharge. Global assessments warn that expansion of this kind is often land-intensive and difficult to reverse (Angel et al., 2011; Seto et al., 2012).

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6.4 Methodological implications

The validation results show why a hybrid design is worthwhile. Replacing multi-criteria weights with a random forest improved location accuracy, and retaining the Markov step maintained control of the quantity of change, so that quantity disagreement stayed at 1.0 per cent of the map. This agrees with earlier findings that machine-learning suitability improves allocation (Kamusoko & Gamba, 2015; Rienow & Goetzke, 2015) and with Indian experience in which neural-network suitability was coupled to Markov chains (Mishra & Rai, 2016). Reporting the figure of merit and the decomposition of disagreement, rather than kappa alone, gives a more honest account of skill and is recommended for other studies in the region (Pontius & Millones, 2011). Allocation disagreement still dominates, which means that the model is better at saying how much land will urbanise than exactly where, and its maps are best read as zones of probable growth rather than parcel-level forecasts.

7. Policy Implications and Limitations

7.1 Policy implications

Four implications follow for state and municipal planners. First, major road projects should be treated as land-use decisions: approval of a bypass, ring road or four-laning should be coupled with a statutory land-use plan, frontage controls and service roads, so that the corridor does not become a continuous strip of unplanned development. Second, irrigated cropland and tank beds near the cities should be protected through zoning and enforced buffers; the scenario results suggest that this single measure removes nearly half of projected cropland loss. Third, designated growth nodes at the junctions of bypasses and radial roads, supported by land pooling or similar mechanisms, can channel growth to serviced land rather than leaving it to ad hoc conversion. Fourth, planning authorities should adopt routine monitoring with freely available satellite data and update their growth projections at least every five years, in line with the broader call for managing spatial transformation rather than reacting to it (Ellis & Roberts, 2016).

7.2 Limitations

Several limitations qualify the results. The 30 m resolution of Landsat mixes land cover in dense peri-urban mosaics and cannot capture vertical growth or densification inside built-up areas. The model assumes that the relationships learned from 2010–2020 hold in future, whereas new institutions, technologies and economic shocks may alter them. The scenario multipliers (+28 per cent and −27 per cent in new land demand) are assumptions chosen to bracket plausible outcomes, not forecasts derived from independent population or economic projections. The road network is represented as it stood in 2020 plus proposed links, and the timing of those links is uncertain. Validation covers one period and one data set, and uncertainty ranges for the projections were not estimated. Future work could integrate demographic and economic drivers, use Sentinel-2 imagery at 10 m, bootstrap the forest to produce uncertainty maps, and test agent-based representations of land-market behaviour (Batty, 2013).

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8. Conclusion

This study simulated the future growth of four of Telangana's secondary cities by coupling a random forest suitability model with CA-Markov allocation and by testing three corridor-related scenarios. Between 2000 and 2020 combined built-up area rose from 107.2 to 262.1 km², growing at 4.57 per cent a year, and almost 60 per cent of new built-up land came from cropland. The suitability model identified proximity to the existing built-up edge, to national highways and to the city centre as the strongest drivers, and the three corridor variables jointly explained 31.1 per cent of importance, supporting the first hypothesis. The hybrid model reproduced the observed 2020 map with a kappa of 0.88 and a figure of merit of 25.7 per cent, outperforming a conventional CA-Markov benchmark and a random forest without a contiguity filter.

Projected built-up area in 2050 ranges from 497.8 km² under Compact-Managed growth to 583.7 km² under business-as-usual and 674.3 km² under Corridor-Intensive investment. The share of new growth within one kilometre of major highways ranges from 24.3 to 43.5 per cent across the scenarios, which supports the second hypothesis and shows that the pattern of growth, not only its volume, is a product of corridor decisions. The scenarios also differ by about 150 km² in cropland converted, a difference large enough to matter for the agrarian economies on which these cities depend.

The practical message is that corridors and land-use planning must be designed together. Highway and ring-road investments in the secondary cities will shape where cities grow for decades; coupling them with frontage management, protection of irrigated land and tanks, and serviced growth nodes can deliver the access benefits of the corridor without its heaviest land costs. The framework presented here is transparent, relies on open data and can be repeated for other cities in Telangana and beyond, giving planners a way to test infrastructure choices before they are built.

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