

Spatial Dynamics of Urban Expansion and Planning Disparities in the Islamabad–Rawalpindi Conurbation

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Abstract

City-regions across South Asia are urbanising quickly, yet planning them well depends on measured evidence of how rapidly, how intensively, and in what spatial form their built-up land grows. This study measures the spatiotemporal dynamics of urban expansion and sprawl for the Islamabad–Rawalpindi conurbation of Pakistan (6,118 km²) between 2011 and 2024, using the region's twin-cities layout, a planned capital beside a largely unplanned district, as a natural experiment in two planning regimes. Six-class land-cover maps for 2011, 2016, 2021, and 2024 were produced by Random Forest classification of dry-season Landsat composites in Google Earth Engine (overall accuracy 78.0–81.3%; Kappa 0.736–0.776) and examined through transition analysis, expansion indices (UER, UEII), zone-based Shannon's entropy, directional analysis, and spatial-cluster statistics (Moran's I, LISA, Getis–Ord Gi*). Built-up land doubled from 383.9 to 772.1 km² (+101%), drawn mainly from vegetation, while forest showed the steepest proportional decline (–20.5%). The pace was irregular: a surge (2011–2016), a slowdown (2016–2021), and record growth in 2021–2024. The 2016 entropy maximum coincided with the Moran's I minimum, marking the first surge as the most fragmented phase, followed by consolidation and renewed dispersal. Expansion clustered along the southern and south-eastern corridors, and built-up land grew almost twice as fast in the unplanned Rawalpindi District (+120.9%) as in the planned capital (+65.6%), which took 76.7% of net urban addition. The findings argue for green-belt enforcement on the Margalla fringe, corridor-focused infill, and conurbation-scale growth governance.

Keywords: urban expansion; urban sprawl; Shannon's entropy; Random Forest; planning regimes; Islamabad–Rawalpindi

Highlights

- Built-up land in the Islamabad–Rawalpindi conurbation doubled between 2011 and 2024
- New urban land was drawn mainly from vegetation, bare soil, and Margalla forest
- Growth was uneven: an early 2011–2016 surge, a slowdown, then a 2021–2024 peak
- The unplanned Rawalpindi District grew nearly twice as fast as the planned capital
- Entropy peak and Moran's I minimum flag the first surge as most fragmented

1. Introduction

Few processes reshape the land surface as extensively as urbanisation. A majority of the world's people now live in cities, and that share is expected to reach close to seventy per cent by 2050, with the sharpest increases falling in Asia and Africa (United Nations, 2019). Global urban land cover is projected to almost triple between 2000 and 2030, much of it advancing into biodiversity hotspots and carbon-rich landscapes (Seto et al., 2012), while cities on the whole grow at about twice the pace of their populations (Angel et al., 2011). As vegetated land, cropland, and bare soil give way to impervious surfaces, the biophysical, hydrological, and ecological behaviour of the landscape changes with them (Grimm et al., 2008), and because urban systems follow consistent regularities of size, scale, and shape, that change can be measured and compared systematically across regions (Batty, 2008). South Asia contains several of the fastest-growing agglomerations on Earth, where the form this growth takes, compact infill or dispersed and fragmented sprawl, has become a central question for sustainable land management.

Remote sensing has long served as the main source of consistent, repeatable observations of urban infrastructure (Jensen & Cowen, 1999), and impervious-surface mapping from satellite imagery is a well-established basis for tracking urban growth (Weng, 2012), while GIS supplies the analytical setting in which growth rates, directions, and morphological patterns are derived from those observations (Bhatta, 2010). In Pakistan, rapid and largely unregulated urban growth has produced substantial built-up expansion in major cities over recent decades (Wahab et al., 2023), documented for Lahore (Fahad et al., 2021), Peshawar (Tariq et al., 2022), the Simly watershed (Butt et al., 2015), and the Islamabad Capital Territory (Hassan et al., 2016), where over four decades the city's built-up area expanded by 377 km² (Shah et al., 2022), coming with measurable land degradation (Shah et al., 2021) and doubts about long-term sustainability (Liu et al., 2021). Newer cloud-based assessments have widened this evidence base, mapping built-up growth and its encroachment on vegetation and cropland with Random Forest classification in Google Earth Engine across Pakistani cities (Aslam et al., 2023; Latif et al., 2025), quantifying the national forest and carbon cost of urban conversion (Waleed et al., 2024), and projecting continued expansion with Landsat time series and predictive models (Duan et al., 2025; Farhan et al., 2024; Hussain et al., 2024; Tahir et al., 2025; Zhang et al., 2025).

Urban sprawl is generally taken to mean an unplanned, uneven, low-density style of outward growth that uses peripheral land inefficiently and breaks up the urban fabric, though its definition and measurement have been debated for decades (Galster et al., 2001); even so, there is

wide agreement that it can be quantified from remote sensing data through a set of spatial metrics (Bhatta et al., 2010a) computed from classified imagery (Herold et al., 2002, 2003; Tsai, 2005; Torrens, 2008). Of the available measures, Shannon's entropy is among the most widely used, since it reads the degree to which built-up land is dispersed or concentrated straight from classified imagery (Yeh & Li, 2001): high entropy points to dispersed, sprawling development and low entropy to compact, concentrated growth. Entropy-based measurement has since been combined with growth metrics for Indian cities (Sudhira et al., 2004; Bhatta, 2009; Jat et al., 2008). A further pair of indices, the Urban Expansion Rate (UER) and the Urban Expansion Intensity Index (UEII), express how quickly and how intensively built-up area grows relative to the size of the study unit, enabling objective comparison across intervals and units (Bhatta et al., 2010b). Recent work in Sustainable Cities and Society has taken these form-based measures further, organising the parameters used to describe three-dimensional urban morphology (Li & Zeng, 2024), quantifying urban form and its environmental effects (Mashhoodi & Muñoz Unceta, 2024), and characterising land transformation through sprawl metrics in South Asian settings (Alam & Banerjee, 2023).

Together these methods now support a large body of applied work across the developing world. Within South Asia, entropy-based measures and landscape metrics have quantified sprawl and urban dynamics across Indian cities and suburbs, from Cuttack, the Jalpaiguri agglomeration, Greater Silchar, and four medium-sized cities to Ghaziabad and Agartala (Barman et al., 2024; Chettry, 2022; Horo & Punia, 2019; Ismael, 2020; Mitra et al., 2023; Mohabey et al., 2024; Patra et al., 2022), and long-term monitoring and cellular-automata/Markov-chain models have traced the expansion of Delhi, its metropolitan growth corridors, Mumbai, and Indian cities more broadly, increasingly with machine-learning and cellular-automata forecasting of future growth (Bharath et al., 2018; Kumar et al., 2025; Rai & Kumar, 2025; Ramachandra et al., 2015, 2019; Shafizadeh Moghadam & Helbich, 2013; Sharma & Chandra, 2025). Elsewhere in the region, comparable work covers Greater Dhaka and its landscape fragmentation (Dewan & Yamaguchi, 2009; Dewan et al., 2012), the Kathmandu Valley (Ishtiaque et al., 2017; Thapa & Murayama, 2009), and the Kaski District of Nepal (Rimal et al., 2018), with parallel studies across Nairobi, Shiraz, Tripoli, Sana'a, Baguio City, Southeast Asian megacities, and Chinese urban regions (Al-shalabi et al., 2013; Alsharif & Pradhan, 2014; Estoque & Murayama, 2011, 2015; Mundia & Aniya, 2005; Sabet Sarvestani et al., 2011; Yu & Ng, 2007; Yue et al., 2013). The ecological price of this expansion recurs throughout the same literature, from the thermal effects of green-space loss and the drivers

of land surface temperature in South Asian cities (Barman et al., 2025; Basu & Das, 2023) to urbanisation-driven vegetation and habitat loss more broadly (Peng et al., 2024; Yang et al., 2020), anticipated through land-use and landscape-pattern simulation (Gao et al., 2022; Jiao et al., 2019).

Any such assessment stands on an accurate, multi-temporal land-use/land-cover (LULC) classification. Supervised classification followed by post-classification comparison remains the most transparent route to detecting land conversion, since it isolates the specific transitions that drive urban growth and produces a full transition matrix (Hussain et al., 2013; Singh, 1989). Classification trustworthiness is conventionally reported through the confusion matrix, overall accuracy, and the Kappa coefficient (Congalton, 1991), with measures matched to the map's purpose (Stehman, 1997) following recognised good practice (Congalton & Green, 2019; Foody, 2002; Olofsson et al., 2014) and a standardised, mutually exclusive class scheme (Anderson et al., 1976). Among the algorithms, Random Forest, an ensemble of decision trees that tolerates noise and assumes nothing about the data's distribution (Breiman, 2001), has become one of the most reliably accurate options for multi-temporal land-cover mapping (Belgiu & Drăguț, 2016), and cloud platforms such as Google Earth Engine now let such classifications run efficiently over large areas and long time series (Gorelick et al., 2017). Pairing Random Forest with Google Earth Engine has become a working standard for change detection and urban-growth assessment across South Asia (Feizizadeh et al., 2023; A. Patel et al., 2024; Pande, 2022; Pande et al., 2023; Tesfaye et al., 2024; Ullah et al., 2025; Zhao et al., 2024), including recent work in Sustainable Cities and Society combining this approach with thermal analysis to map urbanisation-driven surface warming and link land-use dynamics to land-surface temperature (Arunab & Mathew, 2024; Moazzam & Lee, 2024; S. Patel et al., 2024).

The Islamabad–Rawalpindi conurbation presents an unusual natural experiment in contrasting urban form, since both cities sit within one metropolitan region sharing a climate, topography, and economic catchment. Islamabad, a purpose-built planned capital laid out from the 1960s on a sectoral grid with mandated green space, grows under formal regulatory control, whereas Rawalpindi, its older and organically grown twin, has densified and sprawled with comparatively little planning oversight. A comparison of the two cities over 1990 to 2021 recorded rapid built-up gains at the expense of bare land in each, with Islamabad's growth held under tighter regulatory control (Kamran et al., 2023), and neural network forecasts point to further expansion of Islamabad's built-up area over the coming decade (Sarwar et al., 2025). Because the two units

lie side by side, the dynamics of regulated and unregulated growth can be compared directly, a comparison of real value to urban policy across the developing world: the bearing of planning instruments on land-use outcomes is well documented in Sustainable Cities and Society, where zoning plans have been shown to steer land-use change toward more sustainable configurations and multi-objective methods have drawn urban growth boundaries that hold sprawl in check (Domingo et al., 2021; Wang et al., 2020).

Individual studies have looked at land-cover change or single expansion metrics in Pakistani cities, but few have produced an integrated, multi-index assessment of urban expansion for the twin cities, one that measures the amount, rate, intensity, spatial form, and direction of growth at once and sets the planned and unplanned urban forms against each other within a single consistent framework. Integrated assessments of this kind exist for large Indian agglomerations, including the Mumbai Metropolitan Region (Patil et al., 2025), yet the planned–unplanned twin-cities setting of Islamabad–Rawalpindi has received little such attention. The present study fills that gap.

1.1. Objectives

The study sets out four objectives: (1) to map and quantify land-use/land-cover change across the Islamabad–Rawalpindi conurbation for 2011 to 2024 by Random Forest classification of six land-cover classes, backed by formal accuracy assessment; (2) to measure the rate and intensity of built-up expansion with the Urban Expansion Rate (UER) and the Urban Expansion Intensity Index (UEII) over successive intervals; (3) to describe the spatial form of growth through zone-based Shannon's entropy and to identify the leading directions of expansion by directional analysis; and (4) to compare the expansion dynamics of the planned (Islamabad Capital Territory) and largely unplanned (Rawalpindi District) urban forms.

1.2. Significance

The contribution is twofold. First, it treats the Islamabad–Rawalpindi conurbation as a natural experiment, comparing the spatial signature of two planning regimes while holding the physical setting broadly constant. Second, it draws LULC change detection, expansion indices, zone-based sprawl entropy, directional analysis, and spatial-cluster statistics into one comparative framework built entirely from freely available imagery and open-source tools, giving planning authorities a transferable instrument rather than a single index and providing descriptive evidence on how the rate and form of expansion co-vary with the regulatory regime, while recognising that

this administrative contrast also co-varies with development history and land availability. Read this way, the analysis ties local growth metrics to the wider monitoring agenda of SDG 11 (Akuraju et al., 2020).

2. Materials and Methods

2.1. Study Area

The study area is the Islamabad–Rawalpindi metropolitan region of northern Pakistan, comprising the Islamabad Capital Territory (ICT) and Rawalpindi District, which together form a continuous conurbation of about 6,118 km² on the Pothohar Plateau at the foot of the Margalla Hills (Figure 1). Islamabad is a purpose-built planned capital, developed from the 1960s on a sectoral grid with wide boulevards and large tracts of designated green and forested space, and grows under formal regulatory control. Rawalpindi is the older, organically grown twin, which has densified and pushed out into the surrounding district with comparatively little planning oversight. Since the two units share a climate, a topography, and an economic catchment, the conurbation is a well-controlled setting in which the mark left by two contrasting planning regimes on urban growth can be read directly. The region has a humid subtropical climate with a strong summer monsoon; its northern edge rises into the forested Margalla Hills, while the southern and western sectors open onto the cropland and bare-soil mosaic of the Pothohar plain. The two administrative boundary datasets differ modestly from the raster analysis extent due to minor boundary-dataset discrepancies, noted in the limitations.

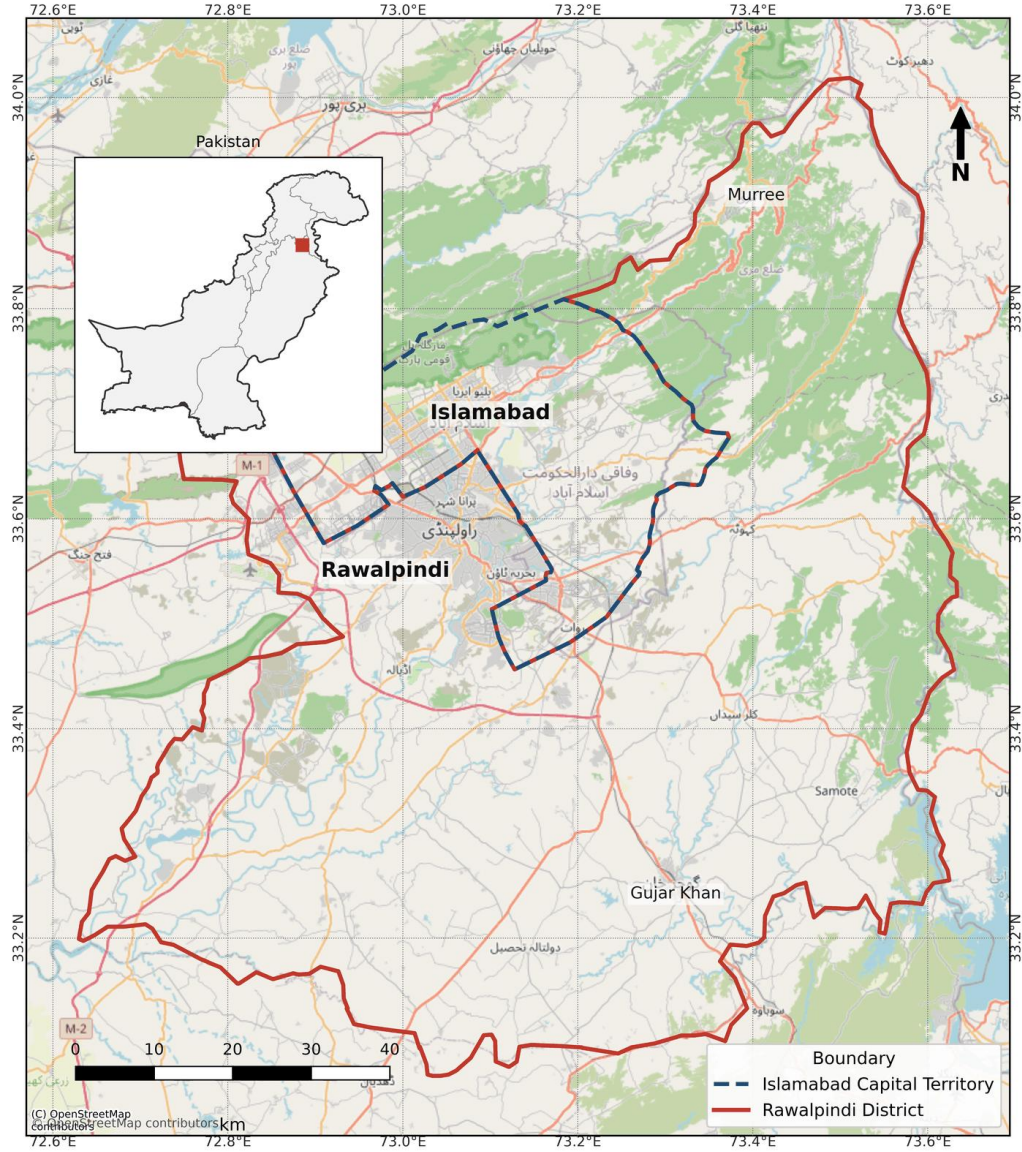


Fig. 1 Location of the study area: Islamabad Capital Territory and Rawalpindi District on the Pothohar Plateau

2.2. Satellite Data

Multi-temporal Landsat surface reflectance imagery mapped land use and land cover (LULC) for four reference years (2011, 2016, 2021, 2024), spaced to give roughly equal intervals. The 2011 imagery came from Landsat 5 TM and the later years from Landsat 8/9 OLI, all at 30 m resolution; reflectance differences between the TM/ETM+ and OLI sensor generations are small and well characterised, supporting a consistent multi-sensor time series (Roy et al., 2016). Every dataset was obtained as USGS Collection 2, Level-2 surface reflectance and processed on Google Earth Engine (Gorelick et al., 2017).

For each reference year, a single cloud-free composite was built instead of relying on individual scenes. All scenes acquired during the dry season (October to March) with scene-level cloud cover below 30% were gathered; cloud and cloud-shadow pixels were masked with the quality-assessment band, and the per-pixel median of the remaining observations served as the compositing statistic. Confining acquisition to the dry season limits cloud contamination and inter-date phenological variation, and median compositing damps residual atmospheric artefacts and short-lived surface conditions. The composites were clipped to the study-area boundary ahead of classification.

All analysis was carried out on the geographic WGS-84 graticule (EPSG:4326). Because pixel dimensions in geographic coordinates change with latitude, every areal statistic reported here was computed from latitude-dependent per-pixel areas rather than a fixed nominal pixel size.

2.3. Image Classification

A supervised classification was run independently for each reference year with the Random Forest (RF) classifier (Breiman, 2001), a non-parametric ensemble of decision trees that tolerates noise, assumes no normality in the training data, and has performed consistently well in land-cover classification from multispectral imagery (Belgiu & Drăguț, 2016). The classifier was implemented in GEE through the `smileRandomForest` algorithm, using 150 decision trees, four variables per split, a minimum leaf population of three, and a fixed random seed for reproducibility, applied to the surface-reflectance bands of the annual composites. Six land-cover classes were defined under a standardised, mutually exclusive scheme (Anderson, Hardy, Roach, & Witmer, 1976), listed in Table 1.

Table 1. Land-cover classification scheme.

Code	Class	Description
1	Waterbody	Rivers, reservoirs, ponds
2	Urban (built-up)	Residential, commercial, and industrial areas, roads, other impervious surfaces
3	Forest	Dense natural tree cover, principally the Margalla Hills
4	Bare Soil	Exposed soil, fallow land, rock, cleared ground
5	Cropland	Cultivated and agricultural land
6	Vegetation	Grass, shrubs, and mixed low or sparse vegetation

Training data were drawn as 10 to 15 polygons per class per year by visual interpretation of the Landsat composites, aided by high-resolution Google Earth reference imagery and spread across the study area to capture each class's spectral variability. Labelled samples were split randomly into 80% for training and 20% for internal testing ahead of the formal accuracy assessment below,

and the trained classifier was applied to the full composite of the matching year to produce the six-class LULC map.

2.4. Accuracy Assessment

The thematic accuracy of each classified map was tested against an independent, stratified sample of 450 reference points per year, split evenly among the six classes and labelled by visual interpretation of high-resolution imagery, following good-practice recommendations for accuracy assessment (Olofsson et al., 2014). The resulting confusion matrix yielded the overall accuracy, the producer's and user's accuracies, and the Kappa coefficient (Congalton, 1991), with measures chosen to suit the change-detection purpose of the maps (Stehman, 1997) and read against the benchmarks of Landis and Koch (1977), under which 0.61 to 0.80 marks substantial agreement, following standard procedural guidance throughout (Congalton & Green, 2019). Because class areas came from pixel counting rather than the error-adjusted estimators of Olofsson et al. (2014), the reported areas carry classification uncertainty, noted in the limitations.

2.5. Change Detection

Land-cover change was measured by post-classification comparison, overlaying the independently classified maps of two dates pixel by pixel to read off class transitions (Singh, 1989), which keeps the advantage of producing a full class-to-class transition matrix (Hussain et al., 2013). The 2011 to 2024 transition matrix established the sources of new built-up land, the persistence of the 2011 urban surface, and the exchanges among non-urban classes.

2.6. Expansion Rate & Intensity

The built-up class was extracted from each classified map to give the urban area of every reference year. Two complementary indices were then computed for each interval (Bhatta et al., 2010b). The Urban Expansion Rate (UER) gives the mean annual addition of built-up land:

$$UER = (A_{t2} - A_{t1}) / T \quad (1)$$

where A_{t1} and A_{t2} are the built-up areas (km^2) at the start and end of the interval and T is the interval length in years. The Urban Expansion Intensity Index (UEII) normalises this rate by the total land area of the spatial unit, enabling objective comparison across intervals and between spatial units of different size:

$$UEII = [(A_{t2} - A_{t1}) / (T \times TLA)] \times 100 \quad (2)$$

where TLA is the total land area of the unit (km^2). Both indices were computed for the three successive intervals (2011–2016, 2016–2021, 2021–2024) and for the full period.

2.7. Measuring Sprawl

The degree of urban sprawl was quantified using Shannon's entropy, which measures the extent to which built-up land is dispersed or concentrated across n spatial sub-zones of the study area (Yeh & Li, 2001) and is among the most widely applied sprawl metrics derivable from classified imagery (Bhatta et al., 2010a):

$$H = -\sum p_i \ln p_i \quad (3)$$

where p_i is the proportion of the total built-up area located in zone i . For the spatial zoning, the study area was partitioned into 14 concentric annular rings of 5 km width centred on the geometric core of the conurbation (the Islamabad–Rawalpindi urban junction) and clipped to the study boundary, so that each ring constitutes one entropy zone ($n = 14$). The relative entropy, obtained by dividing H by its maximum $\ln(n)$, scales the measure to the 0–1 range; values above 0.5 are conventionally taken to indicate a dispersed, sprawling urban form, and values approaching 0 a compact, concentrated form. Entropy was computed for each reference year from the latitude-corrected built-up area within each ring, so that the temporal trajectory of urban form could be traced.

2.8. Directional Growth

To fix the orientation of expansion, the study area was split into eight directional sectors, 45° wedges centred on the conurbation core and aligned to the cardinal and intercardinal directions. The latitude-corrected built-up area within each sector was tabulated for every reference year, and inter-date differences were used to establish the leading directions of growth. The results are presented as a directional (rose) diagram.

2.9. Spatial Clustering

The spatial structure of the built-up surface was examined for each reference year with global and local spatial statistics, computed on the binary built-up raster using a row-standardised queen-contiguity spatial weights matrix in the Python PySAL ecosystem (libpysal and esda; Rey & Anselin, 2007). Global Moran's I (Moran, 1948; Cliff & Ord, 1973) tested whether built-up land was clustered, dispersed, or randomly distributed; Local Indicators of Spatial Association (LISA; Anselin, 1995) located statistically significant high–high and low–low clusters and spatial outliers; and the Getis–Ord G_i^* statistic (Getis & Ord, 1992; Ord & Getis, 1995) picked out hot spots and cold spots of built-up concentration. Significance was judged by permutation testing (499 permutations for the global statistic, 299 for the local statistics) at the 95% confidence level.

2.10. Planned vs. Unplanned

City-level statistics were computed separately inside the Islamabad Capital Territory and Rawalpindi District boundaries, so that the planned and unplanned urban forms could be compared directly on absolute growth, relative growth, expansion rate, and built-up share of territory. Because the intermediate-date classifications show localised variability, clearest on the south-western periphery in 2016, the city-level comparison rests on the 2011 and 2024 endpoint years. Figure 2 sets out the full analytical workflow.

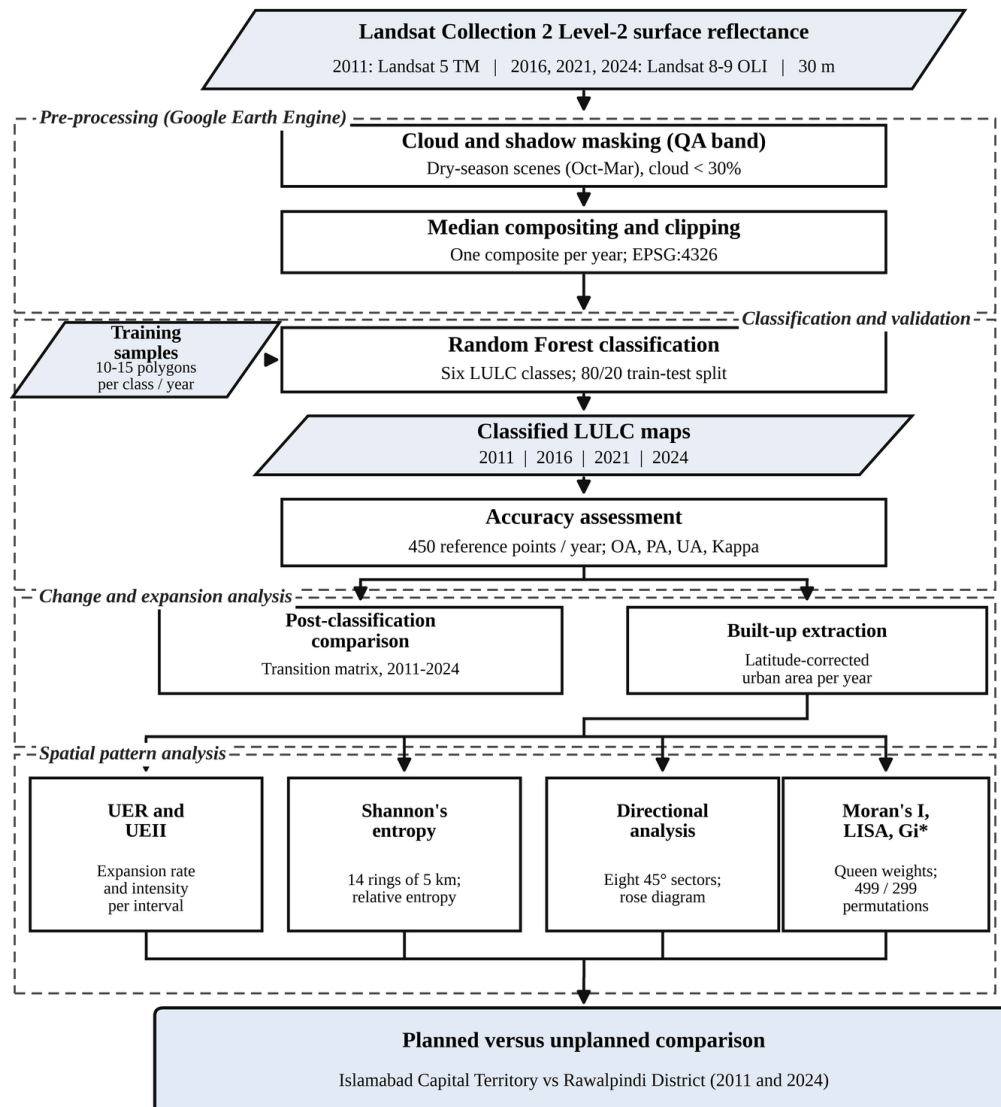


Fig. 2 Methodological workflow of the urban expansion analysis

3. Results

3.1. Classification Accuracy

The supervised Random Forest classification produced six-class LULC maps for 2011, 2016, 2021, and 2024 across the Islamabad–Rawalpindi conurbation (Figure 3). The broad structure of the landscape held together across all four dates: dense forest occupies the northern Margalla Hills, the continuous built-up mass of the twin cities dominates the centre, and a mosaic of bare soil, cropland, and mixed vegetation covers the southern and western sectors of the Pothohar plain.

The classifications reached overall accuracies of 78.0–81.3% across the four dates, with Kappa coefficients of 0.736–0.776, each assessed against 450 stratified random reference points per year. These Kappa values place the classified maps in substantial agreement with the reference data (Landis & Koch, 1977). Class-specific producer's and user's accuracies appear in Table 2. The built-up class, the focus of the expansion analysis, was mapped with consistently high user's accuracy and moderate producer's accuracy, meaning that pixels labelled urban were usually correct while some low-density and peripheral development went unmapped. The main source of confusion throughout the series lay between cropland and bare soil, a consequence of the spectral similarity between fallow or recently ploughed fields and bare surfaces in the dry-season composites; it peaked in 2024 and accounts for most of that year's drop in overall accuracy, but since it is largely confined to the non-urban classes it bears little on the delineation of built-up land, which held its second-highest user's accuracy of the series that year.

Table 2. Accuracy assessment of the LULC classifications, 2011 to 2024. PA = producer's accuracy; UA = user's accuracy.

Class	2011 PA	2011 UA	2016 PA	2016 UA	2021 PA	2021 UA	2024 PA	2024 UA
Waterbody	85.3	98.5	86.5	100.0	88.0	100.0	82.7	98.4
Urban (built-up)	74.7	91.8	76.0	74.0	74.7	83.6	70.7	86.9
Forest	96.0	79.1	98.7	96.1	96.0	81.8	100.0	78.1
Bare soil	81.3	67.0	80.0	74.1	89.3	65.1	88.0	63.5
Cropland	69.3	92.9	52.0	92.9	62.7	92.2	46.7	85.4
Vegetation	78.7	68.6	92.0	63.9	77.3	77.3	80.0	70.6
Overall accuracy (%)	80.9		80.9		81.3		78.0	
Kappa	0.771		0.770		0.776		0.736	

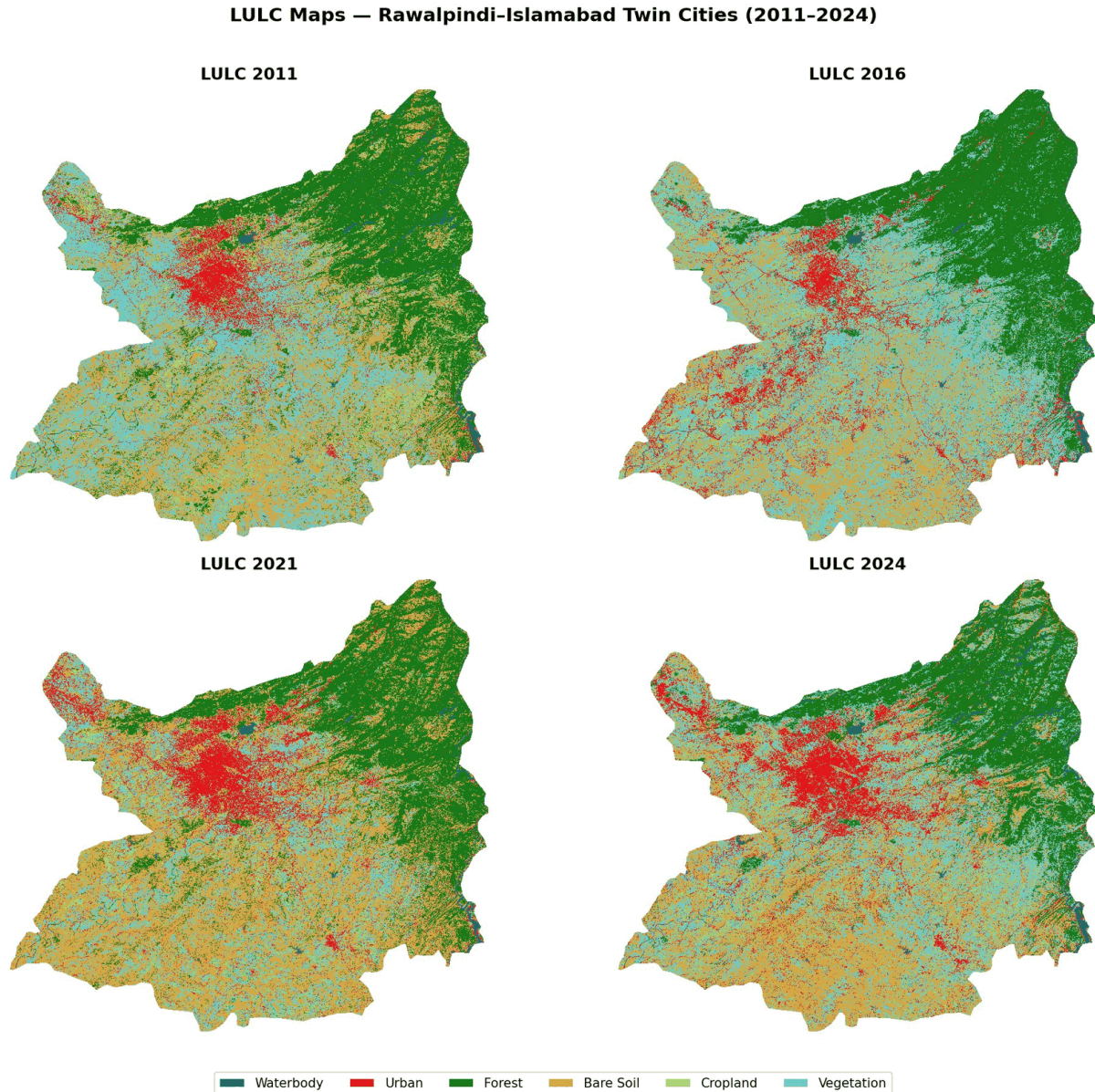


Fig. 3 Land-use/land-cover maps of the Islamabad–Rawalpindi conurbation for 2011, 2016, 2021, and 2024, classified into six classes

3.2. Composition & Net Change

Class-wise area statistics (Table 3, Figure 4) point to substantial land-cover change over the study period. The largest change in any class was in the built-up category, which nearly doubled over thirteen years (Table 3). This expansion ran alongside a marked contraction of forest cover, concentrated along the forest–urban fringe of the lower Margalla Hills, while cropland edged up, waterbody moved with reservoir levels at the acquisition dates, and bare soil and vegetation were close to stable overall. The intermediate dates show that the non-urban classes did not follow steady trends: bare soil, cropland, and vegetation each swung between observation dates, a

reflection of inter-date differences in rainfall timing and surface condition within the dry-season compositing window rather than of real land conversion. The built-up class, by contrast, rose at every step; this steady gain against a fluctuating non-urban background is the clearest sign of sustained urban expansion in the conurbation, and it sets up the interval-based analysis that follows.

Table 3. Class-wise area (km²) and share of the study area (%), 2011 to 2024, with net change.

Class	2011 km ²	2011 %	2016 km ²	2021 km ²	2024 km ²	2024 %	Net km ²
Waterbody	55.6	0.91	45.9	35.4	68.5	1.12	+12.9
Urban (built-up)	383.9	6.27	583.7	639.2	772.1	12.62	+388.2
Forest	1,646.1	26.91	1,496.3	1,542.6	1,309.0	21.40	-337.1
Bare soil	1,867.0	30.52	1,317.8	2,443.5	1,824.0	29.81	-43.0
Cropland	393.7	6.44	316.8	439.8	422.8	6.91	+29.1
Vegetation	1,771.3	28.95	2,357.3	1,017.1	1,721.4	28.14	-49.9
Total	6,117.6	100	6,117.8	6,117.6	6,117.8	100	

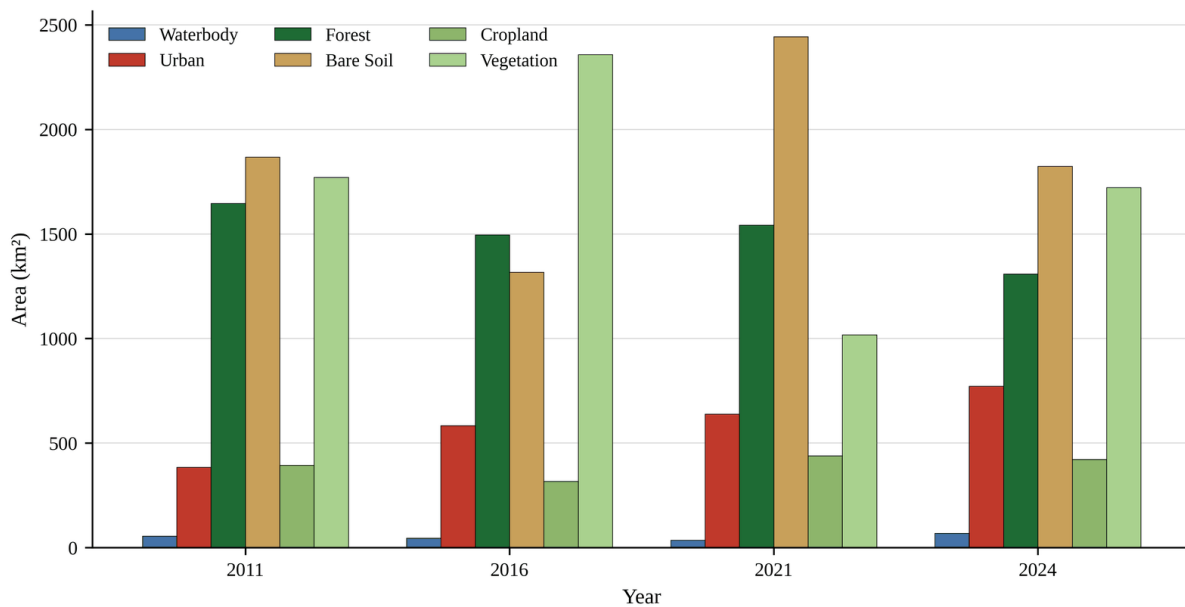


Fig. 4 Land-cover class area (km²) for each reference year, 2011 to 2024

3.3. Transitions & Land Sources

The 2011 to 2024 transition matrix (Table 4) traces where the new built-up land came from. Natural vegetation was the single largest donor (59.5% of all conversion to urban), followed by bare soil (18.7%) and forest (18.0%), with cropland and waterbody contributing only marginally. That vegetation and bare soil supplied most of the land shows expansion moving mainly across peri-urban scrub, rangeland, and open ground at the urban fringe, while the forest loss taken together with the 20.5% net forest decline marks the wooded slopes around the conurbation as the land resource under the greatest pressure. Of the land mapped as urban in 2011, most remained urban in 2024; the apparent reversion of a small share of 2011 urban pixels to non-urban classes

is driven by mixed boundary pixels at the edges of built-up patches rather than by real de-urbanisation, and is treated as a classification limitation in Section 4.6. The matrix also shows substantial exchange among the bare soil, cropland, and vegetation classes, consistent with the cyclic cultivation and clearance dynamics noted in Section 3.2.

Table 4. Land-cover transition matrix, 2011 to 2024 (km²). Rows denote the 2011 class and columns the 2024 class.

2011 \ 2024	Waterbody	Urban	Forest	Bare soil	Cropland	Vegetation
Waterbody	41.7	4.3	8.9	0.2	0.1	0.4
Urban	1.9	269.5	5.5	35.5	17.6	54.0
Forest	22.1	90.6	1,243.7	73.3	3.6	212.7
Bare soil	1.3	93.9	24.1	997.7	125.0	625.0
Cropland	0.3	14.5	19.4	82.6	32.3	244.5
Vegetation	1.1	299.2	7.4	634.7	244.1	584.7

3.4. Urban Extent & Pattern

The urban-extent maps (Figure 5) isolate the built-up class at each date and show a steady outward advance from the dense central core: in 2011 the urban footprint sat mainly around the Rawalpindi–Islamabad centre with only sparse peripheral development, while by 2024 the urban mass had thickened at the core and reached outward along the main transport corridors into the adjacent plain. The bi-temporal change composite (Figure 6) shows conversion to built-up land strongest in the central and southern sectors, where vegetation, cropland, and bare soil were displaced, while the forested northern belt stayed broadly stable apart from localised fringe encroachment. The pattern reflects two growth modes at once, infill and edge expansion radiating from the established core alongside scattered peripheral development sharpest during the rapid growth phases, a duality the entropy and spatial-autocorrelation analyses quantify in Sections 3.6 and 3.8.

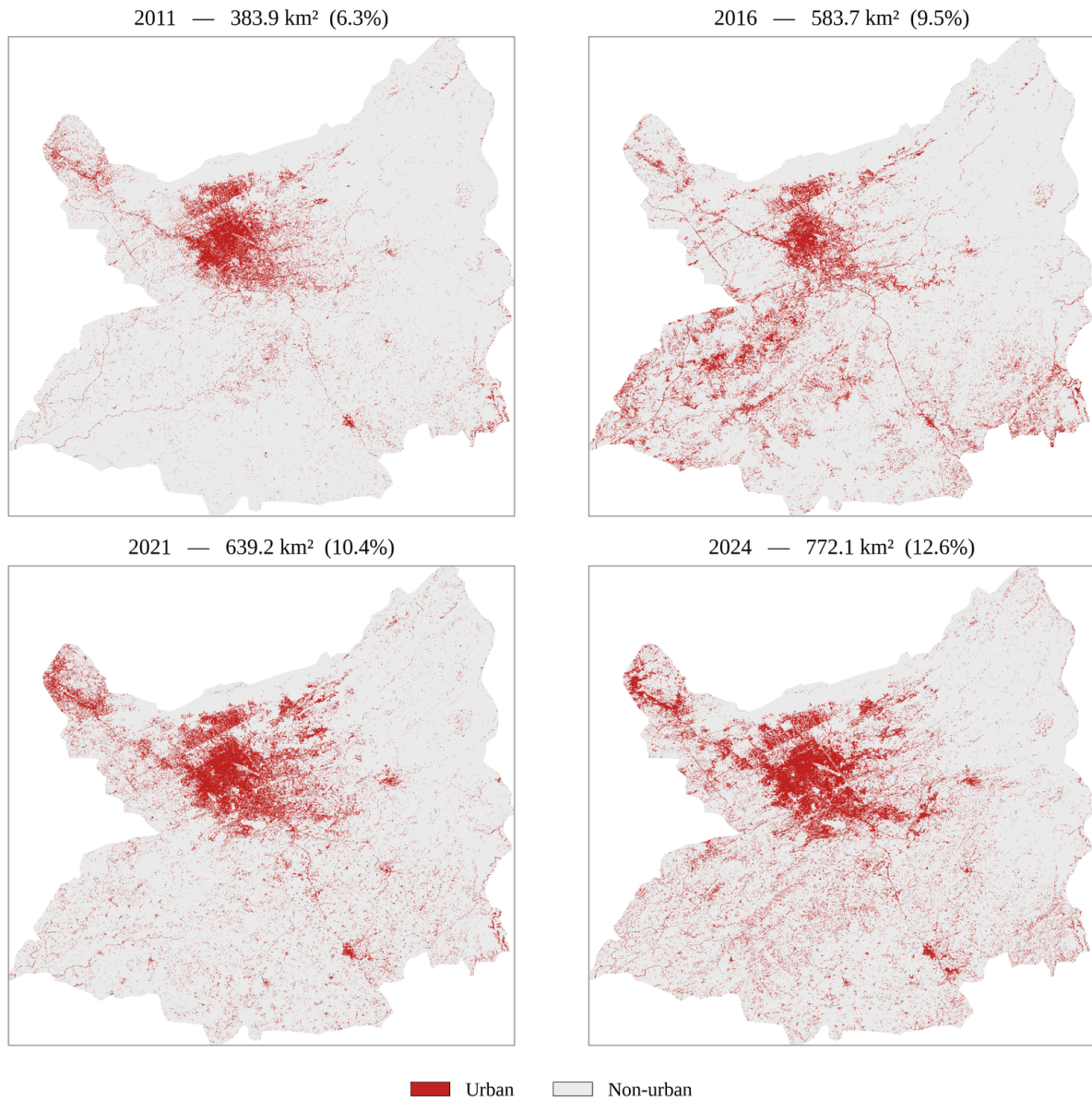


Fig. 5 Urban extent of the conurbation for 2011, 2016, 2021, and 2024, with built-up area and its percentage of the study area

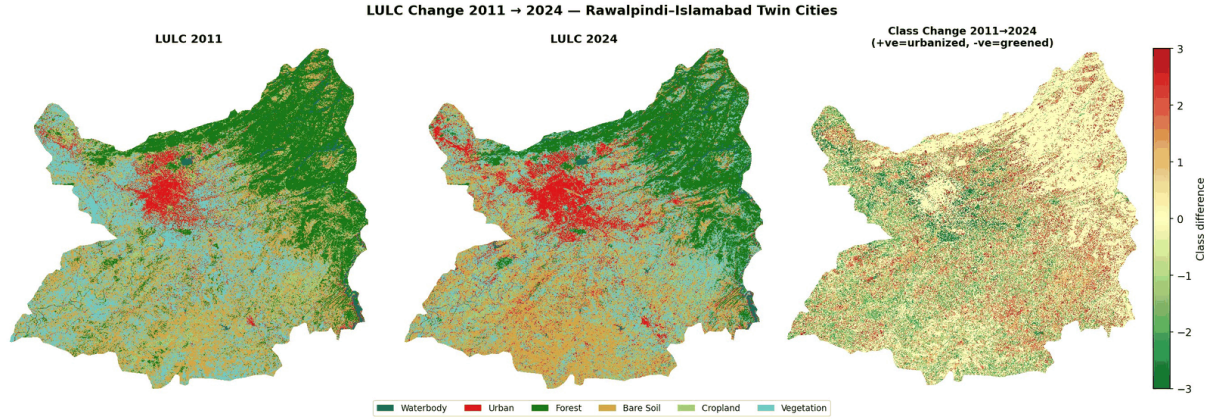


Fig. 6 Land-cover change between 2011 and 2024, showing the per-pixel class difference (positive values indicate urbanization)

3.5. Expansion Rate & Intensity

Built-up accumulation was distinctly uneven over the study period (Table 5; Figures 7 and 8). The first interval (2011–2016) saw a rapid 52.0% rise, growth then slowed sharply in 2016–2021, a span that overlaps the COVID-19 disruption of construction though the slowdown cannot be pinned on the pandemic alone, before expansion climbed to the fastest rate of the record in 2021–2024. Across the full period the conurbation added built-up land at a mean rate of about 30 km² per year. That the UER and UEII agree in naming 2021–2024 the most active interval shows recent growth to be both large in absolute terms and intense relative to the size of the study area. This three-phase pattern, an opening surge, a middle deceleration, and a late resurgence, shows urban growth to have been uneven rather than continuous, with the most intense episode falling in the final and shortest interval.

Table 5. Urban Expansion Rate (UER) and Urban Expansion Intensity Index (UEII) by interval, 2011 to 2024.

Interval	Urban start (km ²)	Urban end (km ²)	Change (km ²)	Change (%)	UER (km ² yr ⁻¹)	UEII (% yr ⁻¹)
2011-2016	383.9	583.7	+199.8	52.0	+39.9	0.653
2016-2021	583.7	639.2	+55.5	9.5	+11.1	0.182
2021-2024	639.2	772.1	+132.9	20.8	+44.3	0.724
2011-2024	383.9	772.1	+388.2	101.1	+29.9	0.488

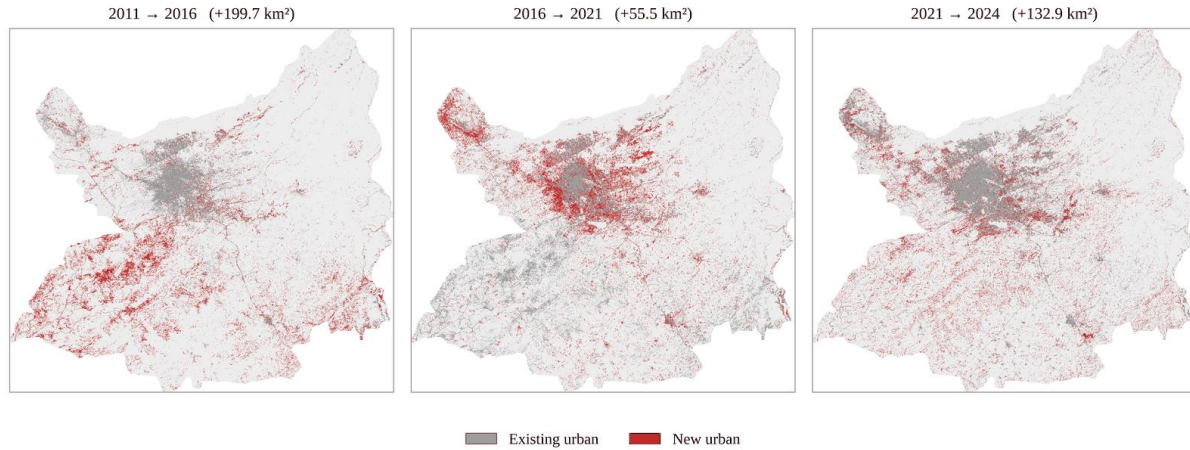


Fig. 7 Urban expansion across the three intervals, distinguishing existing built-up land from newly urbanised land.

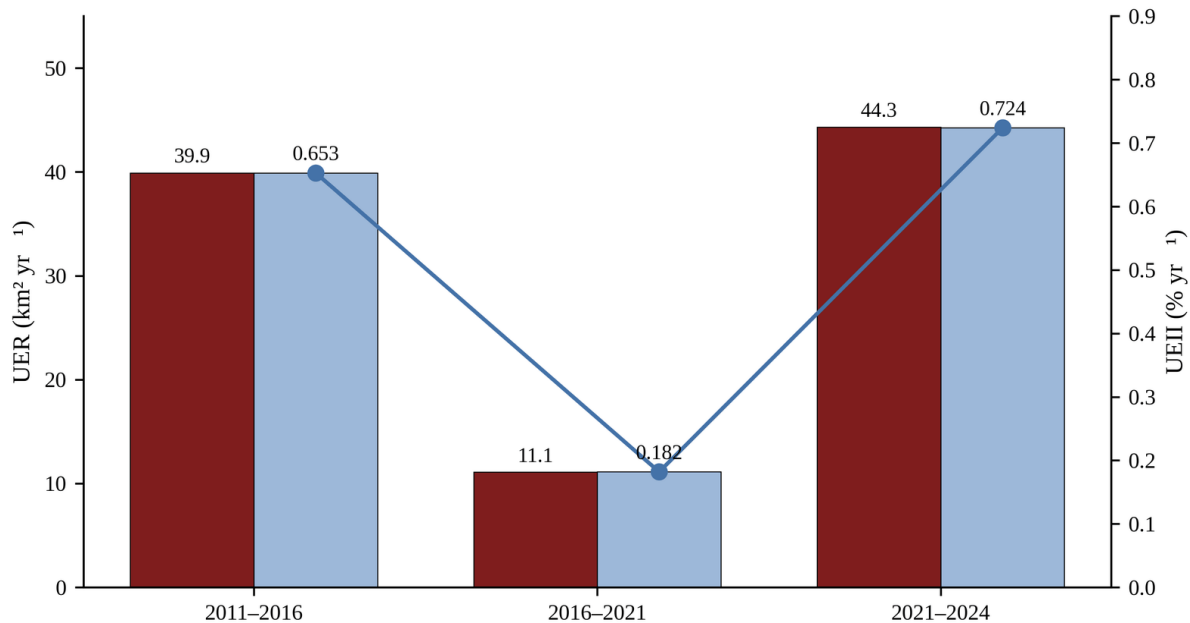


Fig. 8 Urban Expansion Rate (UER) and Urban Expansion Intensity Index (UEII) across the three study intervals

3.6. Urban Sprawl

Relative Shannon's entropy, computed over 14 concentric 5 km rings, stayed high throughout the study period, which points to a persistently dispersed built-up form (Table 6; Figure 9). Every value sits well above the 0.5 threshold conventionally used to separate compact from sprawling development (Bhatta et al., 2010a; Yeh & Li, 2001). Entropy peaked in 2016, showing the rapid 2011–2016 surge (Section 3.5) to have been the most spatially dispersed phase of the record, as new built-up land in that interval scattered widely across the rings rather than gathering around the existing cores. The partial fall by 2021 marks a phase of relative infill and consolidation,

after which the renewed acceleration in 2021–2024 again came with greater dispersal. This trajectory tracks that of the global spatial-autocorrelation statistic in Section 3.8, where the 2016 minimum in Moran's I lines up with the entropy maximum, both signalling maximal fragmentation during the first growth surge.

Table 6. Zone-based Shannon's entropy of built-up land, 2011 to 2024 (n = 14 concentric rings of 5 km width; $H_{\max} = \ln 14 = 2.639$).

Year	Shannon H	H _{max}	Relative entropy	Urban (%)	Sprawl level
2011	2.272	2.639	0.861	6.3	High
2016	2.563	2.639	0.971	9.5	High
2021	2.387	2.639	0.904	10.4	High
2024	2.464	2.639	0.934	12.6	High

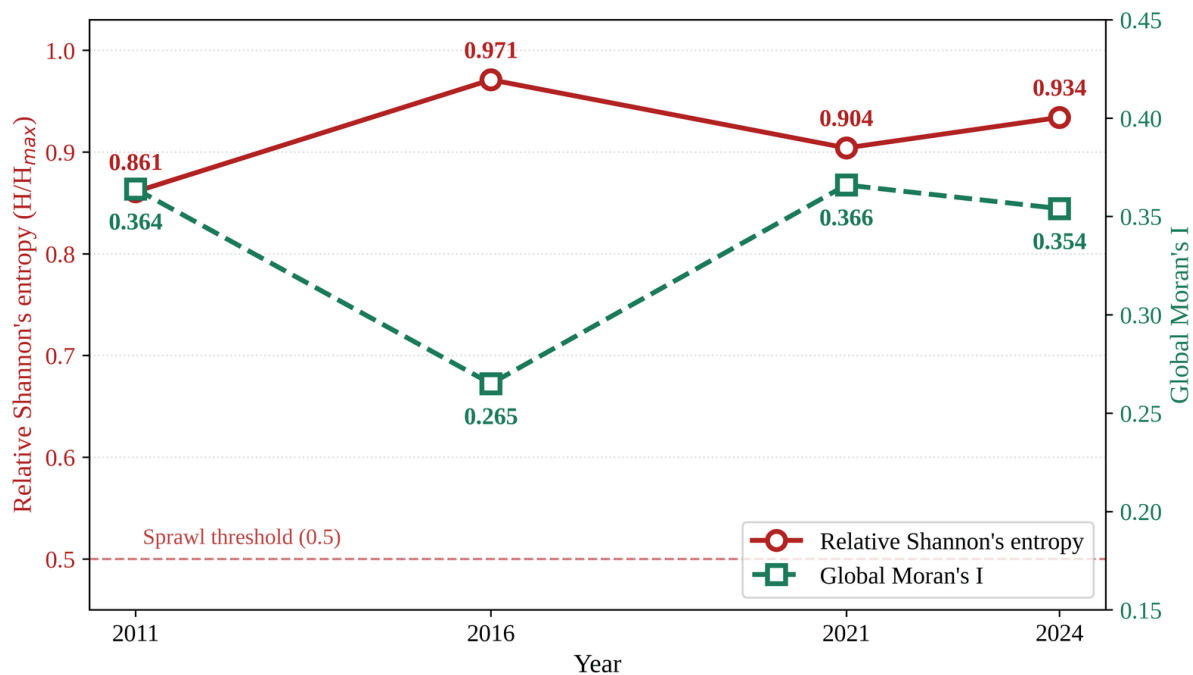


Fig. 9 Temporal trends in relative Shannon's entropy and global Moran's I of built-up land, 2011 to 2024

3.7. Directional Growth

The directional distribution of built-up land (Table 7; Figure 10) shows expansion to have been strongly anisotropic. Growth was heavily concentrated in the southern and south-eastern sectors, which more than doubled and together trace Rawalpindi's expansion toward the Gujar Khan and Grand Trunk Road corridors, while the south-western, western, and eastern sectors made intermediate gains, in line with development along Islamabad's western fringe and the Taxila corridor. Expansion northward was blocked by the Margalla Hills, so the northern sector showed no net gain. The high southern and south-western figures for 2016, and their apparent fall by 2021, partly reflect the localised classification variability of that year on the south-western periphery

(Section 4.6); the directional pattern is therefore read from the 2011 to 2024 endpoint change rather than from any single intermediate date. The dominant south-to-south-east axis of growth matches the concentration of unregulated peripheral development within Rawalpindi District identified in Section 3.9.

Table 7. Built-up area (km²) within eight 45-degree directional sectors centred on the conurbation core, 2011 to 2024.

Sector	2011	2016	2021	2024	Change 2011-2024
North	13.9	11.8	16.1	12.9	-1.0
North-east	17.7	21.8	40.5	38.9	+21.2
East	28.0	20.6	56.4	61.6	+33.6
South-east	89.2	136.4	160.0	188.0	+98.8
South	94.2	182.4	145.3	207.5	+113.3
South-west	65.1	151.0	93.9	127.2	+62.1
West	47.8	37.6	84.7	98.8	+51.0
North-west	28.1	22.4	42.6	37.6	+9.5

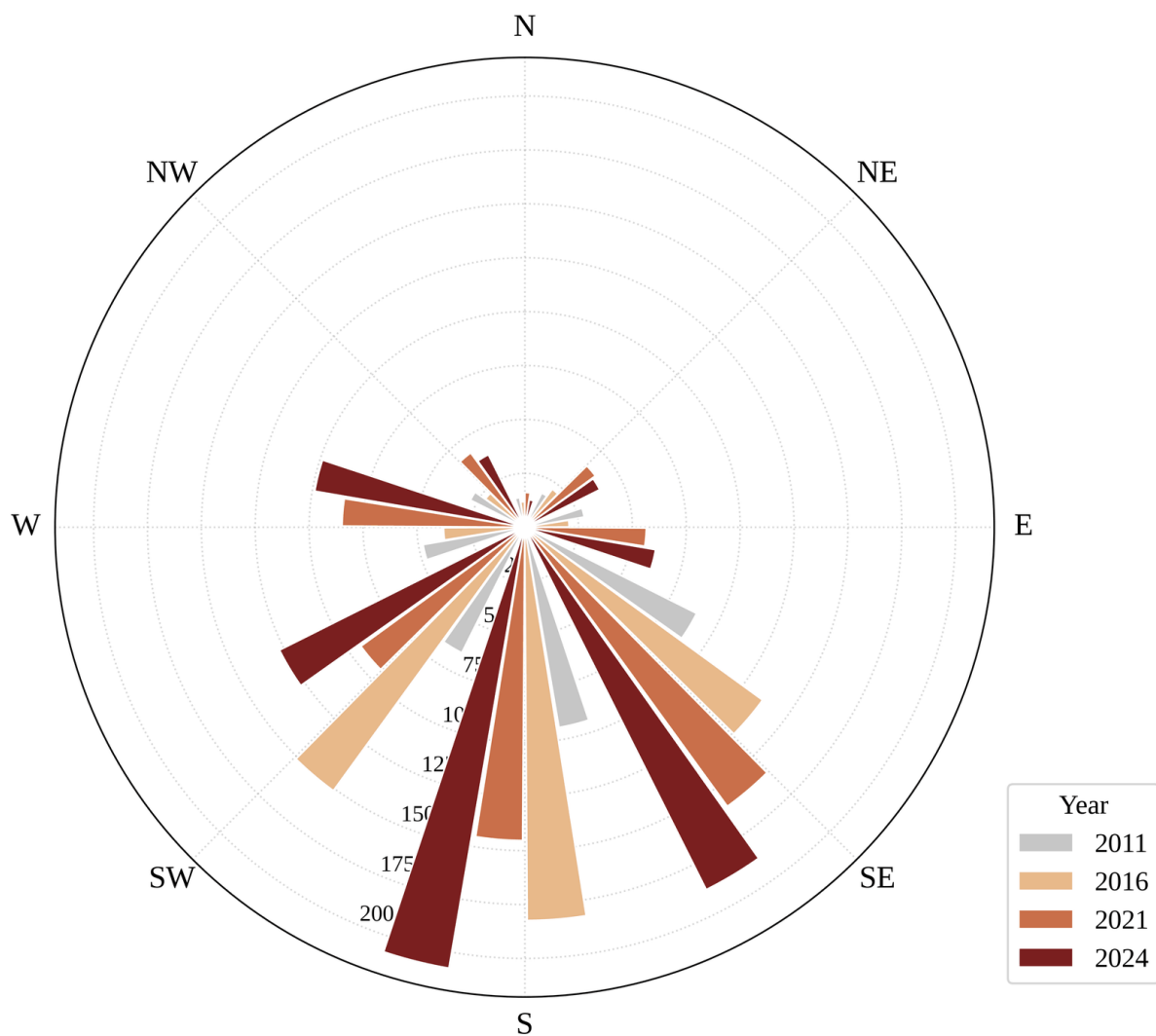


Fig. 10 Directional (rose) diagram of built-up area (km²) within eight 45-degree sectors centred on the urban core, 2011 to 2024

3.8. Spatial Clustering

Global Moran's I confirmed that the built-up surface was significantly clustered, not randomly distributed, in every reference year (Table 8), staying positive and highly significant throughout under 499 permutations. The pronounced dip in 2016 fits the character of the 2011–2016 surge: a large volume of new development arrived in a comparatively scattered, leapfrog pattern that briefly diluted global clustering, after which infill and consolidation over the slower 2016–2021 interval brought Moran's I back to its earlier level. This 2016 minimum coincides with the entropy maximum in Section 3.6, the two statistics independently naming the first surge the most fragmented phase of expansion.

Table 8. Global Moran's I of the built-up surface, 2011 to 2024. p-values are pseudo p-values from 499 permutations.

Year	Moran's I	p-value	Pattern
2011	0.364	0.002	Clustered
2016	0.265	0.002	Clustered
2021	0.366	0.002	Clustered
2024	0.354	0.002	Clustered

The LISA cluster maps (Figure 11) place this clustering, showing a persistent and strengthening high–high built-up cluster over the Rawalpindi–Islamabad core, ringed by an expanding transitional band of outlier zones at the urban fringe that is the spatial signature of active edge expansion. The Getis–Ord Gi* hot spot analysis (Figure 12) reinforces the picture, with statistically significant hot spots massed over the central core and reaching outward along the main growth corridors across successive years. Read together, the global and local statistics show expansion organised around a strengthening central cluster rather than proceeding as spatially uniform or fully dispersed development, a paired dynamic of core consolidation with fringe dispersal.

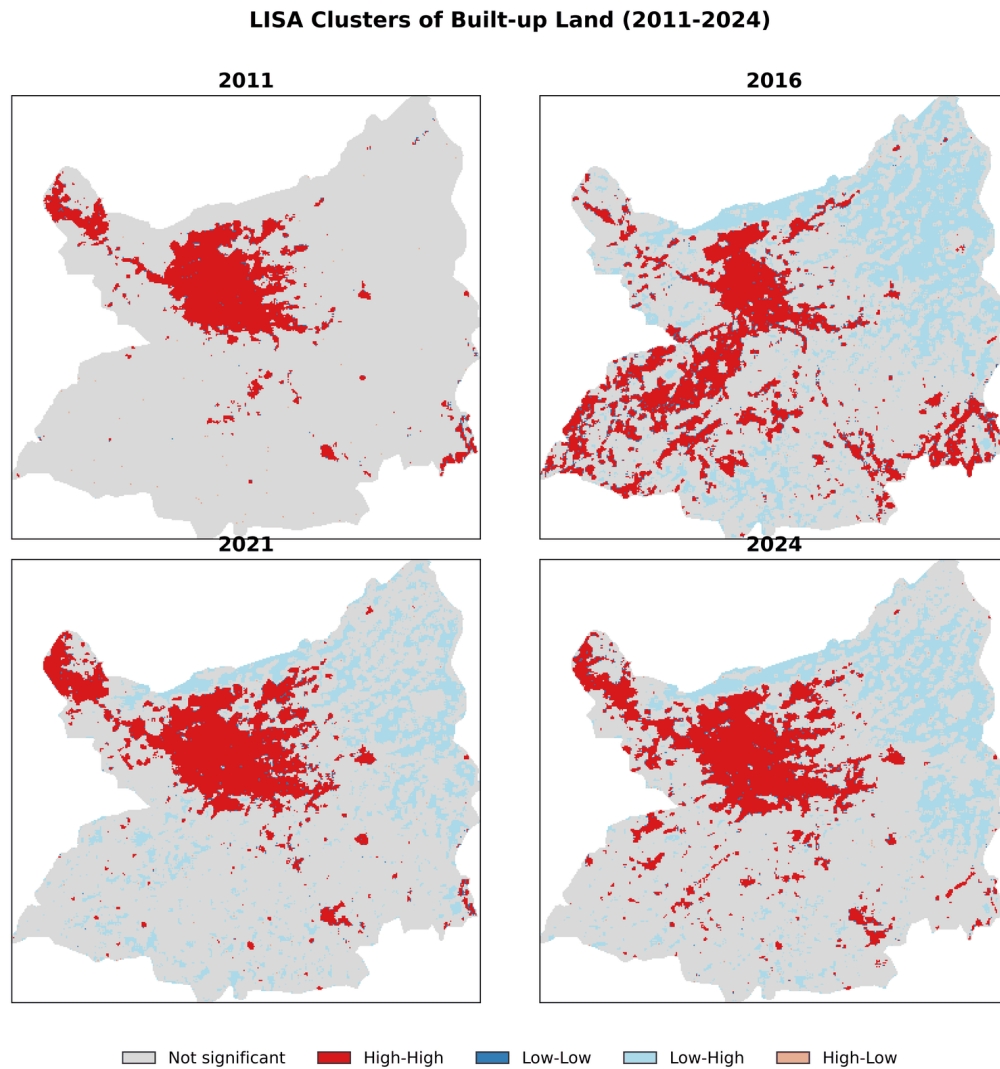


Fig. 11 Local Moran's I (LISA) urban cluster maps for 2011 to 2024

Getis-Ord Gi* Hot and Cold Spots of Built-up Land (2011-2024)

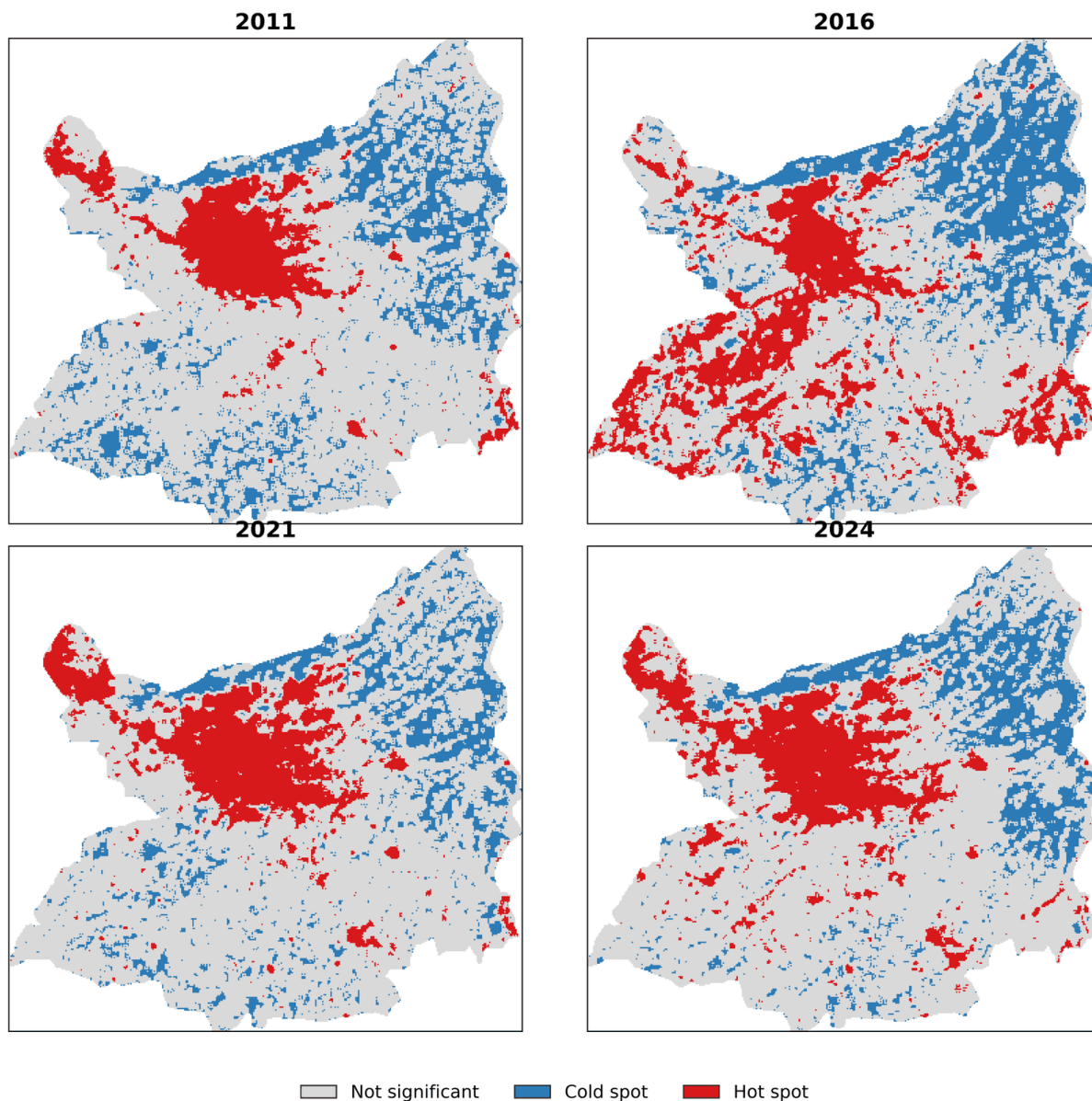


Fig. 12 Getis–Ord Gi* urban hot spot maps for 2011 to 2024

3.9. Planned vs. Unplanned Growth

City-level statistics computed inside the Islamabad Capital Territory and Rawalpindi District put a figure on the contrast between the two planning regimes (Table 9). Between 2011 and 2024, built-up land within the planned capital grew by 65.6%, while the largely unplanned district grew by 120.9%, nearly twice the relative rate, and took in 76.7% of all net urban addition across the conurbation. Islamabad thus remains the more intensively urbanised unit in proportional terms, a reflection of its compact administrative extent and regulated core, while Rawalpindi holds

both the larger absolute built-up area and the substantially faster expansion, consistent with its comparatively light planning oversight. Because of the localised classification instability on the south-western periphery in 2016 (Section 4.6), the city-level comparison rests on the 2011 and 2024 endpoint years.

Table 9. Built-up area within the Islamabad Capital Territory (planned) and Rawalpindi District (largely unplanned), 2011 and 2024.

Unit	Area (km ²)	Urban 2011 (km ²)	Urban 2011 (%)	Urban 2024 (km ²)	Urban 2024 (%)	Growth (%)
Islamabad Capital Territory	897.8	137.6	15.3	227.9	25.4	+65.6
Rawalpindi District	5,211.0	246.3	4.7	544.2	10.4	+120.9
Conurbation total	6,108.8	383.9	6.3	772.1	12.6	+101.1

3.10. Urban Form: Fragmentation and Compactness

To measure the physical form of built-up growth directly rather than infer it from administrative labels, class-level landscape metrics were computed for the built-up class within each administrative unit for 2011 and 2024 from the classified maps. Six complementary indices were derived, following standard landscape-metric definitions (McGarigal & Marks, 1995; He, DeZonia, & Mladenoff, 2000): the number of patches, patch density, edge density, mean patch area, the largest patch index, and the aggregation index, with the density metrics normalised by the area of the respective administrative unit (Table 10).

The two units follow contrasting trajectories of urban form (Table 10). Within the planned Islamabad Capital Territory, built-up land became more consolidated over the study period: although its built-up area grew by roughly 70%, the number of built-up patches fell, the mean patch area doubled, and the aggregation index rose, the signature of infill-oriented, contiguous growth. Within the largely unplanned Rawalpindi District, built-up land stayed fragmented: its built-up area grew by about 117%, yet the number of patches rose in step, the mean patch area remained small, and the aggregation index changed little. The opposing movement of area and patch count between the two units, area rising while patches fall in the planned territory and area and patches rising together in the unplanned district, provides direct, measured evidence of the compact-versus-fragmented contrast interpreted in Section 4 in terms of the two planning regimes.

Table 10. Class-level landscape metrics for the built-up class in the planned Islamabad Capital Territory and the unplanned Rawalpindi District, 2011 and 2024.

	ICT 2011	ICT 2024	Rawalpindi 2011	Rawalpindi 2024
Number of patches	12,718	10,611	40,393	68,958
Patch density (n per 100 ha)	14.17	11.82	7.75	13.23
Edge density (m per ha)	75.76	88.34	25.84	52.66

Mean patch area (ha)	1.03	2.09	0.63	0.80
Largest patch index (%)	6.00	10.72	2.08	2.98
Aggregation index (%)	61.16	73.39	60.36	62.74

3.11. Summary of Growth Patterns

Read as a whole, the results describe a conurbation whose built-up area doubled between 2011 and 2024, expanding unevenly in time, strongly anisotropic in direction, and combining high spatial dispersion at the fringe with strong, persistent clustering around a central core. This paired character, fringe dispersal alongside core consolidation, is the central spatial finding of the analysis and frames the planned-versus-unplanned reading developed in the Discussion.

4. Discussion

4.1. A Conurbation Doubled

The results record a substantial restructuring of the land surface across the Islamabad–Rawalpindi conurbation between 2011 and 2024. The near-doubling of built-up land sets the twin cities among the fastest-expanding urban regions of South Asia and sits comfortably alongside trajectories reported for other Pakistani cities over comparable spans, including Islamabad itself across the longer 1979–2019 period (Shah et al., 2022; Wahab et al., 2023) and Lahore between 2000 and 2020 (Fahad et al., 2021). The scale of change matches that reported for other regional capitals, among them Greater Dhaka (Dewan & Yamaguchi, 2009), the Kathmandu Valley (Ishtiaque et al., 2017; Thapa & Murayama, 2009), and Indian megacities tracked over similar periods (Ramachandra et al., 2015). This expansion did not fall on empty land: the transition matrix names natural vegetation, bare soil, and forest as the main sources of new built-up land, and the parallel net loss of forest cover, through both direct conversion and thinning of the forest fringe, marks the natural and semi-natural margin of the conurbation, chiefly the lower Margalla foothills, as the land resource under the greatest pressure. The slight net rise in cropland alongside heavy exchange among the bare soil, cropland, and vegetation classes points to an ongoing reshuffling of agricultural and semi-natural land uses at the urban periphery even as the built-up core grows, a pattern seen repeatedly at the advancing edge of South Asian cities (Patra et al., 2022) and tied to progressive fragmentation of the peri-urban landscape (Dewan et al., 2012).

4.2. Pace of Expansion

A central result of this study is that built-up expansion has been uneven rather than linear. The UER and UEII agree in setting out three distinct phases: a rapid opening surge (2011–2016), a pronounced deceleration (2016–2021), and a renewed acceleration to the fastest rate of the record

in the final interval (2021–2024). The mid-period slowdown most plausibly reflects a mix of macroeconomic constraints, pandemic-era disruption of construction, and the absorption and consolidation of gains from the preceding surge, though the data cannot separate these contributions. The sharp post-2021 rebound, by contrast, signals the start of a fresh wave of peripheral development. That the fastest annual expansion rate of the record falls in the final and shortest observation interval carries a direct planning message: pressure on the conurbation's remaining open and peri-urban land is rising, not easing.

4.3. Dispersal & Consolidation

The morphological indicators give an internally consistent account of how the form of growth shifted over time. Zone-based relative entropy stayed high across the record, placing the urban form in the dispersed, sprawling range in every year, at levels on a par with other fast-sprawling cities of the Global South such as Shiraz and Tripoli (Alsharif & Pradhan, 2014; Sabet Sarvestani et al., 2011). More telling than the level is the trajectory: entropy peaked in 2016, the same date global Moran's I hit its minimum, so two independent statistics name the 2011–2016 surge the most spatially fragmented phase, when new development arrived in a scattered, leapfrog pattern that both raised dispersion and diluted global clustering. The slower 2016–2021 interval reversed both signals, the signature of infill and consolidation around the earlier scattered development, before the 2021–2024 acceleration again brought rising entropy and slightly weakened clustering. This alternation points to a two-stroke growth mechanism, in which bursts of rapid, dispersed land conversion give way to phases of consolidation that stitch scattered fragments into the contiguous urban mass, consistent with the diffusion–coalescence account of urban growth phases (Dietzel et al., 2005) and with intensity patterns seen across Southeast Asian megacities (Estoque & Murayama, 2015). At the same time, the LISA and G_i^* analyses show a strong, statistically significant central cluster that persisted and strengthened across the record: the conurbation's growth is therefore best read not as sprawl or compaction but as the two at once, dispersed expansion at the fringe organised around, and steadily absorbed into, a consolidating core.

4.4. Directional Contrast

The directional analysis gives this paired dynamic a clear geography. Growth was heavily concentrated along the southern and south-eastern sectors, tracing Rawalpindi's expansion toward the Grand Trunk Road and Gujar Khan corridors, with secondary gains to the south-west and west along the Taxila corridor and Islamabad's western fringe; the northern sector, walled off by the Margalla Hills, made no net gain. This south-to-south-east axis falls squarely on the largely unregulated territory of Rawalpindi District, which grew nearly twice as fast as the Islamabad Capital Territory and took in more than three-quarters of all net urban addition (Table 9). The twin-cities layout thus lets the spatial signature of two planning regimes be read from a single landscape: the densest, most contiguous, and most strongly clustered built-up growth belongs to the regulated capital, whereas the more fragmented, corridor-following development that drives the conurbation's high entropy sits in the less regulated district, consistent with comparative evidence for the two cities over 1990–2021 (Kamran et al., 2023). Three qualifications frame this interpretation. First, the analysis characterises the spatial signature associated with the two planning regimes rather than isolating planning as a causal driver, since the administrative contrast also co-varies with topography, development history, and land availability. Second, Islamabad's lower relative growth rate partly reflects its earlier development and higher initial built-up share, which leaves proportionally less convertible land, so the comparison is read across the absolute annual rate, the percentage of 2011 built-up area, and their convergence rather than percentage growth alone. Third, that a sprawling overall form persists despite firm planning control at the core carries a lesson of its own: regulatory oversight of a metropolitan centre does not by itself stop fragmented growth at the margins, since expansion simply shifts to the least regulated land beyond the planning boundary, a displacement pressure that neural-network forecasts suggest will grow (Sarwar et al., 2025).

4.5. Planning Implications

Four practical implications follow. First, the fastest recorded expansion rate falling in the most recent interval, set against sustained forest loss along the Margalla fringe, argues for stronger green-belt protection and enforceable growth boundaries on the conurbation's northern margin, where direct forest-to-urban conversion is concentrated. Second, because fringe growth follows the corridors so closely, transit-oriented development and infill-focused strategies along the southern and south-eastern corridors offer the most realistic way to channel expansion into a more compact, land-efficient form. Third, the persistence of a strong central cluster shows that

substantial densification capacity remains within the existing core, an opening to house growth within a smaller land footprint. Fourth, the pronounced asymmetry between the two administrative units means that effective growth management has to operate at the scale of the whole conurbation, since planning instruments confined to the Islamabad Capital Territory will keep displacing peripheral development rather than containing it, as district-scale mapping approaches have shown elsewhere (Aslani et al., 2025). The integrated multi-index framework applied here, built entirely from freely available imagery, gives planning authorities a replicable, low-cost instrument for tracking these dynamics.

4.6. Robustness of the Findings

Three checks support the robustness of the main findings. First, the apparent reversion of built-up land to non-urban classes between 2011 and 2024 is small beside the volume of newly built-up land over the same period and mostly lies immediately adjacent to land still classified as built-up in 2024, consistent with mixed-pixel effects along patch edges rather than a threat to the net expansion trend. Second, the zone-based entropy result is robust to the choice of ring width: recomputing relative entropy with 3 km and 7 km rings, rather than 5 km, leaves the built-up form well within the dispersed range in both endpoint years and preserves the increase in dispersion from 2011 to 2024. Third, the directional pattern is robust to sector count, with the southern and south-eastern sectors remaining the two leading directions of built-up growth whether eight or sixteen sectors are used. Together these checks indicate that the pace, dispersion, and directional concentration reported above are properties of the observed growth rather than artefacts of the reversion, the entropy zoning, or the directional binning.

4.7. Limitations

Several constraints qualify the findings. The analysis rests on 30 m Landsat imagery which, though suited to regional-scale mapping, under-represents small and linear built-up features and produces mixed pixels at class boundaries; the apparent reversion of a small share of 2011 urban land to non-urban classes by 2024 is put down chiefly to such boundary-pixel effects rather than to real de-urbanisation. Class areas came from pixel counting rather than the error-adjusted estimators recommended by Olofsson et al. (2014); a formally error-adjusted area estimate with confidence intervals would require a map-stratified validation design, identified here as a priority for future work, and the reported areas accordingly carry the uncertainty quantified in the accuracy assessment. The pronounced inter-date swings in the bare soil, cropland, and vegetation classes

reflect seasonal and surface-condition differences between composites rather than durable land conversion. Localised classification instability at intermediate dates, clearest on the south-western periphery in 2016, is what confined the city-level comparison to the 2011 and 2024 endpoints, and the two administrative boundary datasets differ modestly from the raster analysis extent due to boundary-dataset discrepancies. The entropy results depend on the chosen zoning (14 concentric 5 km rings centred on the conurbation core); other zonings, such as administrative units, would give different absolute values, though the temporal trajectory should hold. Finally, this study describes the spatial pattern of expansion but does not model its socio-economic drivers; joining these findings with population, land-market, and governance data is a priority for future work.

5. Conclusion

This study measured the spatiotemporal dynamics of urban expansion and sprawl across the Islamabad–Rawalpindi conurbation for 2011 to 2024 through an integrated framework combining Random Forest classification, post-classification change detection, expansion indices, zone-based Shannon's entropy, directional analysis, and spatial-cluster statistics. Built-up land doubled over the study period (+101%), drawn mainly from vegetation, bare soil, and forest, with forest taking the steepest proportional loss (−20.5%). Growth was uneven in time, unfolding as a rapid surge (2011–2016), a deceleration (2016–2021), and the most intense expansion episode of the record (2021–2024). The morphological indicators revealed a two-stroke dynamic in which dispersed expansion alternates with consolidation: the 2016 entropy maximum coincided with the Moran's I minimum, together naming the first surge the most fragmented phase, after which infill restored clustering before renewed dispersal came with the post-2021 acceleration. Expansion was strongly anisotropic, concentrated along the southern and south-eastern corridors of Rawalpindi, and nearly twice as fast in relative terms within the largely unplanned district as within the planned capital, which absorbed only a quarter of net urban addition. Throughout, high fringe dispersion went hand in hand with strong, persistent clustering around the central core.

Data availability statement

All satellite data used in this study are freely available: Landsat Collection 2 Level-2 surface reflectance products are distributed by the United States Geological Survey (<https://earthexplorer.usgs.gov>) and were accessed through the Google Earth Engine data catalogue (<https://earthengine.google.com>). The classified land-cover maps, derived statistics, and

Google Earth Engine and Python analysis scripts generated in this study are available from the corresponding author on reasonable request

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