

Article

Blue–Green Landscape Structure and Development–Terrain Coupling in Metropolitan Flood-Susceptibility Contexts: Shanghai, Tokyo, and Istanbul

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Abstract

Metropolitan flood-resilience planning requires understanding how development and blue–green landscapes intersect with low-lying terrain. This study compared flood-susceptibility contexts in Shanghai, mainland Tokyo, and Istanbul using a harmonized geospatial framework integrating 2021 land-cover and impervious-surface baselines with elevation, hydrography, surface water, 2020–2025 satellite rainfall, and administrative population data. The analysis distinguished landscape coverage, vegetation configuration, proximity to development, and development–terrain overlap. Of the impervious surface mapped for 2021, 96.31% occurred below the elevation product's 10 m threshold in Shanghai, compared with 23.24% in Tokyo and 4.12% in Istanbul. In Tokyo, this share exceeded the metropolitan low-elevation share of 15.76%, revealing a concentration of development in lowlands obscured by citywide terrain summaries. Shanghai had less non-agricultural vegetation than Istanbul (25.15% versus 64.50%), yet greater built-up proximity to vegetation (94.27% versus 89.10% within 100 m). Despite this proximity, only 23.04% of Shanghai's vegetation qualified as interior vegetation, compared with 79.60% in Tokyo and 82.06% in Istanbul. Within-city analysis at 2 km showed strong vegetation coverage–adjacency associations ($r = 0.803\text{--}0.936$), alongside substantial variation in adjacency and built-up proximity within comparable coverage bands; association directions persisted at 5 km. Shanghai's widespread low-elevation development calls for finer differentiation of drainage and storage conditions, whereas Tokyo's terrain contrast supports distinguishing low-land development from upland areas. Joint assessment of blue–green structure and development–terrain overlap thus provides a basis for targeting detailed drainage assessment and sustainable metropolitan landscape planning.

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Keywords: urban flood susceptibility; blue–green landscape; landscape configuration; development–terrain coupling; urban resilience; sustainability; nature-based solutions; remote sensing

1. Introduction

Urban flooding poses a persistent challenge to sustainable metropolitan development because the locations of runoff-generating surfaces, low-lying development, drainage pathways, and potential storage areas influence the conditions under which heavy rainfall becomes damaging. Remote sensing and global geospatial products increasingly

support the assessment of these conditions across large urban regions. Reviews identify elevation and land-use/land-cover data as central inputs to flood-susceptibility studies, alongside satellite precipitation, surface-water observations, and cloud-based processing [1,2]. However, consistent data coverage does not by itself ensure that metropolitan indicators capture the spatial relationships most relevant to planning.

Green infrastructure and nature-based approaches connect stormwater management with broader sustainability objectives, including ecological function and the provision of public open space [3–6]. Sustainable urban drainage, low-impact development, water-sensitive urban design, and Sponge City approaches share an emphasis on managing water within the urban landscape, although their terminology and implementation differ [5,7]. Their relevance depends on spatial placement and available capacity as well as total area. A large metropolitan vegetation share may therefore indicate substantial landscape resources without establishing their relationship to developed districts or their ability to manage runoff.

Globally consistent products make it possible to examine these relationships across cities with otherwise incompatible local inventories. Sentinel-based land-cover products distinguish vegetation, cropland, built-up land, and water within a common classification framework [8], while Landsat-based impervious-surface information provides a complementary measure of development relevant to runoff generation [9,10]. This study derives spatial relationships from these existing products rather than producing a new land-cover classification.

The importance of landscape configuration is already established. Sohn et al. [6] related green-infrastructure patterns to flood damage using longitudinal data from coastal Texas. Other approaches identify priority areas for green infrastructure within a city [11], simulate neighbourhood flooding under alternative infrastructure layouts [12], or optimize blue–green placement using detailed flood models [13]. These approaches address different planning questions and require different evidence; modelling reviews emphasize matching methods and validation to the intended inference [14]. A review of urban form and flood resilience further highlights the relevance of multiple spatial scales [15]. The question examined here is how metropolitan coverage, internal vegetation structure, proximity to development, and development–terrain overlap change the comparative interpretation when assessed together using common source products.

The gap addressed here concerns the joint interpretation of these dimensions within a harmonized metropolitan comparison. Coverage measures landscape quantity; adjacency, interior share, and edge density characterize vegetation structure; and built-up proximity measures the spatial relationship between development and vegetation or water. A second distinction concerns terrain: the share of a metropolitan region below an elevation threshold does not identify how much developed land occupies that elevation zone. Examining both distinctions together can reveal planning-relevant contrasts that separate land-cover or terrain summaries leave unresolved. Within-city comparisons further test how much configuration and proximity vary among areas with comparable vegetation coverage, extending the evidence beyond metropolitan averages. The contribution is a comparative spatial diagnosis that brings these relationships together for metropolitan planning.

Shanghai, mainland Tokyo, and Istanbul were selected as contrasting coastal megacity cases, rather than as a representative sample or a ranking of the most flood-prone cities. Shanghai provides a predominantly flat deltaic setting with a changing urban open-space structure [16]; mainland Tokyo combines intensively developed eastern lowlands with mountainous western Tama; and Istanbul includes extensive peripheral forest alongside developed districts. This contrast allows the analysis to examine whether metropolitan landscape totals and mean terrain conditions give the same interpretation as their

spatial relationships with development. The selection is purposive: it demonstrates the framework across these contrasting administrative settings and does not establish that the findings characterize other coastal megacities.

The analysis situates these spatial relationships within a broader flood-susceptibility context. Here, this term denotes landscape, development, terrain, hydrographic, and rainfall conditions relevant to flooding; it does not denote an estimated inundation probability or a validated susceptibility map [1,2,15]. This perspective is informed by resilience-based planning that recognizes the role of natural floodplain functions [17]. IMERG precipitation provides a common basis for describing rainfall over the study period, with interpretation constrained by its 0.1° grid and retrieval uncertainty [18,19]. Administrative population totals provide demographic context. These complementary domains retain distinct meanings, enabling the landscape analysis to inform flood-resilience planning without equating vegetation proximity with hydraulic connectivity.

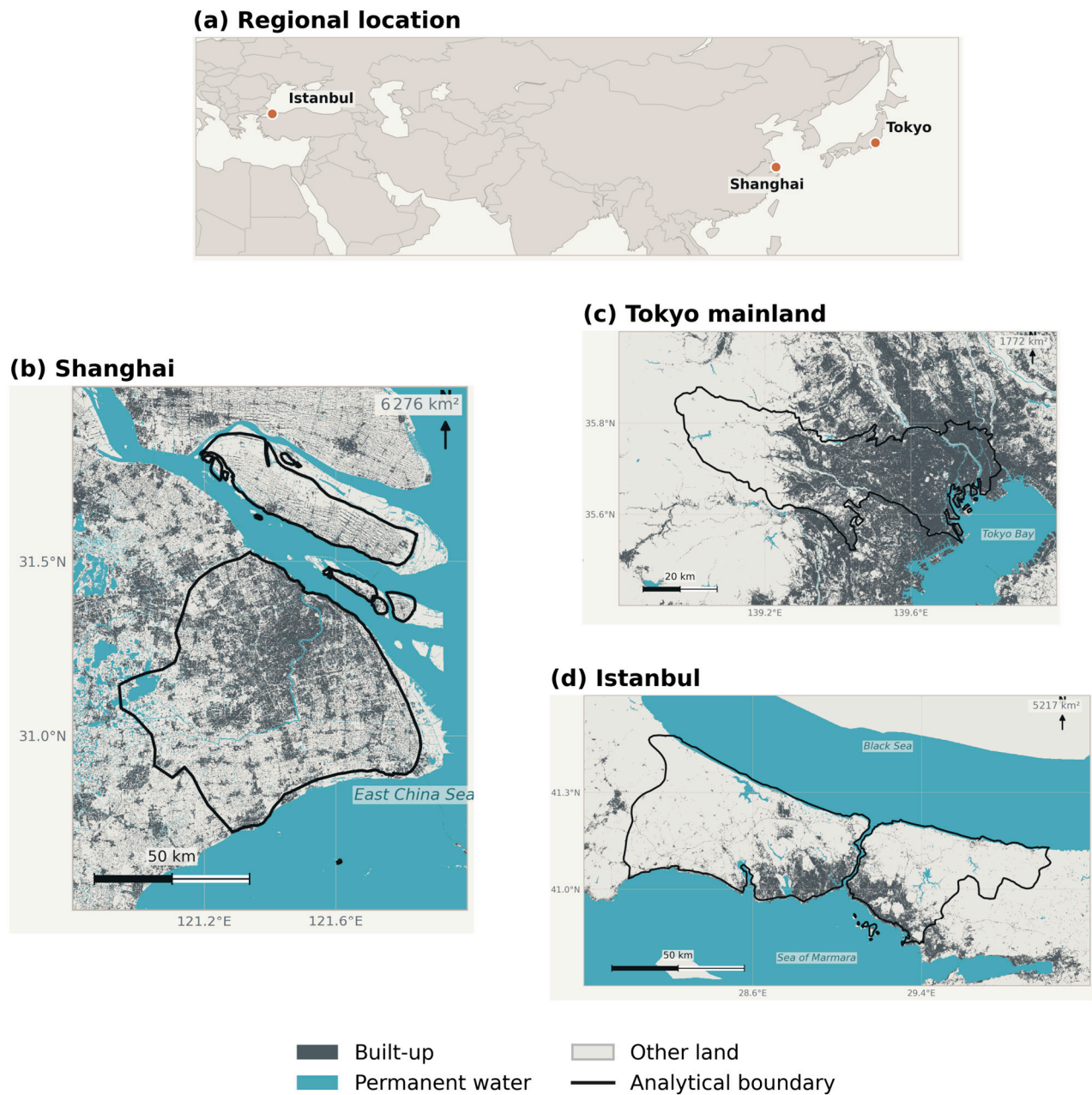
The indicators have different relevance to pluvial, fluvial, and coastal flooding. Rainfall, imperviousness, and vegetated land describe conditions associated with runoff generation and potential retention in pluvial flooding. Modelled hydrography and surface-water proximity describe the setting of drainage pathways and receiving waters, but do not represent river discharge or overbank inundation. Low elevation describes a topographic condition that can matter for riverine or coastal flooding only in relation to water levels, hydraulic connections, and protection. The framework therefore provides broad context across flood mechanisms, without estimating their separate or combined probabilities. Coastal water levels, river stages, sewer capacity, and flood-defence operation were not modelled.

The study addresses three questions: (1) how do blue–green quantity, internal vegetation configuration, and proximity to developed land relate across metropolitan regions and among areas with comparable vegetation coverage within each city? (2) What information does development–terrain overlap add to separate metropolitan summaries of elevation and urbanization? (3) How do these relationships inform differentiated planning priorities when interpreted alongside rainfall, hydrography, and population context? The principal contribution is to identify and interpret these contrasts within one reproducible framework. The results show that Shanghai’s lower vegetation coverage coexists with greater built-up proximity, while Tokyo’s metropolitan terrain summary understates the relative concentration of its developed surface in lowlands. Within-city results show strong associations between vegetation coverage and adjacency, while configuration and proximity still vary among areas with comparable coverage. These findings provide a basis for targeting more detailed drainage and landscape assessments. The indicators are retained separately rather than combined into a composite flood-risk or resilience score.

2. Materials and Methods

2.1. Study Areas and Comparative Design

The analytical units were Shanghai Municipality, mainland Tokyo, and Istanbul Province (Figure 1). Shanghai and Istanbul were evaluated using their full first-order administrative boundaries. Tokyo was restricted to the mainland metropolitan territory comprising the 23 special wards and Tama area; the Izu and Ogasawara island groups were excluded because their spatial separation and distinct physical settings would distort metropolitan-scale terrain and proximity metrics. The resulting analytical areas were 6275.69 km² for Shanghai, 1772.34 km² for mainland Tokyo, and 5217.46 km² for Istanbul.



WorldCover 2021 context; GAUL 2015 boundaries. Tokyo excludes offshore island groups.

Figure 1. Study areas of Shanghai, mainland Tokyo, and Istanbul. Panel (a) shows regional locations; panels (b–d) show analytical boundaries with WorldCover built-up and permanent-water classes. Mainland Tokyo excludes the Izu and Ogasawara islands.

Administrative boundaries were obtained from FAO GAUL 2015 Level 1 data [20]. Administrative metropolitan units were selected because they provide recognizable planning jurisdictions and allow official population totals to be paired with consistently extracted geospatial indicators. Tokyo's offshore exclusion is an explicit adaptation of this approach, not a functional urban-area delineation. Consequently, the units share a data source but are not equivalent in urban extent, catchment composition, or the proportion of peripheral land. Western Tama increases Tokyo's mean elevation and vegetation aggregation; extensive peripheral forests also influence Istanbul's landscape percentages. Population densities and citywide terrain or coverage statistics are therefore conditional on these boundaries. Development-based denominators complement these summaries by

describing the land actually mapped as built-up or impervious. All extractions used the same geometry within each city, while product-specific mapped areas were retained for class percentages. The comparison consequently concerns the specified administrative regions, not equivalent functional urban systems; development-based denominators reduce some compositional differences but do not eliminate boundary dependence.

2.2. Geospatial and Ancillary Datasets

The datasets in Table 1 were assigned distinct analytical roles and processed in Google Earth Engine (GEE) [21]. WorldCover and GISA-new provide the 2021 development and land-cover baseline; IMERG describes rainfall during 2020–2025; official population totals refer to 2025; and elevation and hydrography are static products. This is a comparison of spatial conditions using complementary reference periods, not a synchronized observation of one flood event. Published land-cover and impervious-surface products were used directly, with no new classifier training. The derived analysis comprises area summaries, neighbourhood configuration, distance transforms, development–elevation intersections, and rainfall aggregation. These operations retain product-specific definitions and account for differences in spatial resolution.

ESA WorldCover 2021 v200 was selected as the primary land-cover product because it provides a global 10 m classification based on Sentinel-1 and Sentinel-2 observations [22]. The choice is supported by comparative evaluation of contemporary global 10 m land-cover datasets, which shows strong utility for water, built area, and tree classes while also demonstrating that class-specific uncertainty should be considered in application-specific interpretation [8]. Imperviousness was derived independently from GISA-new, a 30 m global impervious-surface time series produced from multi-temporal Landsat observations through 2021 [23]. Using a separate impervious dataset avoids treating WorldCover’s built-up class as equivalent to hydrologically impervious surface.

Terrain was represented by Copernicus DEM GLO-30, a digital surface model (DSM) at approximately 30 m resolution that includes buildings and vegetation rather than representing bare-earth terrain [24]. Its surface elevations are referenced to the EGM2008 vertical datum. Water seasonality was characterized using the 30 m JRC Global Surface Water v1.4 seasonality layer for 2021 [25]. Modelled hydrography was derived from MERIT Hydro v1.0.1 at approximately 3 arc seconds (~90 m) [26].

Rainfall was characterized using NASA GPM IMERG Final Run V07 at 0.1° and 30 min resolution [27]. The Final Run combines satellite precipitation estimates with gauge analysis. A common 2020–2025 interval was retained for all cities. Evaluation of earlier IMERG products in coastal urban China found intensity-dependent errors, including underestimation of heavy precipitation [18]. Evaluation of V07 documents improvements relative to V06 but also remaining missed, hit, and false-detection errors [19]. The earlier coastal evaluation therefore supports caution about retrieval conditions, not an assumption that it directly validates V07 in all three cities.

Table 1. Multi-source remote-sensing and ancillary datasets used in the comparative workflow.

Dataset/Product	Observation Basis	Nominal Resolution	Period Used	Role in Analysis
FAO GAUL 2015 Level 1	Administrative boundaries	Vector	2015	Common metropolitan boundaries
ESA WorldCover 2021 v200	Sentinel-1 and Sentinel-2	10 m	2021	Land cover; vegetation, tree, built-up, permanent water; proximity

GISA-new	Multi-temporal Land-sat	30 m	Cumulative extent through 2021	Impervious-surface proportion
Copernicus DEM GLO-30	TanDEM-X/WorldDEM with in-filling	30 m	Static product	Elevation, slope, <5 m and <10 m shares
JRC Global Surface Water v1.4	Landsat archive	30 m	2021 seasonality	Permanent and seasonal water
MERIT Hydro v1.0.1	DEM and satellite/open water datasets	~90 m	Static product	Standardized modelled drainage-network density
GPM IMERG Final V07	Multi-satellite PMW + IR + gauges	0.1°; 30 min	2020–2025	Annual rainfall, P99, threshold days, grid-cell daily maxima
Official population statistics	Municipal/national statistical agencies	Administrative	2025	Population and administrative population density

Notes: Versions and reference periods identify the products used, rather than a common observation date. WorldCover and GISA-new refer to 2021; population refers to 2025; rainfall covers 2020–2025. Nominal pixel size is not equivalent to positional or measurement accuracy. PMW = passive microwave; IR = infrared.

2.3. Land-Cover and Impervious-Surface Metrics

WorldCover classes were summarized for each metropolitan boundary using native class values. The main vegetation definition combined tree cover, shrubland, and grassland (classes 10, 20, and 30), with cropland retained separately. This definition distinguishes non-agricultural vegetation for landscape comparison; it does not imply that cropland is hydrologically inactive. To test the effect of its exclusion, a supplementary paired analysis compared this baseline with an alternative adding cropland (class 40), using identical settings for both definitions (Table S3). Vegetation coverage, adjacency, interior share, edge density, and built-up proximity were recalculated. Tree cover was also reported separately in the main analysis. Permanent water was extracted from the WorldCover permanent-water class to retain temporal consistency between coverage and proximity measures.

Impervious-surface extent was derived from GISA-new using all positive detection codes to identify pixels mapped as impervious by 2021. The resulting binary mask represents cumulative impervious extent through the reference year. Impervious percentage was calculated at 30 m resolution as the area of positive-valued pixels divided by the area of valid, unmasked GISA pixels within each metropolitan boundary. This product-specific denominator excluded areas outside valid raster coverage rather than treating them as non-impervious land. WorldCover built-up percentage was retained as a descriptive land-cover variable during exploratory analysis, but GISA-new imperviousness was used as the primary runoff-related urbanization indicator.

For an area operator $A(\cdot)$ evaluated within the relevant metropolitan boundary, the share of class X is:

$$f_x = 100 A(X)/A(\Omega_x). \quad (1)$$

Here Ω_x denotes the mapped domain used for that product. X denotes non-agricultural vegetation, tree cover, permanent water, built-up land, or impervious surface. Percentages from different products need not sum to a common total because their classifications and valid mapped domains differ.

2.4. Topographic and Hydrographic Metrics

Elevation and slope were derived from Copernicus DEM GLO-30. Elevation tiles were mosaicked while retaining the native projection for slope calculation, and metropolitan terrain statistics were summarized at 30 m resolution. Low-elevation zones were defined using thresholds of <5 m and <10 m. These thresholds refer to the product's vertical reference; they are not flood depths, local tidal datums, or mapped floodplain boundaries. They provide common elevation cut-offs for descriptive comparison, rather than equivalent hydrological thresholds across cities. Their flood relevance depends on local drainage, river and tidal levels, catchment position, and protective infrastructure.

Development–terrain overlap was calculated by intersecting each elevation threshold with WorldCover built-up land and, separately, GISA-new impervious surface. For each intersection, the numerator is the developed area below the threshold; the denominator is the total mapped area of the corresponding development class. This differs from metropolitan low-elevation extent, whose denominator is the mapped metropolitan area. GISA-new is the principal runoff-related development layer, while WorldCover provides a comparison using a different development definition. Development–terrain overlap was evaluated on the respective grids of WorldCover built-up land (10 m) and GISA-new impervious surface (30 m). Binary low-elevation masks were aligned to these grids using nearest-neighbour resampling, preserving their categorical values without increasing the spatial detail of the elevation data.

Writing z for the mapped surface elevation, h for a threshold of 5 or 10 m, and D for either development layer, the two measures are:

$$L(h) = 100 A(z < h)/A(\Omega z); C_D(h) = 100 A(D \cap \{z < h\})/A(D). \quad (2)$$

$L(h)$ describes metropolitan low-elevation extent; $C_D(h)$ describes the share of development below the threshold. Their difference, $C_D(h) - L(h)$, is a descriptive percentage-point contrast, not a flood-risk score.

Because GLO-30 is a DSM, buildings and tree canopies can place low-lying ground above a threshold and reduce the mapped low-elevation share or development overlap [24]. Its elevations are referenced to EGM2008; the product specification reports absolute vertical accuracy of <4 m at 90% linear error, which is not a local bare-earth error bound. Sensitivity was assessed by adding uniform offsets of −4, −2, 0, +2, and +4 m to the original DSM before applying the strict <5 m and <10 m thresholds. Binary masks were evaluated on the respective development grids using nearest-neighbour alignment, with total development-class areas retained as denominators (Table S4). These scenarios quantify dependence on vertical shifts; they are not confidence intervals, a correction for buildings or vegetation, or validation against local terrain measurements.

Surface-water seasonality was characterized using the 30 m JRC Global Surface Water v1.4 seasonality layer for 2021. Permanent water comprised pixels assigned 12 months of water presence, whereas seasonal water comprised pixels assigned 1–11 months. These indicators describe within-year water persistence and complement the WorldCover permanent-water class through a separate observation and classification approach [25,28]. Class areas were expressed as percentages of the mapped metropolitan area.

Modelled drainage networks were extracted from MERIT Hydro v1.0.1 using upstream drainage-area thresholds of ≥ 10 , ≥ 50 , and ≥ 100 km², with ≥ 10 km² retained for the principal comparison. Network length was approximated from eight-direction raster flow paths, assigning a nominal segment length of 0.09277 km to cardinal directions and $\sqrt{2}$ times this length to diagonal directions. Cells without a valid downstream direction contributed zero length. Segment lengths were summed within each metropolitan boundary and divided by metropolitan area to obtain drainage-network density. The resulting density represents modelled hydrographic structure, not drainage capacity or a complete

inventory of canals and underground pipes. A higher value therefore has no universal positive or negative implication for flood susceptibility.

The drainage-density definition is:

$$DD(u) = L_{stream}(u)/A_{metro}, u \in \{10, 50, 100\} \text{ km}^2. \quad (3)$$

2.5. Blue–Green Proximity Metrics

Two proximity measures were derived to complement area-based land-cover percentages. The first measures the proportion of WorldCover built-up area located within 100 m of non-agricultural vegetation. The second measures the proportion of built-up area located within 500 m of permanent water. These distances were selected as standardized descriptive thresholds: 100 m represents immediate neighbourhood-scale adjacency to vegetated land, whereas 500 m captures a broader spatial relationship with surface-water features. They were not calibrated as hydraulic, accessibility, or flood-response thresholds and are therefore interpreted only as comparative spatial-proximity measures. Water-body types were not separated by hydrographic function, so the water-proximity metric does not distinguish rivers, canals, reservoirs, or tidal connections, nor does it indicate whether proximity is beneficial or hazardous.

Final proximity calculations were performed at native WorldCover resolution using a Euclidean distance transform. A 600 m external search buffer was applied around each metropolitan boundary before distance calculation so that built-up pixels near the boundary could identify vegetation or water immediately outside the analytical polygon, reducing artificial edge effects. Results were then clipped back to the metropolitan boundary and summarized over WorldCover built-up pixels only. A 30 m implementation was retained as a resolution-sensitivity check.

For WorldCover built-up land B and target class T , the proximity share is:

$$Q_T(r) = 100 A(B \cap \{\text{distance}(T) \leq r\})/A(B). \quad (4)$$

T denotes non-agricultural vegetation at $r = 100$ m or permanent water at $r = 500$ m. The denominator is built-up area, not total metropolitan area. The external search buffer affects target detection only; the summarized built-up area remains within the analytical boundary.

Vegetation configuration was assessed on 30 m grids in the respective local UTM projections. The 10 m vegetation mask was aggregated using mean vegetation coverage, with cells classified as vegetated where coverage was $\geq 50\%$. Mean adjacency and interior vegetation share were calculated using eight neighbouring cells, with interior vegetation requiring all eight neighbours to be vegetated. Edge length was measured along exposed orthogonal cell boundaries. Cells outside the metropolitan boundary or lacking data were treated as non-vegetation in these calculations. The 30 m implementation was used to reduce sensitivity to isolated 10 m classification fragments and to permit computationally consistent metropolitan-scale comparison; these indicators describe aggregation and edge structure and are not direct measures of ecological connectivity or hydrological performance.

On the 30 m vegetation grid, let N_v be the number of vegetation cells and n_i the number of vegetated cells among the eight neighbours of vegetation cell i . The configuration indicators are:

$$\text{Adjacency} = 100 \sum_i n_i / (8N_v); \text{Interior share} = 100 \sum_i 1(n_i = 8) / N_v. \quad (5)$$

$$\text{Edge density} = E_v / A_{metro}. \quad (6)$$

The indicator function $1(\cdot)$ equals one when its condition is met and zero otherwise. E_v is the total vegetation/non-vegetation boundary length in kilometres, measured along

orthogonal cell edges; Ametro is the metropolitan area in km². The interior criterion means a fully vegetated eight-cell neighbourhood at this grain, rather than a specified ecological distance from an edge.

Within-City Quantity, Configuration, and Proximity Context

Within-city relationships were examined using regular 2 km grids in the city-specific UTM projections, with 5 km grids used to assess sensitivity to spatial aggregation. Squares were retained where at least 80% of their area lay within the metropolitan boundary, and summaries covered their metropolitan portions. Vegetation and built-up coverage were calculated relative to valid WorldCover area. Adjacency and interior share were summarized over vegetated 30 m pixels using the definitions above, while proximity measured the proportion of built-up area within 100 m of vegetation. Proximity analyses included cells with at least 5% built-up coverage, limiting the influence of cells containing very little development.

For this within-city analysis, neighbourhood and proximity calculations preceded grid summarization and included a 200 m buffer beyond the metropolitan boundary. This preserved surrounding vegetation across analytical grid boundaries and, unlike the metropolitan configuration summaries, retained external vegetation context at the metropolitan edge. Missing vegetation values were treated as non-vegetation during neighbourhood calculations. Relationships were described using Pearson correlations and 10th–90th percentile ranges within 10-percentage-point vegetation-coverage bands. Percentile summaries were calculated from the exported cell-level data using linear interpolation between ordered observations. Correlations used cells with valid values for each pair of variables and were interpreted descriptively, without significance tests assuming spatial independence. Adjacency and proximity analyses had different eligible subsets, so their correlation magnitudes were not treated as a controlled comparison.

2.6. Satellite Precipitation Metrics

Precipitation was obtained from the calibrated IMERG V07 precipitation band. Half-hourly precipitation rates (mm h^{−1}) were multiplied by 0.5 h and summed over UTC calendar days to obtain daily depths. The 2020–2025 record comprised 105,216 half-hourly images and 2192 daily totals, consistent with the expected number of observations over the study period. No explicit day-by-day completeness filter was applied.

Two complementary daily series were derived. Metropolitan-average rainfall was obtained by spatially averaging daily grid-cell precipitation within each boundary and summing daily means to annual totals. The second series, $M(d)$, is the maximum daily grid-cell depth within the analytical boundary. Annual P99, counts of days with $M(d) \geq 50$ mm and ≥ 100 mm, and the annual maximum of $M(d)$ were calculated from this second series. Thus, a threshold day indicates exceedance in at least one included grid cell, not rainfall of that magnitude across the entire metropolitan region. Mean annual P99 is the average of the six annual percentiles, not a percentile calculated from the pooled six-year record.

With $r(k,d,t)$ denoting precipitation rate in half-hour t for grid cell k on day d , daily depth and the spatial-maximum series are:

$$P(k,d) = 0.5 \sum_t r(k,d,t); M(d) = \max_k P(k,d). \quad (7)$$

$$N_\gamma(q) = \sum d \in \gamma \mathbf{1}(M(d) \geq q); X_\gamma = \max d \in \gamma M(d), q \in \{50, 100\} \text{ mm}. \quad (8)$$

$N_\gamma(q)$ is the annual count of any-cell threshold days, and X_γ is the annual maximum grid-cell depth. Six-year threshold counts sum $N_\gamma(q)$, whereas mean annual P99 averages

the six annual 99th percentiles. For the six annual metropolitan-average totals R_y , the summary statistics are:

$$\bar{R} = \sum_y R_y / 6; SD = \sqrt{[\sum_y (R_y - \bar{R})^2 / 5]}; CV = 100 SD / \bar{R}. \quad (9)$$

At 0.1°, IMERG describes precipitation over grid-cell footprints approximately 10 km across, not station-scale or neighbourhood storm peaks. No downscaling was applied. Spatial maxima and any-cell exceedance counts are also sensitive to the number and arrangement of included grid cells: a larger analytical area provides more opportunities to register an exceedance. Counts therefore characterize rainfall encountered somewhere within each specified metropolitan boundary, rather than an area-independent ranking of storm frequency. Coastal retrieval uncertainty and the short six-year window further limit interpretation; the results do not establish long-term return periods or observed flood-event frequencies [18,19,27].

2.7. Population Context

Official 2025 population totals were used for metropolitan population context rather than gridded modelled population products. Shanghai's year-end resident population was 24,854,100 [29]. Tokyo's preliminary 2025 Population Census total was 14,246,219, of which 22,051 residents were in the island area; subtracting the islands gives a mainland total of 14,224,168 [30]. Istanbul's 2025 population was 15,754,053 [31].

Administrative population density was calculated as population divided by analytical area (persons km⁻²). These totals and densities provide demographic context; they do not locate residents within low-elevation areas, quantify population exposure to a flood footprint, or represent socioeconomic vulnerability.

$$\text{Population density is } D_p = P_{2025} / A_{\text{metro}}. \quad (10)$$

2.8. Comparative Synthesis and Sensitivity Analysis

The framework compares four domains in parallel: rainfall characteristics, physical conditions relevant to susceptibility, blue–green landscape structure, and population context (Figure 2). The calculation model consists of explicitly defined indicators rather than a fitted predictive model. No weights or composite susceptibility scores were calculated, because compensating one domain with another would impose assumptions not tested here. In particular, high vegetation coverage does not mathematically offset low-lying development, and dense hydrography does not by itself indicate effective stormwater conveyance.

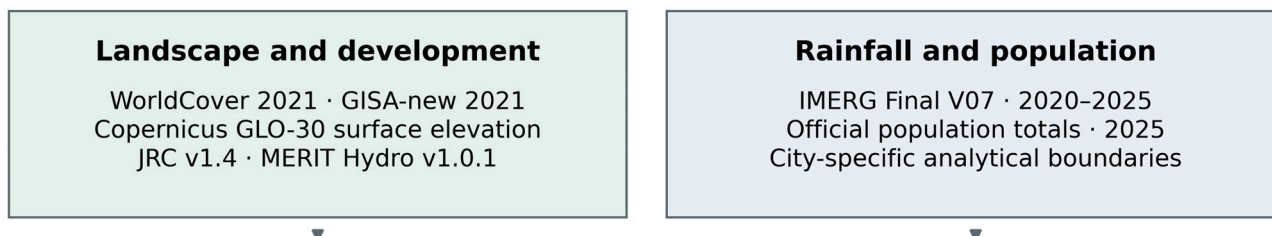
For comparative indicator profiles only, each selected indicator was min–max normalized across the three metropolitan regions to display relative position on a common axis. Original values are printed beside the normalized profiles and remain the basis for interpretation. Sensitivity and robustness checks examined drainage-network density at three upstream-area thresholds, low-elevation shares at both 5 m and 10 m, development–terrain coupling using both GISA-new impervious surface and WorldCover built-up land, and blue–green proximity at 30 m and native WorldCover resolution. Vegetation configuration was evaluated separately at a common 30 m grid using adjacency, interior-share, and edge-density metrics. Within-city quantity–configuration and quantity–proximity relationships were additionally compared at 2 km and 5 km aggregation scales (Section Within-City Quantity, Configuration, and Proximity Context). Supplementary analyses additionally tested the inclusion of cropland in the vegetation definition (Table S3) and uniform vertical offsets in the DSM (Table S4).

For display only, indicator j in city i was transformed as:

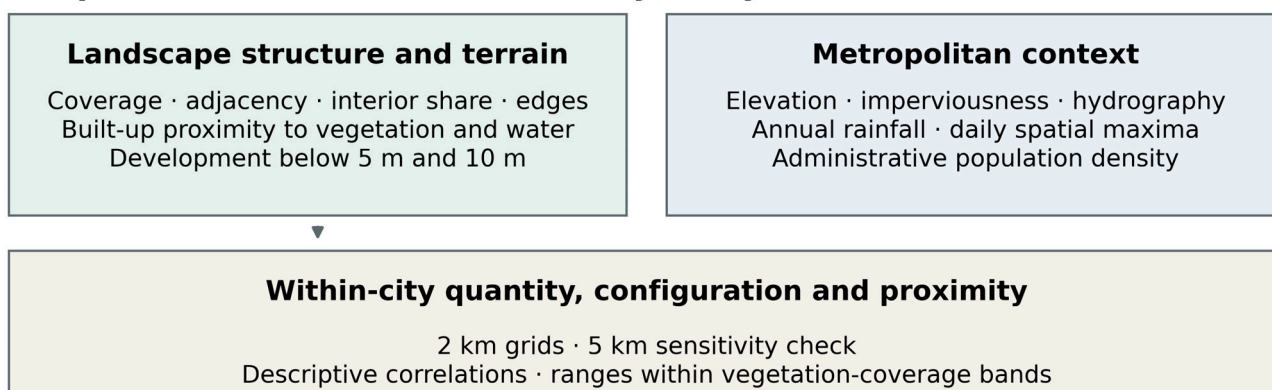
$$Z_{ij} = (x_{ij} - \min_i x_{ij}) / (\max_i x_{ij} - \min_i x_{ij}). \quad (11)$$

Each indicator has its own minimum and maximum across the three cities. Endpoints therefore represent the observed range within this comparison, not external risk standards. Normalized values are not averaged or interpreted as uniformly beneficial or adverse.

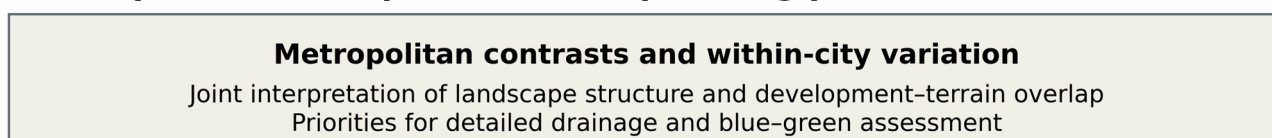
1 Source products and reference periods



2 Spatial indicators and within-city analysis



3 Comparative interpretation and planning priorities



Parallel indicators; no composite score or estimated inundation probability

Figure 2. Analytical framework linking source products, metropolitan indicators, within-city comparisons, and planning interpretation. Domains are interpreted in parallel without a composite susceptibility score.

3. Results

3.1. Metropolitan Context and Topography

The three study areas differ markedly in scale, population density, and terrain (Table 2). Shanghai and Istanbul cover substantially larger administrative areas than mainland Tokyo, while Tokyo has by far the highest population density at approximately 8026 persons km⁻². Shanghai's density is about 3960 persons km⁻², and Istanbul's about 3019 persons km⁻².

Topography provides the sharpest physical contrast (Figure 3). Shanghai has a mean elevation of only 3.55 m and a mean slope of 2.12°. Approximately 79.41% of the mapped area lies below 5 m and 97.91% below 10 m. Tokyo's mean elevation is much higher (254.72 m) because the analytical boundary includes the mountainous western Tama area, and the mean slope reaches 11.89°. Nevertheless, 15.76% of mainland Tokyo remains below 10

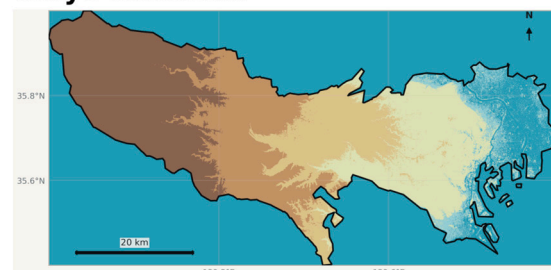
m, principally in the eastern metropolitan lowlands. Istanbul occupies an intermediate terrain setting with a mean elevation of 111.03 m and a mean slope of 7.84°; only 7.03% lies below 10 m.

(a) Elevation context

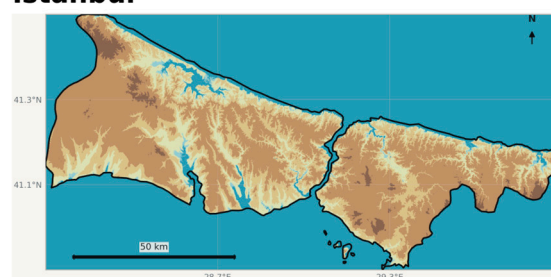
Shanghai



Tokyo mainland

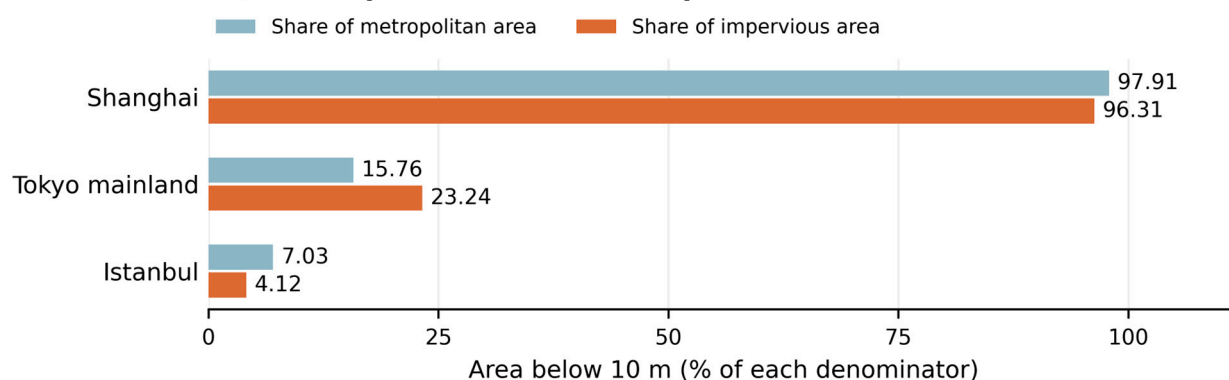


Istanbul



<5 m 5-10 m 10-50 m 50-100 m 100-250 m >250 m

(b) Development-terrain overlap



Area below 10 m (% of each denominator)
Copernicus GLO-30 surface elevations; thresholds are not inundation boundaries.

Figure 3. Metropolitan elevation context and development–terrain overlap. (a) Surface-elevation maps; (b) mapped metropolitan area and impervious area below 10 m, each expressed relative to its own denominator. Elevation thresholds do not represent inundation boundaries.

Table 2. Study-area characteristics, population context, and elevation metrics.

Metropolitan Region	Study Area (km ²)	Official Population (2025)	Population Density (persons km ⁻²)	Mean Elevation (m)	Mean Slope (°)	Area <5 m (%)	Area <10 m (%)
Shanghai	6275.69	24,854,100	3960	3.55	2.12	79.41	97.91
Tokyo mainland	1772.34	14,224,168	8026	254.72	11.89	10.28	15.76
Istanbul	5217.46	15,754,053	3019	111.03	7.84	5.46	7.03

Notes: Boundaries: FAO GAUL 2015 Level 1, with offshore Tokyo excluded. Population: official 2025 totals/estimates; density uses the analytical boundary area. Elevation and slope: Copernicus

DEM GLO-30, a DSM rather than a bare-earth DTM. Low-elevation shares refer to the product's vertical datum. Values are rounded independently.

Development–terrain intersections reveal contrasts that separate metropolitan summaries do not express (Figure 3b). In Shanghai, 95.58% of mapped built-up land and 96.31% of impervious surface occurred below 10 m; the respective shares below 5 m were 62.93% and 66.50%. In mainland Tokyo, impervious surface below 10 m accounted for 23.24% of total impervious area, compared with 15.76% of the metropolitan area below that threshold—a difference of 7.48 percentage points. Istanbul showed the reverse pattern: 4.12% of impervious area occurred below 10 m, compared with 7.03% of the metropolitan area, a difference of −2.91 percentage points. These descriptive contrasts use the different denominators explicitly defined in Section 2.4. The impervious overlap ranking remained Shanghai > Tokyo > Istanbul at both elevation thresholds.

The vertical-offset scenarios show that absolute overlap percentages are sensitive to surface elevation, especially in Shanghai (Table S4). Across offsets from −4 to +4 m, Shanghai's impervious share below 5 m ranged from 2.49% to 94.36%, and its share below 10 m from 78.63% to 99.21%. The Shanghai > Tokyo > Istanbul ordering of development overlap persisted at each matching offset for both development products and thresholds. Tokyo's impervious share below 10 m remained above its metropolitan low-elevation share in every scenario, whereas its corresponding contrast at 5 m did not.

3.2. Land-Cover Composition and Imperviousness

Imperviousness and vegetation produce different city rankings (Table 3; Figure 4). Tokyo has the highest GISA-new impervious proportion at 56.55%, followed closely by Shanghai at 51.24%. Istanbul is substantially less impervious at 18.81%. Non-agricultural vegetation shows the opposite ordering: Istanbul contains 64.50%, Tokyo 43.84%, and Shanghai 25.15%.

The vegetation contrast is also evident in tree cover. Trees account for 50.98% of Istanbul, 41.51% of Tokyo, and 16.75% of Shanghai. These values describe metropolitan land-cover composition rather than formal park systems. In Shanghai, the relatively low total non-agricultural vegetation share coexists with a more dispersed pattern through the developed landscape, which becomes apparent in the subsequent proximity and configuration analyses.

Table 3. Land cover, imperviousness, built-up proximity, and modelled drainage density.

Metropolitan Region	Impervious Surface (%)	Non-Agricultural Vegetation (%)	Tree Cover (%)	Built-up ≤100 m from Vegetation (%)	Permanent Water (%)	Built-up ≤500 m from Water (%)	Modelled Drainage-Network Density (km km ^{−2})
Shanghai	51.24	25.15	16.75	94.27	5.10	78.08	0.318
Tokyo mainland	56.55	43.84	41.51	77.12	2.63	46.59	0.357
Istanbul	18.81	64.50	50.98	89.10	4.91	25.78	0.262

Notes: Land-cover and proximity values use WorldCover 2021 v200; imperviousness uses GISA-new 2021; drainage density uses MERIT Hydro v1.0.1 at ≥10 km² upstream area. Impervious percentages use valid, unmasked GISA area within each metropolitan boundary as the denominator. Proximity percentages use built-up area as the denominator. Values are rounded independently.

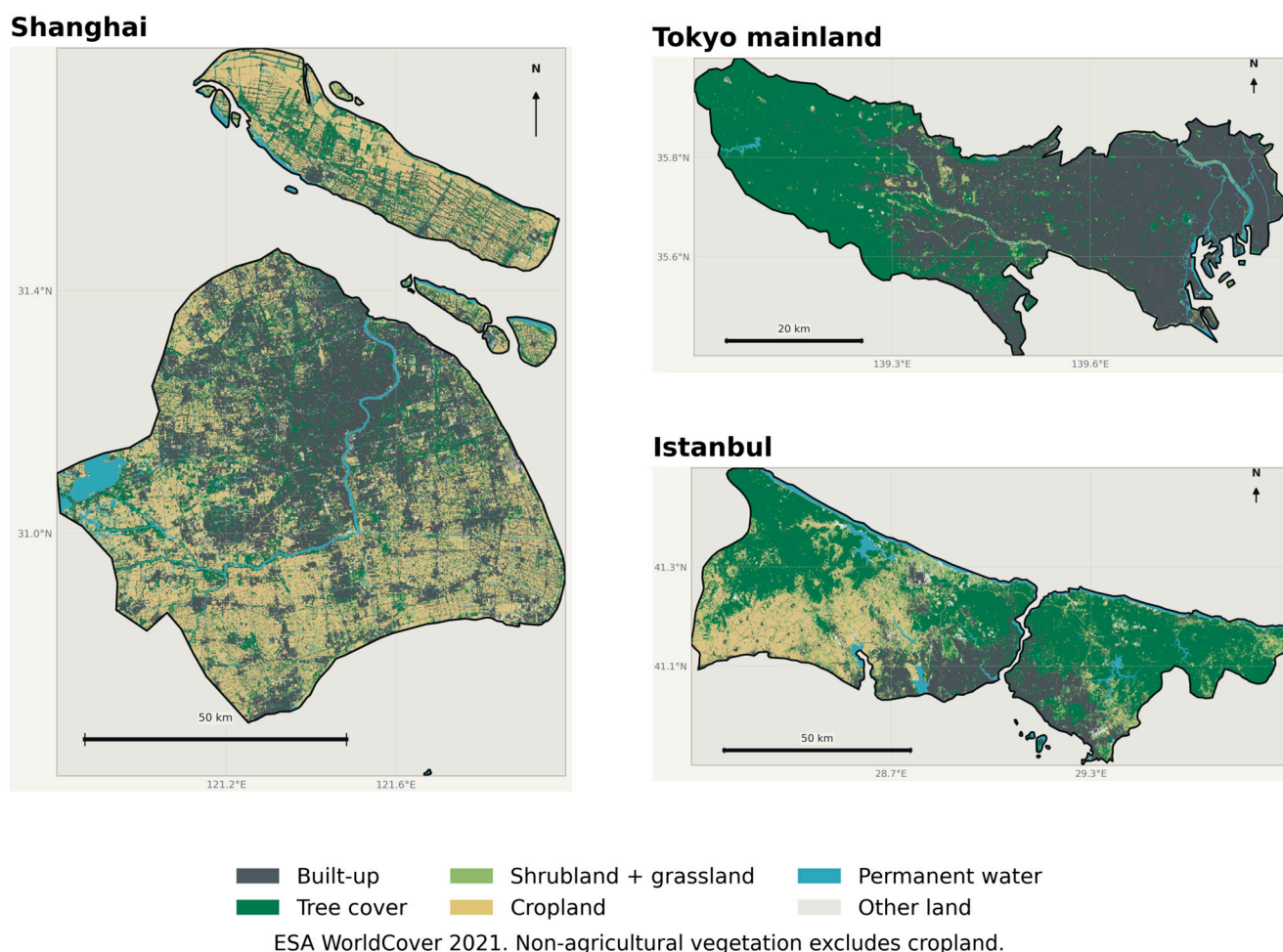


Figure 4. WorldCover 2021 land-cover patterns in Shanghai, mainland Tokyo, and Istanbul.

3.3. Blue–Green Spatial Configuration

The proximity metrics alter the interpretation obtained from coverage alone (Figure 5). Shanghai has the lowest metropolitan non-agricultural vegetation coverage, yet 94.27% of its built-up area lies within 100 m of vegetation—the highest proportion among the three cities. Istanbul follows at 89.10%, despite having by far the highest vegetation coverage. Tokyo has an intermediate vegetation share but the lowest built-up–vegetation proximity at 77.12%.

The contrast is stronger for water. Shanghai and Istanbul have nearly identical WorldCover permanent-water coverage (5.10% and 4.91%, respectively), but their built-up–water proximity differs by 52.30 percentage points. In Shanghai, 78.08% of built-up land lies within 500 m of permanent water, compared with 46.59% in Tokyo and 25.78% in Istanbul. The result indicates that metropolitan water coverage alone does not describe the proportion of developed land located near mapped water features.

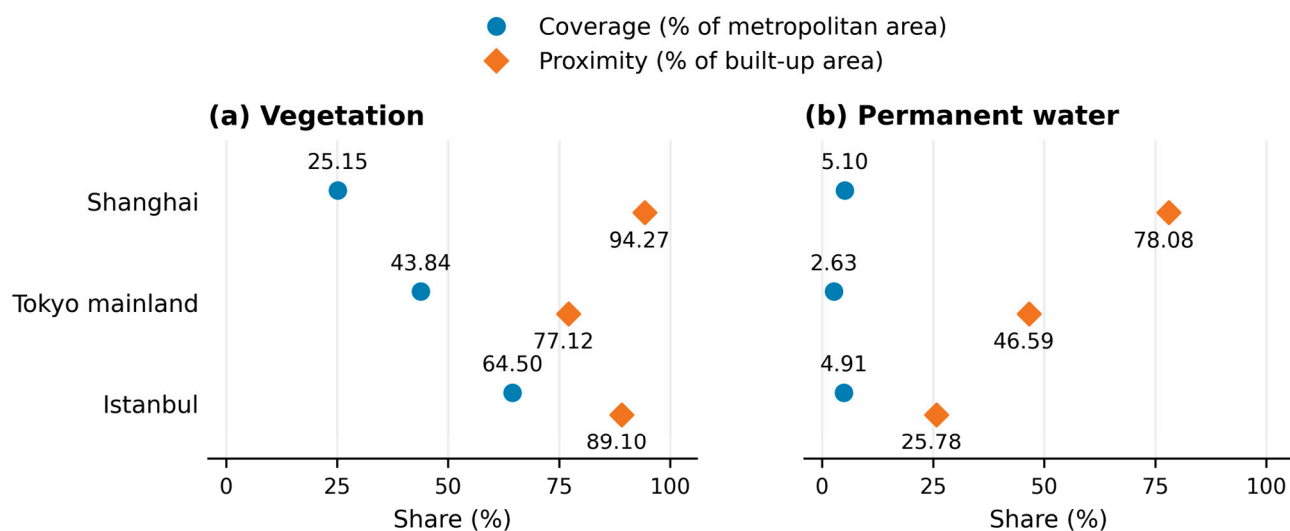
The additional vegetation-configuration metrics (Table 4) provide a structural context for the differences between vegetation quantity and built-up proximity. At the common 30 m analysis grid, mean vegetation adjacency was only 64.34% in Shanghai, compared with 91.38% in mainland Tokyo and 93.65% in Istanbul. Only 23.04% of Shanghai’s vegetation qualified as interior vegetation, whereas the corresponding shares were 79.60% in Tokyo and 82.06% in Istanbul. Shanghai also exhibited substantially higher vegetation edge density (11.64 km km^{−2}) than Tokyo (5.40 km km^{−2}) or Istanbul (6.36 km km^{−2}). Together, these indicators show that Shanghai’s smaller vegetation resource is markedly more edge-dominated and finely interspersed, whereas vegetation in Tokyo and Istanbul

is substantially more internally aggregated. Tokyo is particularly informative: despite relatively high vegetation aggregation, it has the lowest built-up–vegetation proximity, illustrating why internal vegetation structure and proximity to development should be reported separately.

Table 4. Development–terrain overlap and vegetation configuration.

Metropolitan Region	Built-up < 10 m (%)	Impervious <10 m (%)	Impervious <5 m (%)	Mean Vegetation Adjacency (%)	Interior Vegetation Share (%)	Edge Density (km km ⁻²)
Shanghai	95.58	96.31	66.50	64.34	23.04	11.64
Tokyo mainland	23.42	23.24	14.10	91.38	79.60	5.40
Istanbul	3.07	4.12	1.97	93.65	82.06	6.36

Notes: Development layers: WorldCover 2021 v200 built-up and GISA-new 2021 impervious surface; elevation: Copernicus DEM GLO-30. Overlap percentages use the corresponding development area as the denominator. Vegetation configuration calculated on 30 m UTM grids; see Section 2.5 for aggregation and boundary treatment. Metrics comprise eight-neighbour adjacency, fully surrounded vegetation cells, and orthogonal edge length per metropolitan area. Values are rounded independently.



Proximity: within 100 m of vegetation or 500 m of water.
Coverage and proximity use different denominators.

Figure 5. Blue–green quantity and proximity to built-up land. Panel (a) compares vegetation coverage with built-up proximity to vegetation; panel (b) compares permanent-water coverage with built-up proximity to water.

Including cropland changed vegetation quantity and structure more than metropolitan built-up proximity (Table S3). In the paired analysis, vegetation coverage increased by 31.14 percentage points in Shanghai, 1.23 in Tokyo, and 14.09 in Istanbul. Adjacency increased by 22.57, 0.25, and 3.08 percentage points, respectively, while built-up proximity increased by 0.98, 0.43, and 0.15 percentage points. Including cropland placed Shanghai above Tokyo in vegetation coverage, but the vegetation–proximity ordering remained

Shanghai > Istanbul > Tokyo. The effects of the vegetation definition therefore differed among indicators and cities.

3.4. Within-City Quantity, Configuration, and Proximity

The 2 km analysis retained 1482 cells in Shanghai, 398 in mainland Tokyo and 1233 in Istanbul. Adjacency was defined for 1479, 398 and 1233 cells, respectively; proximity analyses included 1415, 291 and 462 cells meeting the built-up eligibility criterion. Vegetation coverage was strongly positively associated with adjacency ($r = 0.803$, 0.936 and 0.909 , respectively; Figure 6). Among proximity-eligible cells, vegetation coverage was also positively associated with built-up proximity to vegetation ($r = 0.472$, 0.701 and 0.519). Built-up coverage was negatively associated with proximity in all three cities ($r = -0.537$, -0.660 and -0.618).

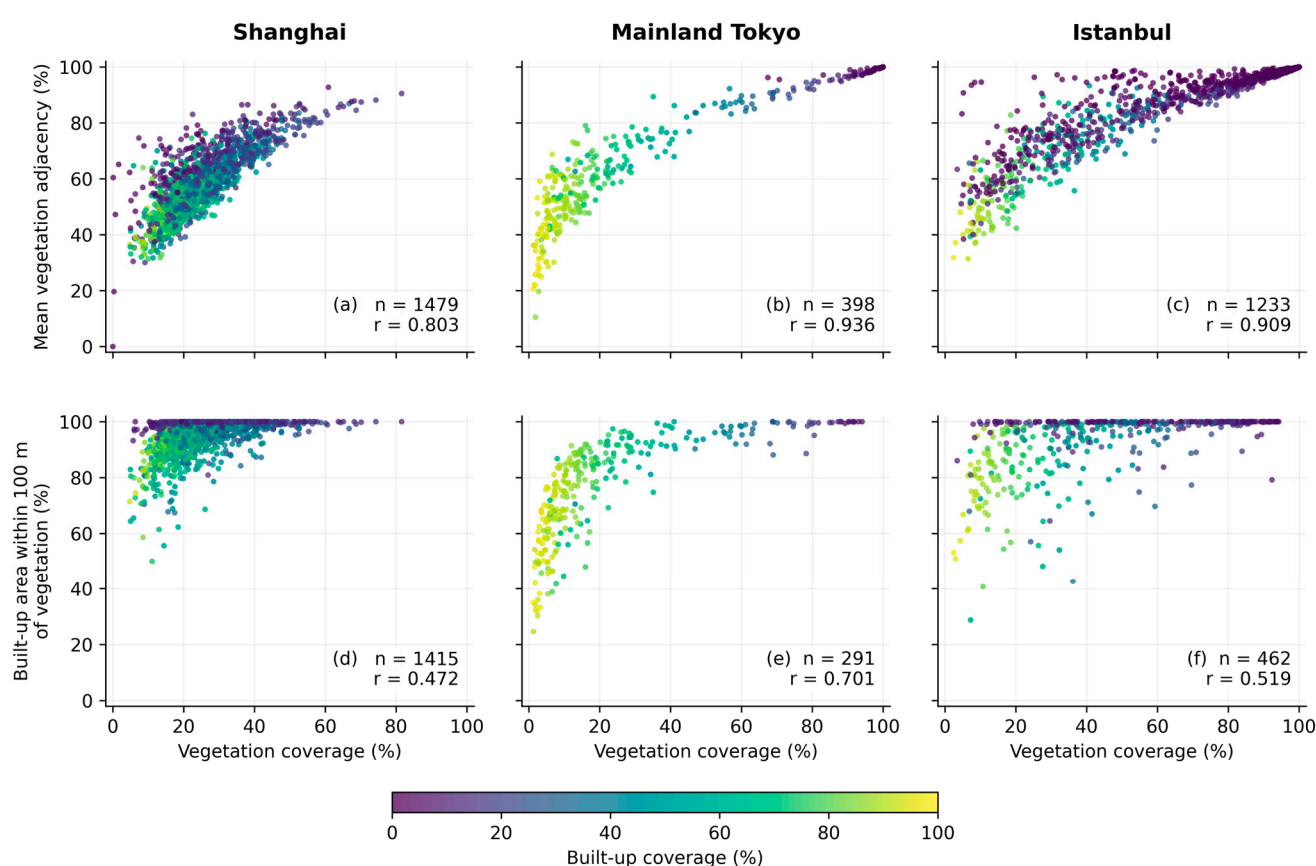


Figure 6. Within-city relationships at the 2 km scale. Columns represent Shanghai, mainland Tokyo and Istanbul. Panels (a–c) show vegetation coverage and mean vegetation adjacency; panels (d–f) show vegetation coverage and the proportion of built-up area within 100 m of vegetation. Point colour denotes built-up coverage. Each panel reports its valid sample size (n) and Pearson correlation (r). Proximity panels include only cells with $\geq 5\%$ built-up coverage; adjacency panels include all cells with defined adjacency. Correlations are descriptive.

Substantial variation remained within comparable vegetation-coverage bands (Table S2). For cells with 10–20% vegetation coverage, the 10th–90th percentile adjacency ranges were 40.6–60.5% in Shanghai, 48.0–68.3% in Tokyo and 46.0–69.0% in Istanbul. Corresponding proximity ranges among eligible cells were 83.5–99.3%, 63.8–89.0% and 70.1–99.8%. Variation also persisted in the 20–30% band, where adjacency ranged from 50.0 to 67.9%, 59.3–74.1% and 59.2–78.2%, respectively. These bands describe comparable rather than identical vegetation coverage.

The 5 km analysis retained 219, 56 and 183 cells in Shanghai, Tokyo and Istanbul, respectively. Vegetation coverage–adjacency correlations remained positive ($r = 0.744$, 0.960 and 0.929), as did vegetation coverage–proximity correlations ($r = 0.516$, 0.727 and 0.418); built-up coverage–proximity correlations remained negative ($r = -0.572$, -0.692 and -0.527). Thus, association directions were consistent at the two tested grid sizes. Complete sample sizes and correlations, including interior vegetation share, are provided in Table S1.

3.5. Surface-Water Seasonality and Drainage Structure

JRC Global Surface Water provides a complementary classification of water seasonality in 2021 (Table 5). Total permanent-plus-seasonal water proportions are similar in Shanghai (5.12%) and Istanbul (5.20%), but their composition differs. Shanghai contains 2.72% permanent and 2.41% seasonal water, whereas Istanbul contains 4.57% permanent and 0.64% seasonal water. Tokyo has the lowest total water share at 2.64%.

Modelled drainage-network density is highest in Tokyo at the primary ≥ 10 km² threshold (0.357 km km⁻²), followed by Shanghai (0.318 km km⁻²) and Istanbul (0.262 km km⁻²). The same ordering persists at the ≥ 50 km² and ≥ 100 km² thresholds. The metric therefore provides a stable standardized description of hydrographic network structure even though it does not include the full engineered urban drainage system.

Table 5. Surface-water seasonality and drainage-network sensitivity.

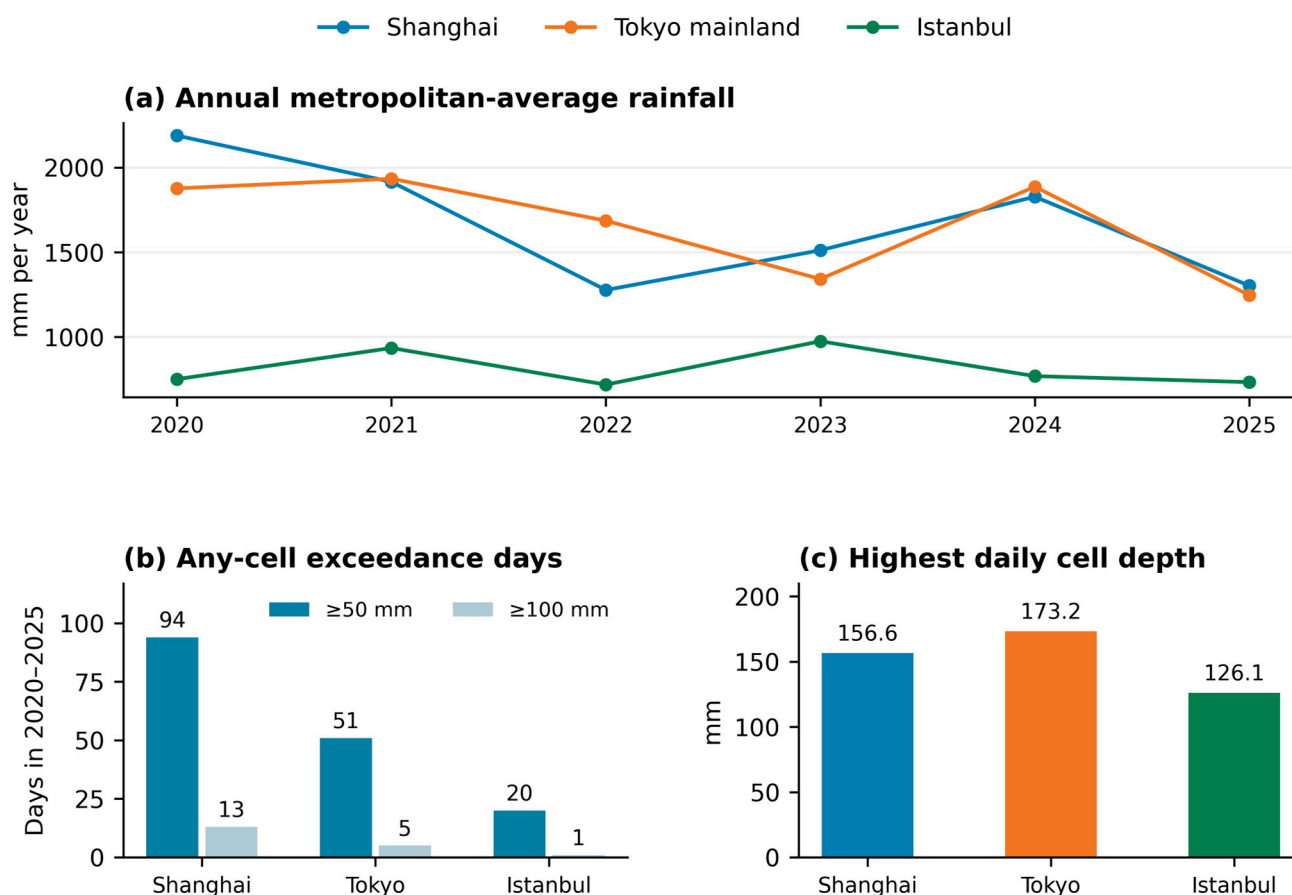
Metropolitan Region	JRC Permanent Water (%)	JRC Seasonal Water (%)	JRC Total Surface Water (%)	Drainage Density ≥ 10 km ² (km km ⁻²)	Drainage Density ≥ 50 km ² (km km ⁻²)	Drainage Density ≥ 100 km ² (km km ⁻²)
Shanghai	2.72	2.41	5.12	0.318	0.130	0.090
Tokyo mainland	1.81	0.83	2.64	0.357	0.153	0.125
Istanbul	4.57	0.64	5.20	0.262	0.111	0.069

Notes: JRC Global Surface Water v1.4 seasonality refers to 2021: permanent water = 12 months; seasonal water = 1–11 months. MERIT Hydro v1.0.1 thresholds specify minimum upstream drainage area. Lengths estimated from raster flow directions using nominal grid spacing. Rounded water components can differ from displayed totals by 0.01 percentage points.

3.6. Satellite Precipitation and Grid-Cell Extremes

Shanghai and Tokyo have almost identical six-year mean annual precipitation: 1670.5 mm and 1662.2 mm, respectively (Table 6; Figure 7a). Istanbul receives approximately half as much, with a mean of 813.5 mm. Interannual variability is greatest in Shanghai (coefficient of variation 21.9%), followed by Tokyo (18.0%) and Istanbul (13.7%).

Before comparing extremes, two qualifications are necessary: IMERG retrieval uncertainty can affect heavy-rainfall estimates in coastal settings, and any-cell exceedance counts depend on the spatial extent sampled (Section 2.6). Within the specified boundaries, Shanghai recorded 94 days with at least one IMERG grid cell receiving ≥ 50 mm during 2020–2025, compared with 51 in Tokyo and 20 in Istanbul (Table 7; Figure 7b). The respective ≥ 100 mm totals were 13, 5, and 1. Mean annual P99 of the daily spatial-maximum series was 89.5 mm, 64.1 mm, and 50.7 mm. These describe boundary-specific satellite rainfall statistics, not observed flood counts or rainfall exceedance at a typical location.



IMERG Final V07 · 0.1° grid. Any-cell counts and spatial maxima depend on the analytical boundary and are not area-normalized.

Figure 7. IMERG Final V07 rainfall during 2020–2025: (a) annual metropolitan-average totals; (b) six-year any-cell exceedance counts; and (c) highest daily grid-cell depth. Spatial maxima and counts depend on the analytical boundary.

The largest individual daily grid-cell maximum was 173.2 mm in Tokyo, occurring in 2022. Shanghai's six-year maximum was 156.6 mm, and Istanbul's was 126.1 mm (Figure 7c). The resulting profiles distinguish annual rainfall amount from spatial-maximum frequency and magnitude. Their differences should be interpreted for the sampled boundaries and period, with the uncertainties described above.

Table 6. Metropolitan-average annual precipitation, 2020–2025.

Year/Summary	Shanghai (mm yr ⁻¹)	Tokyo Mainland (mm yr ⁻¹)	Istanbul (mm yr ⁻¹)
2020	2188.6	1877.1	750.9
2021	1915.3	1934.1	934.7
2022	1277.1	1686.0	718.5
2023	1511.8	1341.8	974.7
2024	1827.7	1886.9	768.7
2025	1302.5	1247.0	733.3
2020–2025 mean	1670.5	1662.2	813.5
Interannual SD	365.6	298.7	111.4
Coefficient of variation	21.9%	18.0%	13.7%

Notes: Source: GPM IMERG Final Run V07, 2020–2025. Half-hourly precipitation rates were converted to depths and aggregated daily. Annual totals are metropolitan spatial means accumulated over each year. SD is the sample standard deviation across six annual totals; $CV = 100 \times SD/\text{mean}$. Displayed values are rounded independently.

Table 7. Grid-cell extreme-rainfall statistics within the analytical boundaries, 2020–2025.

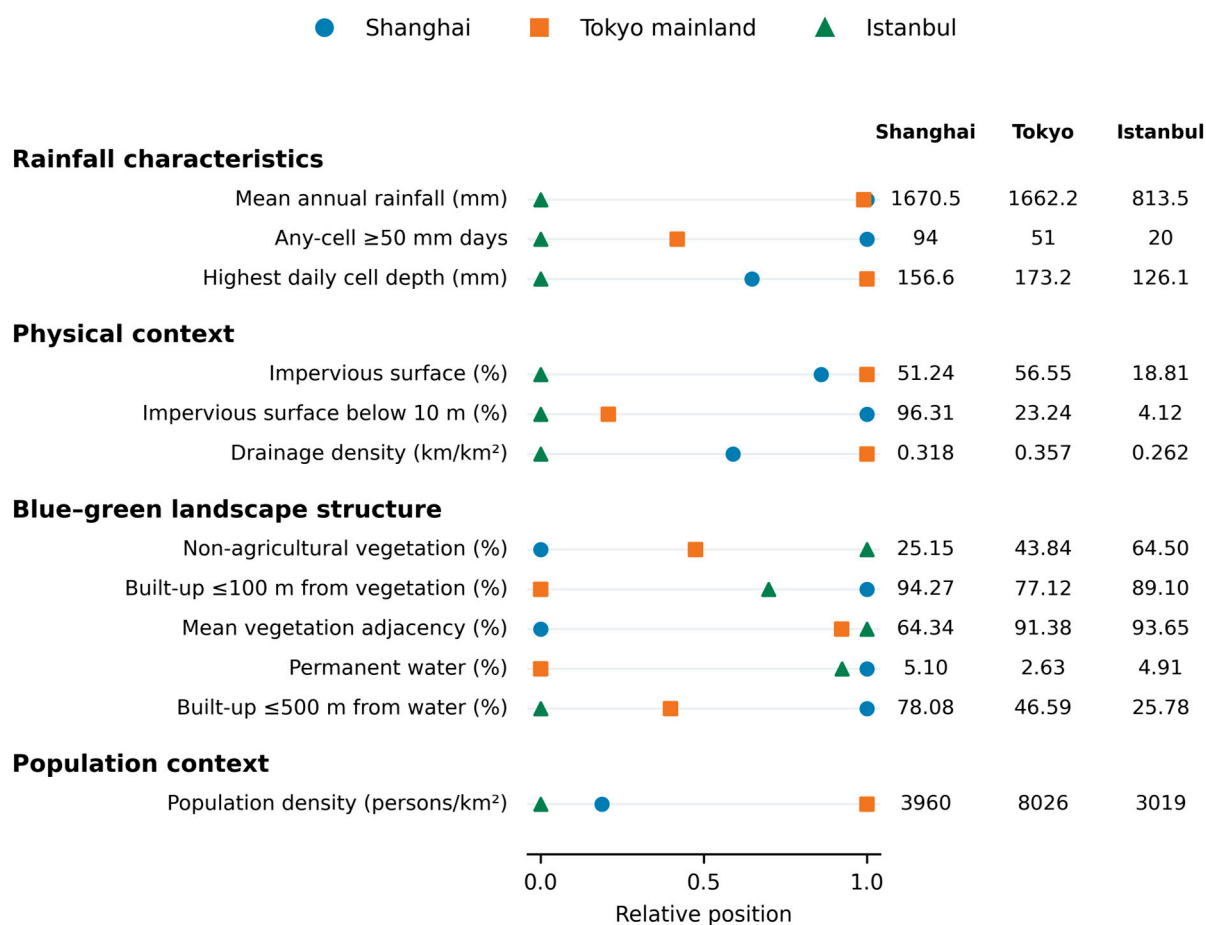
Metric	Shanghai	Tokyo Mainland	Istanbul
Mean annual P99 of daily spatial maxima (mm)	89.5	64.1	50.7
Days with any IMERG cell ≥ 50 mm	94	51	20
Days with any IMERG cell ≥ 100 mm	13	5	1
Highest grid-cell daily maximum (mm)	156.6	173.2	126.1

Notes: Source: GPM IMERG Final Run V07 at 0.1° . P99 is calculated for each year from the daily spatial-maximum series and averaged across six years. Threshold counts are six-year totals of days with exceedance in any included cell. Spatial support differs among cities; the counts are not area-normalized. The highest maximum is a daily grid-cell depth, not a metropolitan mean.

3.7. Comparative Profiles and Sensitivity Analysis

The profiles compare original indicator values alongside their relative positions without producing a single score (Figure 8). Shanghai combines high imperviousness, extensive development below the elevation thresholds, high rainfall totals, low vegetation aggregation, and strong built-up proximity to vegetation and water. Tokyo has the highest imperviousness and administrative population density, relatively aggregated vegetation, and intermediate development–terrain overlap. Istanbul has the highest vegetation coverage and aggregation, lower imperviousness and low-elevation overlap, and the lowest built-up proximity to permanent water. Rainfall exceedance counts are retained as boundary-specific descriptors. No overall ranking of flood probability or resilience is inferred.

The principal comparative patterns are stable under the tested alternative specifications (Table 8). Drainage-network density remains Tokyo > Shanghai > Istanbul at upstream thresholds of 10, 50, and 100 km². Low-elevation extent remains Shanghai > Tokyo > Istanbul at both the 5 m and 10 m thresholds. Development–terrain coupling preserves the same Shanghai > Tokyo > Istanbul ordering when calculated with either GISA-new impervious surface or WorldCover built-up land and under both elevation thresholds. Repeating the proximity analysis at 30 m changes the absolute percentages—as expected when fine boundaries and narrow landscape elements are generalized—but preserves the ranking Shanghai > Istanbul > Tokyo for vegetation proximity and Shanghai > Tokyo > Istanbul for water proximity.



Each indicator is normalized separately. Higher values do not uniformly imply greater susceptibility. Original values appear at right; no composite score is used.

Figure 8. Comparative indicator profiles. Min–max normalization is applied separately to each indicator across three cities; original values are retained alongside. Higher normalized values do not consistently indicate greater susceptibility. Population density provides demographic context.

Table 8. Sensitivity and robustness of the principal comparative patterns.

Indicator	Sensitivity Dimension	Alternative Specifications	Comparative Ranking	Interpretation
Drainage-network density	Upstream-area threshold	$\geq 10/\geq 50/\geq 100$ km ²	Tokyo > Shanghai > Istanbul	Stable at all thresholds
Low-elevation extent	Elevation threshold	<5 m/<10 m	Shanghai > Tokyo > Istanbul	Large separation; ranking stable at both thresholds
Built-up proximity to vegetation	Raster analysis resolution	30 m/native WorldCover (~10 m)	Shanghai > Istanbul > Tokyo	Ranking unchanged; absolute values differ
Built-up proximity to permanent water	Raster analysis resolution	30 m/native WorldCover (~10 m)	Shanghai > Tokyo > Istanbul	Ranking unchanged; absolute values differ
Development–terrain coupling	Development layer/elevation threshold	GISA impervious/WorldCover built-up; <5 m/<10 m	Shanghai > Tokyo > Istanbul	Large separation; ranking stable across both development layers and both elevation thresholds

4. Discussion

4.1. Blue–Green Landscape Structure and Spatial Configuration

The Shanghai–Istanbul comparison illustrates why metropolitan coverage and proximity should be reported separately (Figure 5). Shanghai has less non-agricultural vegetation but a larger share of development close to vegetation. Similar water coverage also coexists with substantially different built-up proximity to water. These contrasts concern the spatial arrangement of mapped classes within the selected administrative regions, and cannot be inferred from their total areas alone.

Configuration adds a further distinction: Shanghai’s vegetation is more edge-dominated, whereas Tokyo and Istanbul contain larger internally aggregated vegetated areas (Table 4). This is consistent with the relevance of landscape patterns identified by Sohn et al. [6], but the evidence differs. Their longitudinal analysis relates patterns to flood damage; our comparison describes how structure and proximity qualify the interpretation of metropolitan coverage. It does not estimate their effects on flood losses.

Within-city results show that vegetation quantity is strongly associated with adjacency, while substantial variation in adjacency and built-up proximity remains within comparable coverage bands (Figure 6). These dimensions are related but non-equivalent. The bands do not isolate a configuration effect independent of quantity, because coverage still varies within each band. The negative built-up coverage–proximity associations indicate that more intensively developed cells tend to have a smaller fraction of development close to vegetation, supporting attention to provision within developed districts alongside metropolitan totals.

The mapped patterns help interpret the numerical contrasts (Figure 4). Shanghai’s vegetated elements are interspersed within a more extensively developed and agricultural setting, whereas large vegetated areas occupy western Tokyo and the less urbanized parts of Istanbul. This visual interpretation is consistent with the adjacency and proximity indicators, but does not establish connected runoff pathways. High edge density should not be treated as an ecological benefit: it can accompany habitat fragmentation and greater exposure to edge effects, with consequences for biodiversity and ecosystem function [32]. The present raster measure does not directly assess those consequences. For sustainable landscape planning, urban interspersed and the conservation of larger interior habitats should therefore be considered together.

The cropland sensitivity qualifies the interpretation of vegetation quantity and configuration. Adding agricultural land substantially changes Shanghai’s landscape profile and alters some cross-city orderings, while the change in built-up proximity is small in all three cases (Table S3). The baseline should therefore be read as non-agricultural vegetation, not as the full extent of potentially permeable or water-storing land. Agricultural soil condition, crop cover, field drainage, and water management were not evaluated, so the alternative definition tests landscape classification rather than cropland’s runoff-reduction performance.

4.2. Flood-Susceptibility Contexts and Planning Implications

Development–terrain overlap describes where development lies relative to common surface-elevation thresholds. Tokyo’s metropolitan mean elevation obscures its concentration of development in lowlands, whereas Shanghai’s low-elevation class includes most developed land. These are topographic relationships within the selected boundaries, not a ranking of physical flood susceptibility. The same elevation can have different hydrological implications depending on river or tidal levels, drainage, embankments, pumping, and catchment position.

The Tokyo result is relevant to the transition from mountainous western Tama to the eastern urban lowlands: a high metropolitan mean elevation does not eliminate the planning importance of low-lying developed areas. Ogawa et al. [33] evaluated green-space contributions to combined sewer overflow mitigation in the Tokyo metropolitan area. Their sewer-shed assessment addresses a hydrological response that the present metropolitan indicators do not estimate. The two approaches are complementary: comparative overlap and landscape metrics identify spatial conditions for further investigation, while drainage-scale modelling evaluates the performance of particular interventions.

Istanbul illustrates why extensive peripheral vegetation should not be interpreted as stormwater provision within all developed districts. Its high vegetation share coexists with substantially lower built-up proximity to water than in Shanghai. Ertan and Çelik [34] examined urbanization and sustainable drainage in a flood-hazard assessment, providing a local analytical connection between land development and drainage interventions. The present comparison adds a consistent metropolitan description of where landscape resources and low-elevation development occur; it does not establish that Istanbul's lower imperviousness or overlap translates directly into a lower flood probability.

Planning interpretation should distinguish spatial proximity from hydrological function. Interspersed vegetation may offer locations for stormwater measures, but storage volume, infiltration conditions, and runoff connections must be assessed locally. Similarly, mapped water may include a canal or reservoir with managed storage, a river that conveys floodwater, or water connected to tidal fluctuations. The present classification does not separate these roles. Built-up proximity to water is therefore a descriptive spatial relationship and should not be interpreted as beneficial blue–green integration or effective flood protection.

The Shanghai interpretation also connects to studies at different scales. Research on urban open-space change documents the evolution of its landscape structure [16], while Du et al. [35] examine block-scale waterlogging severity using a rainfall-stratified modelling framework. Those contributions address temporal change and event-related response, respectively. The present study's contribution is the harmonized comparison of landscape structure and development–terrain overlap across contrasting metropolitan settings; it does not reproduce their temporal or predictive analyses.

Sponge City interventions can exploit or modify these spatial preconditions through site-specific storage, planting, drainage connections, and multifunctional open-space design. Tong et al. [36] examine the combination of stormwater management and park services in Shanghai, providing a local example of this connection to sustainable urban development. The metropolitan indicators describe the wider setting for these projects, while policy effectiveness requires local evaluation.

The rainfall descriptors complement the spatial comparison over 2020–2025. Annual totals and any-cell exceedance counts describe different aspects of that period, but the latter also depend on boundary size and the number of sampled IMERG cells. Together with retrieval uncertainty [18,19], this prevents interpreting the counts as an area-independent ranking of storm frequency or a characterization of long-term rainfall extremes.

4.3. Methodological Consistency, Scale, and Planning Transferability

The contribution is the joint interpretation of established indicators within a comparative administrative-region framework. Li et al. [11] developed a method for identifying green-infrastructure priority areas in Ghent, while Zellner et al. [12] used spatially explicit simulations to examine neighbourhood flooding under different infrastructure layouts. Ur Rehman et al. [13] optimized placement using detailed flood modelling. Our framework addresses an earlier comparative task: it identifies contrasts among coverage, configuration, proximity, and development–terrain overlap without simulating runoff or

selecting optimal interventions. Its additional evidence comes from within-city comparisons and explicit definition and elevation sensitivity tests. Following the emphasis of Pons et al. [14] on aligning modelling choices with objectives, these outputs support the selection of questions for local assessment rather than claims of validated flood-mitigation performance.

The checks in Table 8 assess selected changes in analysis grain and indicator thresholds; the within-city comparison additionally tests 2 km and 5 km aggregation units (Table S1). These checks do not remove boundary dependence or classification uncertainty [8]. Configuration metrics remain conditional on the raster grain and boundary treatment, and the interior criterion is not an ecological core-habitat depth. Drainage density uses nominal segment lengths that do not account for latitude-dependent grid dimensions and should be treated as an approximate network measure. The added cropland analysis shows that even city ordering can depend on the vegetation definition (Table S3).

The elevation scenarios distinguish stability of a comparative pattern from precision of its percentage (Table S4). Development-overlap ordering persisted under the same offset applied to each city, but Shanghai's absolute percentages varied substantially, especially at 5 m. Different local elevation errors could affect the cities differently, and uniform shifts do not represent the spatial distribution of DSM error. The Tokyo development-terrain contrast is supported at 10 m across the tested shifts, but should not be generalized to every threshold. Local bare-earth elevation and water-level data remain necessary before interpreting these classes for flood planning.

Transferability rests on the use of accessible source products and repeatable indicator definitions, rather than on transferring a city ranking or a fixed intervention standard. GEE supports consistent processing [21], while integrated flood-risk assessments demonstrate the importance of tailoring management strategies to local physical and social conditions [37]. A practical application is to use the metropolitan profiles to structure subsequent catchment, district, or project-level assessment, where drainage networks, land ownership, infrastructure condition, and flood observations can be incorporated.

For Tokyo, the development-terrain contrast suggests that zoning review and infrastructure screening should distinguish the eastern lowlands from the mountain-to-lowland transition, rather than use the metropolitan mean elevation as a development criterion. Lowland sites require local floodplain, drainage, and protection data; transition areas also require attention to catchment pathways. In Shanghai, where almost all mapped impervious development lies below 10 m, that threshold offers limited discrimination within the city. Planning priorities must therefore be refined using local drainage capacity, storage opportunities, microtopography, and flood observations. Istanbul's profile supports examining blue-green provision within developed districts alongside the protection of extensive peripheral vegetation. These are planning implications of the observed profiles, not proposed legal thresholds or validated intervention designs.

4.4. Scope and Interpretation

The comparison covers three contrasting administrative regions and does not establish a general ranking of coastal megacities. Within-city cells broaden the spatial evidence but do not add independent city cases; descriptive correlations neither control for spatial autocorrelation nor establish causation. No flood inventory, observed inundation, hydraulic simulation, or historical flood-loss series was used to validate the indicators against flooding. The framework therefore describes conditions relevant to several flood mechanisms without estimating hazard probabilities or actual population exposure. Temporal differences among datasets also preclude interpretation as a synchronized event assessment. A next application should combine the spatial profiles with observed flooding

and catchment-scale drainage and protection data, and examine whether conclusions persist under a common functional urban-area or developed-footprint boundary.

5. Conclusions

This study compared Shanghai, mainland Tokyo, and Istanbul as contrasting administrative regions using a common framework for landscape coverage, vegetation configuration, proximity to development, and development–terrain overlap. Its contribution is to show how these established measures provide related but non-equivalent descriptions, supported by within-city comparisons at two aggregation scales.

Vegetation quantity was strongly associated with adjacency, yet comparable coverage bands contained varied configuration and proximity conditions. Including cropland changed coverage and structure more than metropolitan built-up proximity. Development–terrain overlap also added information beyond citywide terrain summaries: Tokyo’s concentration of impervious development below 10 m persisted across the tested elevation offsets. Absolute low-elevation percentages, especially in Shanghai, remained sensitive to those offsets.

The framework can guide the selection of districts and catchments for detailed drainage and landscape assessment. It does not predict inundation, establish the hydrological performance of nearby vegetation or water, or measure population exposure. Its next application should connect these spatial contrasts to flood observations, local terrain and water levels, and infrastructure capacity, while testing boundary dependence. Such work would link the comparative diagnosis more directly to sustainable landscape and storm-water-management decisions.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su182010300/s1>, Table S1: Within-city sample sizes and Pearson correlations at 2 km and 5 km; Table S2: Vegetation-coverage-band summaries at both scales; Table S3: Metropolitan sensitivity to including cropland; Table S4: Sensitivity of low-elevation shares and development overlap to uniform DSM offsets.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

Abbreviation	Definition
DEM	Digital elevation model

DSM	Digital surface model
GEE	Google Earth Engine
GISA	Global impervious-surface area
GPM	Global Precipitation Measurement
IMERG	Integrated Multi-satellitE Retrievals for GPM
JRC	Joint Research Centre
LULC	Land use/land cover
PMW	Passive microwave

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