

Article

Built-Up Fraction and Residential Expansion Under Hydrologic Constraints: Quantifying Effects of Terrain, Groundwater and Vegetation Root Depth on Urbanization in Kunming, China

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Abstract

Urbanization in mountainous regions alters hydrologic systems, yet the spatial patterning of residential (RA) and non-residential (NRA) areas in response to hydrologic constraints remains poorly quantified. In this study, we analyzed how such constraints shaped the distinct locational logic of RA and NRA expansion in the mountainous Kunming Core Region (KCR), Southwest China, from 1975 to 2020. Using the Global Human Settlement Layer (GHS-BUILT-S) built-up fraction data and its functionally classified RA and NRA layers at 100 m resolution, we quantified multi-decadal urban land changes via regression and centroid migration analyses. Six hydrologic factors, namely altitude, slope, surface roughness, distance to river (DTR), depth to water table (DTWT) and vegetation root depth (VRD), were derived from global terrain, groundwater, and rooting depth datasets, and harmonized to a common grid. Results show a two-phase urbanization pattern: moderate, compact growth before 1995 followed by rapid, near-exponential expansion, dominated by RA. RA consistently clustered in hydrologically favorable zones (low–moderate roughness, mid-altitudes, lower slopes, proximal rivers, shallow–moderate DTWT, moderate VRD), whereas NRA expanded into more hydrologically variable terrain (higher roughness, intermediate DTR, deeper DTWT, higher altitudes, deeper VRD). Contribution-weighting analysis revealed a temporal shift in dominant drivers: for RA, from river proximity and slope in 1975 to terrain roughness in 2020; for NRA, from vegetation root depth and moderate topography to root depth plus altitude. Geographic centroids of both RA and NRA migrated northeastward, indicating coordinated yet functionally distinct peri-urban and corridor-oriented growth. These findings provide a hierarchical, factor-based framework for integrating hydrologic constraints into risk-informed land-use planning in topographically complex basins.

Keywords: urban hydrologic constraints; residential expansion; regional scale; hydrologic controls; Kunming Core Region



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1. Introduction

Urbanization in mountainous subtropical regions presents significant challenges for sustainable development, as rapid expansion of built-up areas alters hydrologic regimes by increasing impervious surfaces, modifying infiltration–runoff partitioning, and amplifying peak discharges [1–3]. Yet, understanding of hydrologic constraints on urban growth in heterogeneous terrains remains limited, particularly regarding the distinct spatial responses (termed functional differentiation) of residential (RA) and non-residential (NRA) areas to biophysical limitations [4]. Most studies focus on lowland or homogeneous urban settings, overlooking complex interactions among groundwater dynamics, hillslope hydrological processes (including interflow and subsurface stormflow), terrain variability and vegetation–water relations [5]. This gap impedes predictive modeling of urbanization pathways, which is a critical need for anticipating infrastructure demand and environmental impacts, and undermines adaptive planning in rapidly developing basins where hydrologic risks escalate with uncontrolled growth [6,7].

Current research on urbanization under hydrologic constraints primarily includes three partially overlapping domains: urban land-use dynamics, hydrologic impact assessment, and spatial modeling of environmental limitations. Studies of urban expansion typically quantify aggregate urban expansion using medium-resolution datasets, often neglecting functional differentiation between residential and non-residential areas [8–10]. Research on hydrologic impacts primarily emphasizes runoff generation and flood vulnerability, yet rarely examines how different urban functions respond distinctly to terrain, groundwater depth, and the hydraulic constraints associated with soil and vegetation rooting-zone depth [11]. Moreover, spatial modeling frameworks increasingly incorporate topographic or riverine factors to predict urban expansion, but most studies overlook the synergistic interactions among critical hydrologic factors, which jointly govern urban spatial patterns [12]. Consequently, the relative contributions of different hydrologic factors to urban growth and their temporal evolution remain poorly understood.

Recent advances in high-resolution remote sensing, global urban datasets and hydrologic modeling now enable systematic examination of these interactions. The Global Human Settlement Layer (GHS) provides multi-decadal, harmonized data on residential and non-residential built-up surfaces [13]. Complementary datasets allow spatially explicit characterization of hydrologic constraints over topographically complex (e.g., high-relief, dissected) landscapes [14]. Analytical methods such as centroid migration, stratified box-plots and contribution-weighting permit quantification of the influence and hierarchy of multiple hydrologic drivers [15].

Despite these advances, regions with extreme topographic and hydrologic heterogeneity, such as the Kunming City in China, pose unresolved challenges. The deeply incised valleys, steep hillslopes, dense river networks and variable vegetation structures create a mosaic of hydrologic opportunities and constraints that interact dynamically with urban expansion [16]. The functional responses of residential and non-residential development to these hydrologic constraints are largely unquantified, and the relative importance of different hydrologic factors is unknown [17–20]. Addressing these knowledge gaps is essential for guiding sustainable urban growth and mitigating hydrologically mediated risks in mountainous metropolitan regions.

This study aims to fill these gaps by (i) quantifying multi-decadal changes in total built-up, residential and non-residential areas from 1975 to 2020; (ii) analyzing the relationships between six key hydrologic factors (altitude, slope, surface roughness, distance to river, depth to water table and vegetation root depth) and urban expansion; and (iii) ranking the contributions of these factors to urban growth, thereby establishing a hydrologic hierarchy to inform risk-sensitive land-use planning. The findings will provide a comprehensive

framework for understanding hydrologically mediated urbanization in complex mountainous regions, offering insights for sustainable urban development in topographically and hydrologically heterogeneous environments.

2. Study Area

This study focuses on the Kunming Core Region (KCR), geospatially situated between 102.15° E–103.1° E and 24.35° N–25.65° N, a rectangular area including the rapidly urbanizing core of Kunming City and its adjacent counties in Yunnan Province, Southwest China (Figure 1). The region spans approximately 14,000 km² and includes eight key administrative units: Anning, Chenggong, Fumin, Guandu, Jinning, Panlong, Wuhua and Xishan. These districts and counties represent the political, economic and cultural nucleus of Kunming, which is the capital and biggest city of Yunnan Province. Topographically, the KCR is characterized by the Dianchi Lake Basin, surrounded by low- to medium-elevation mountains, with elevations ranging from 1800 to 2800 m above sea level. The region experiences a subtropical highland climate, influenced by monsoon patterns, with mild temperatures and distinct wet and dry seasons.

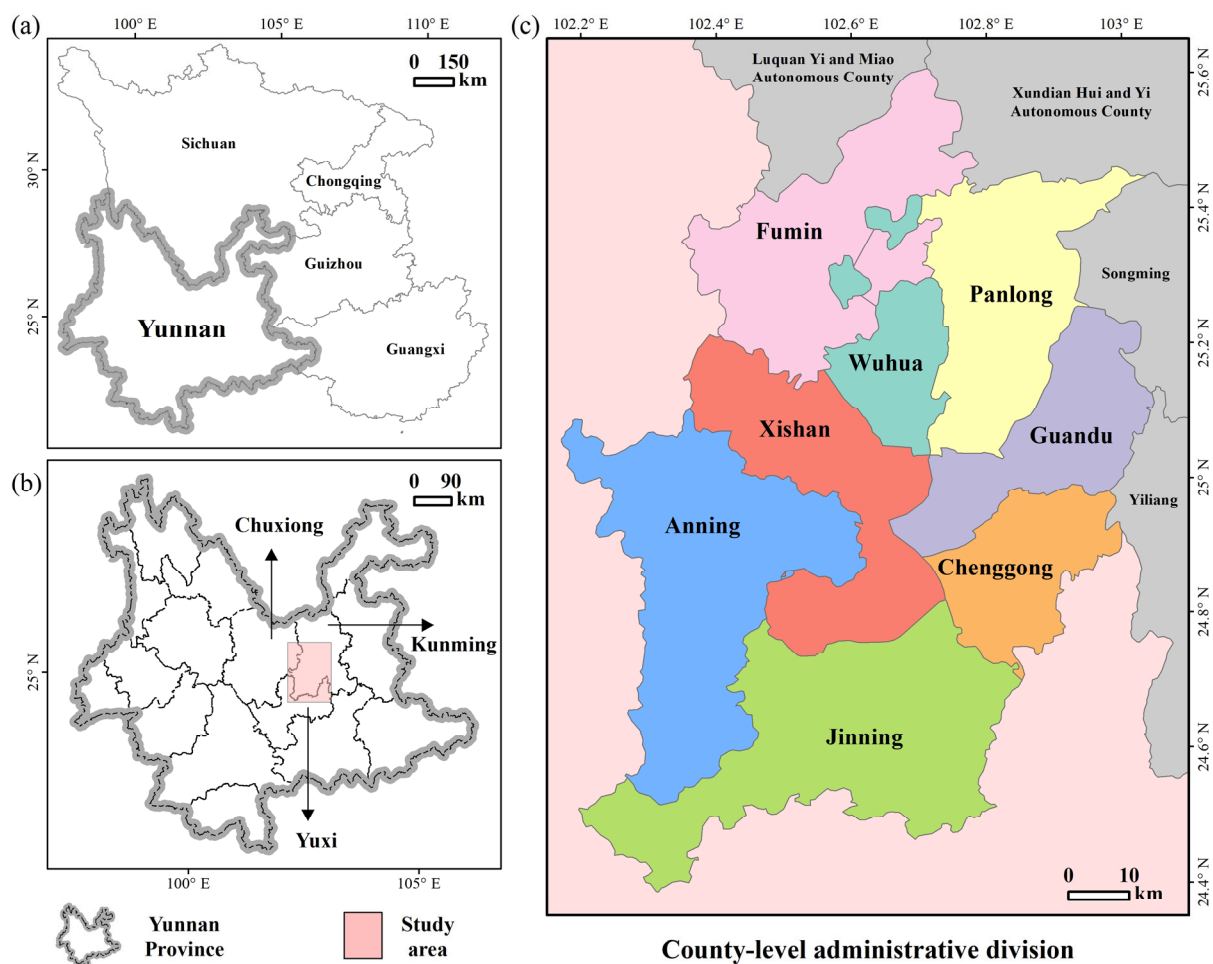


Figure 1. Multi-scale geographic maps and administrative composition of the study area in Central Yunnan Province, China: (a) regional location of Yunnan Province in Southwest China and adjacent provinces; (b) city-level view of the Kunming Core Region (KCR) study area; (c) detailed county-level administrative divisions of the KCR with eight core districts/counties (Anning, Chenggong, Fumin, Guandu, Jinning, Panlong, Wuhua, Xishan) and surrounding autonomous counties/prefectures.

As the most densely populated and economically dynamic zone in central Yunnan, the KCR has undergone accelerated urbanization since the late 20th century, driven by regional

policy initiatives and infrastructure development. Its strategic position as a gateway to Southeast Asia further enhances its significance as a model for studying urban expansion in mountainous regions. The selection of this area enables a high-resolution ($100\text{ m} \times 100\text{ m}$) examination of spatiotemporal patterns in built-up surface evolution, capturing transitions from core urban zones to peri-urban interfaces. The region's topographic and hydrologic complexity (steep slopes, variable roughness and intricate river networks) makes it an ideal testbed for analyzing how heterogeneous environmental constraints shape differentiated urban growth trajectories.

3. Methodology

The description of the integrated workflow implemented in this study is shown in Figure 2. In this study, we employed a multi-stage analytical framework to quantify the spatiotemporal dynamics of urbanization and its coupling with hydrologic constraints in the KCR from 1975 to 2020. The methodology integrated four core components: (1) urban area calculation and trend analysis; (2) geographic centroid analysis to track spatial shifts using weighted coordinate means; (3) urban-hydrologic relationships analysis via stratified boxplot comparisons across six hydrologic factors; and (4) factor contribution analysis combining standardized regression coefficients and partial dependence metrics to rank the relative influence of each hydrologic variable on urbanizations.

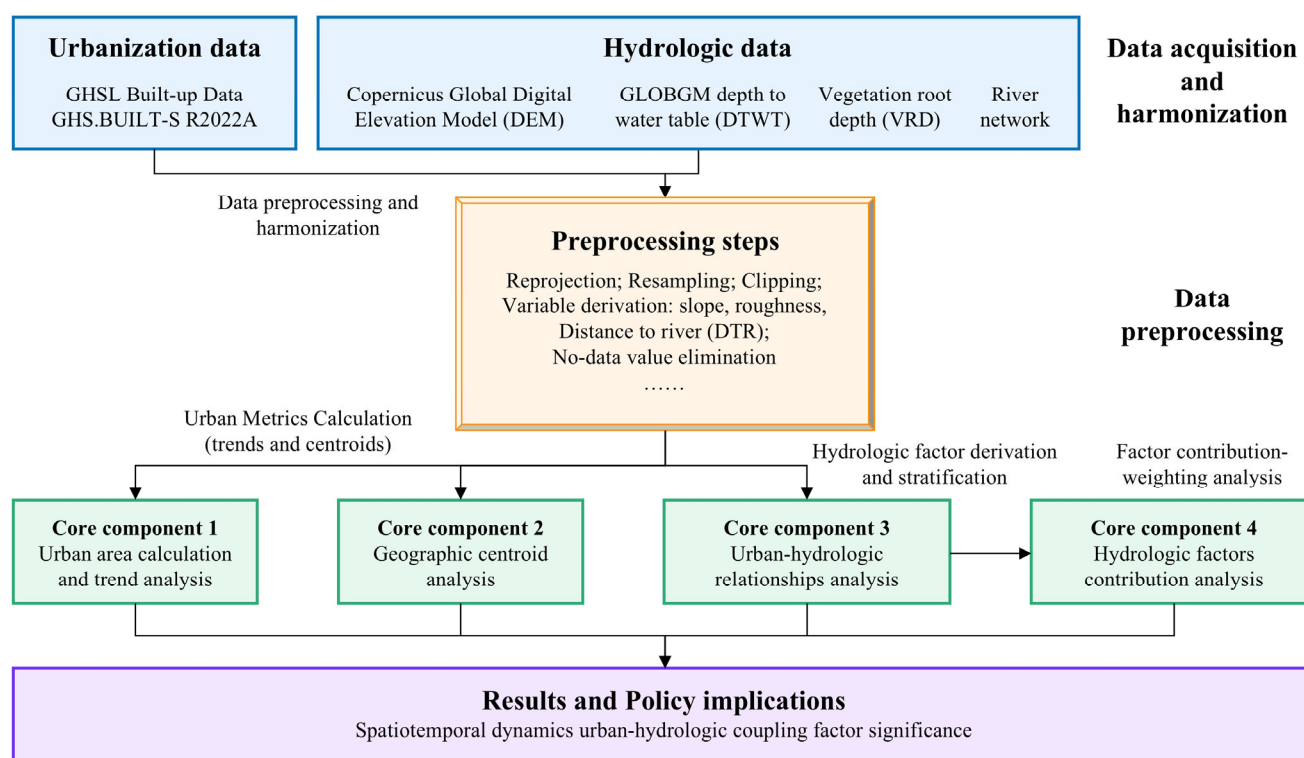


Figure 2. Illustration of the integrated workflow: integrated multi-stage analytical workflow for quantifying spatiotemporal urbanization and its coupling with hydrologic constraints in the Kunming Core Region (1975–2020).

3.1. Data

All the datasets used in this study are shown in Table 1. In this study, we employed the Global Human Settlement Layer (GHSL) Data Package 2022 (GHS P2022) [13], which represents the most comprehensive and internally consistent release of global built environment information. Specifically, we used the built-up fraction (BUFA) and the newly introduced semantic layers distinguishing residential (RA) and non-residential (NRA) built-

up surfaces. BUFA provides sub-cell estimates of built-up surface fraction at 10 m spatial resolution derived from Sentinel-2 optical composites (2017–2018) and legacy Landsat imagery (1975–2014), spatiotemporally harmonized into 100 m grids at 5-year intervals from 1975 to 2020. RA and NRA layers disaggregate the built-up fraction into residential versus non-residential semantic classes, produced through supervised classification algorithms trained on multisource building footprint and land-use data. This allows for a detailed characterization of the urban fabric in both temporal and functional dimensions. For each epoch (1975–2020), the data provide globally consistent grids of built-up fraction, residential fraction and non-residential fraction, together with metadata on projection (World Mollweide, ESRI:54009), resolution and versioning. Collectively, this dataset provides a uniform spatiotemporal framework to quantify the extent, intensity and functional differentiation of the built environment across our study area and to assess the hydrologic drivers of RA and NRA expansion [21,22].

Table 1. Summary of datasets used in this study.

Type	Data	Resource	Originally Domain	Spatial Resolution	Originally Period	Temporal Resolution
Built-up surface	GHS-BUILT-S R2022A	[22,23]	Global	100 m	1975–2030	5-year
	DEM	[24]	Global	1 arc-sec	-	-
Hydrologic data	River	Kunming Water Resources Bureau	Yunnan	Vector	2013	-
	Vegetation root depth	[25]	Global	30 arc-sec	2017	-
	Water table depth	[26]	Global	30 arc-sec	1958–2015	Monthly

The topographic, groundwater and rooting depth conditions of the study area were characterized using three complementary global datasets. Elevation and terrain metrics were obtained from the Copernicus Global Digital Elevation Model (GLO-30) distributed by OpenTopography. This Digital Surface Model (DSM), derived from the WorldDEM TanDEM-X radar mission, provides 30 m resolution global coverage with hydrologically corrected river and coastline representations. Depth to water table (DTWT) was derived from the global GLOBGM groundwater model at 30'' (~1 km) resolution [27]. Vegetation root depth (VRD) was obtained from a global synthesis of >2200 root observations representing >1000 species, aggregated through an inverse modeling framework that estimates effective plant water-uptake depth on ~1 km grids [25,28]. Together, these three datasets allow explicit representation of terrain form, groundwater availability and plant–water interactions across the KCR at a uniform spatial scale.

All hydrologic variables were harmonized to a common grid and projection before analysis. Altitude was directly extracted from the Copernicus DEM, which was reprojected, clipped to the study boundary, and resampled to the working resolution using the bilinear interpolation algorithm. Slope and roughness were subsequently derived from the same DEM using ArcGIS 10.6 spatial analyst tools. A complete, step-by-step description of the algorithms, parameters, and workflow is provided in Supplementary Text S1. Distance to river (DTR) was generated from river vector layers by computing Euclidean distance surfaces in ArcGIS. Both DTWT and VRD underwent identical reprojection, clipping, and resampling (using bilinear interpolation) steps to ensure spatial alignment with the DEM-derived layers. This processing produced six hydrologic variables (altitude, slope, roughness, distance to river, depth to water table and vegetation root depth) that are

internally consistent in resolution and coordinate system and ready for multivariate analysis of their relationships with built-up area expansion.

3.2. Method

3.2.1. Data Processing and Urban Area Calculation

The methodology for analyzing urban expansion patterns was based on the GHS-BUILT-S dataset [13], which provides global built-up surface grids at 100 m resolution for the period 1975–2020. Data processing was performed using MATLAB R2023a with custom scripts designed for geospatial analysis.

The raw data were stored as GeoTIFF files with values ranging from 0 to 10,000, representing the percentage of built-up surface per grid cell. Each cell covered an area of 100×100 m ($10,000 \text{ m}^2$). The area calculation followed the formula [21]:

$$A_{total} = \frac{\sum_{i=1}^n \left(\frac{V_i}{S_f} \times A_{cell} \right)}{10^6} \quad (1)$$

where A_{total} is the total area in km^2 , V_i is the cell value (0–10,000), $S_f = 10,000$ is the scale factor, $A_{cell} = 10,000 \text{ m}^2$ is the area per cell, 10^6 converts m^2 to km^2 . n is the total number of cells in the study area.

Data from nine time points (1975, 1980, . . . , 2020) were processed to generate temporal sequences of urban area changes. Five-year increments were calculated as

$$\Delta A_t = A_t - A_{t-5} \quad (2)$$

where ΔA_t represents the area change between consecutive time points. t is the time index (1, 5, . . . , 10 for 1975–2020). Data quality control included removal of cells with fill values, exclusion of *NaN* values using MATLAB, and validation of spatial consistency across time periods. The processed data were exported to R (version 4.5.2) and Python (version 3.14) for archival and further analysis, containing both absolute values (km^2) and five-year increments.

3.2.2. Trend Analysis

Temporal trends were analyzed using regression techniques to quantify urbanization patterns. For BUFA and RA components, exponential growth models were fitted based on their observed growth patterns:

$$A(t) = a \cdot e^{bt} \quad (3)$$

where $A(t)$ is the urban area at time t , a is the initial area, b is the growth rate parameter.

For NRA, a linear growth model provided better fit:

$$A(t) = c \cdot t + d \quad (4)$$

where c is the slope and d is the intercept.

3.2.3. Geographic Centroid Calculation

The geographic centroid analysis quantifies the spatial shift patterns of RA and NRA built-up areas over time. This method provides a robust metric for understanding urban expansion dynamics and spatial reorganization patterns [29]. The centroid coordinates (longitude and latitude) were calculated for each time point using a weighted average

approach based on built-up surface density distributions. The centroid calculation followed the standard formula for weighted geographic centroids:

$$Lon_c = \frac{\sum_{i=1}^n (Lon_i \times \omega_i)}{\sum_{i=1}^n \omega_i} \quad (5)$$

$$Lat_c = \frac{\sum_{i=1}^n (Lat_i \times \omega_i)}{\sum_{i=1}^n \omega_i} \quad (6)$$

where Lon_c and Lat_c are the centroid coordinates, Lon_i and Lat_i are the geographic coordinates of a certain cell, ω_i is the weight (built-up value) of the cell, n is the total number of cells in the study area. Centroid calculations were performed at decadal intervals from 1975 to 2020.

3.2.4. Urban Hydrologic Relationships Analysis

The grouped boxplot analysis was conducted to examine the relationships between urban built-up areas (both RA and NRA) and various hydrologic factors. This methodological approach provides a robust framework for visualizing distributional patterns across environmental gradients [30]. The analysis employed a stratified-comparison framework using the full population of valid data cells. No subsampling was performed.

The analytical workflow comprised four clearly defined components. First, the sampling frame consisted of the entire population of validated 100 m grid cells within the KCR boundary after preprocessing, excluding only non-urbanized cells ($BUFA = 0$) and invalid data values. Second, stratification was achieved by dividing each continuous hydrologic factor (altitude, slope, surface roughness, DTR, DTWT and VRD) into five equal-interval categories using the boundary algorithm:

$$\Phi_q = \min(F) + \frac{q}{5} \times (\max(F) - \min(F)) \quad (7)$$

where Φ_q are the interval boundaries for $q = 0, 1, \dots, 5$. The quantile group G_q was then defined as

$$G_q = \{x | \Phi_{q-1} \leq x \leq \Phi_q\}, \quad q = 1, 2, \dots, 5 \quad (8)$$

where G_q represents the q -th group. Third, the number of observations (group size) for each stratum represented the complete set of valid urban cells whose factor values fell within each interval range, typically numbering several hundred thousand observations per group. Fourth, no weighting scheme was applied as the analysis incorporated the full population of relevant cells with equal representation.

For each group G_q , the corresponding built-up area values were extracted and analyzed using boxplot statistics, providing a comprehensive view of the distribution characteristics across different factor value ranges [31].

3.2.5. Factor Contribution Analysis

The factor contribution analysis was conducted to quantify the relative influence of six hydrologic factors on the distribution of RA and NRA built-up areas. This analytical approach combines standardized regression coefficients with partial dependence analysis to provide a comprehensive assessment of factor importance, following established practices in spatial predictive modeling [32]. Standardization of all variables to z-scores was performed to ensure scale-invariant comparisons:

$$z = \frac{x - \mu}{\sigma} \quad (9)$$

where x is the original variable value, μ represents the arithmetic mean of the variable, and σ represents the standard deviation of the variable.

Contribution quantification proceeded in three stages. First, standardized regression coefficients (SRCi) were derived from a linear model fitted to standardized data:

$$y_{std} = \beta_0 + \sum \beta_i x_{i,std} + \epsilon \quad (10)$$

where y_{std} is the standardized built-up area values (z-score), $x_{i,std}$ are the standardized factor values (z-score), β_i are the regression coefficients, ϵ is the error term.

Thus, we employed partial dependence analysis to capture nonlinear relationships and interaction effects [33]. For each factor j , the partial dependence function was estimated as

$$PD_j(x_j) = \frac{1}{m} \sum_{k=1}^m f(x_j, \mathbf{x}_{-j}^{(k)}) \quad (11)$$

where $f(\cdot)$ is the prediction function, $\mathbf{x}_{-j}^{(k)}$ are the values of other factors for observation k , and m is the number of observations. The contribution metric was derived from the range of partial dependence values [33]:

$$PDR_j = \max(PD_j) - \min(PD_j) \quad (12)$$

Finally, a composite contribution metric was used to combine these components through multiplicative integration and normalization, ensuring contributions summed to unity [33]:

$$C_i = \frac{SRC_i \times PDR_i}{\sum_{j=1}^6 SRC_i \times PDR_i} \quad (13)$$

$$SRC_i = |\beta| \quad (14)$$

where C_i are final contribution values.

4. Results

4.1. Spatiotemporal Dynamics of Urbanization

In this section, we explored the spatiotemporal evolution of urbanization in the KCR from 1975 to 2020 using a series of decadal built-up land distribution maps derived from the GHS-BUILT-S dataset. Figures 3, S1 and S2 visually summarize the urbanization process over ten time slices at five-year intervals, revealing distinct spatial patterns and transitions in built-up. As illustrated in Figure 3, the BUFA expanded considerably, especially after 2000, showing a transition from compact core development to dispersed and polycentric forms. Figure S1 depicts the evolution of RA, highlighting not only growth in areal extent but also increasing density in both urban and suburban settings. Figure S2 complements these insights by tracing the development of NRA, which often clustered around transport networks and economic zones, reflecting policy-driven industrial and commercial expansion. Together, these maps provide a comprehensive basis for quantifying and interpreting urban land-use changes in one of China's rapidly developing mountainous metropolitan regions.

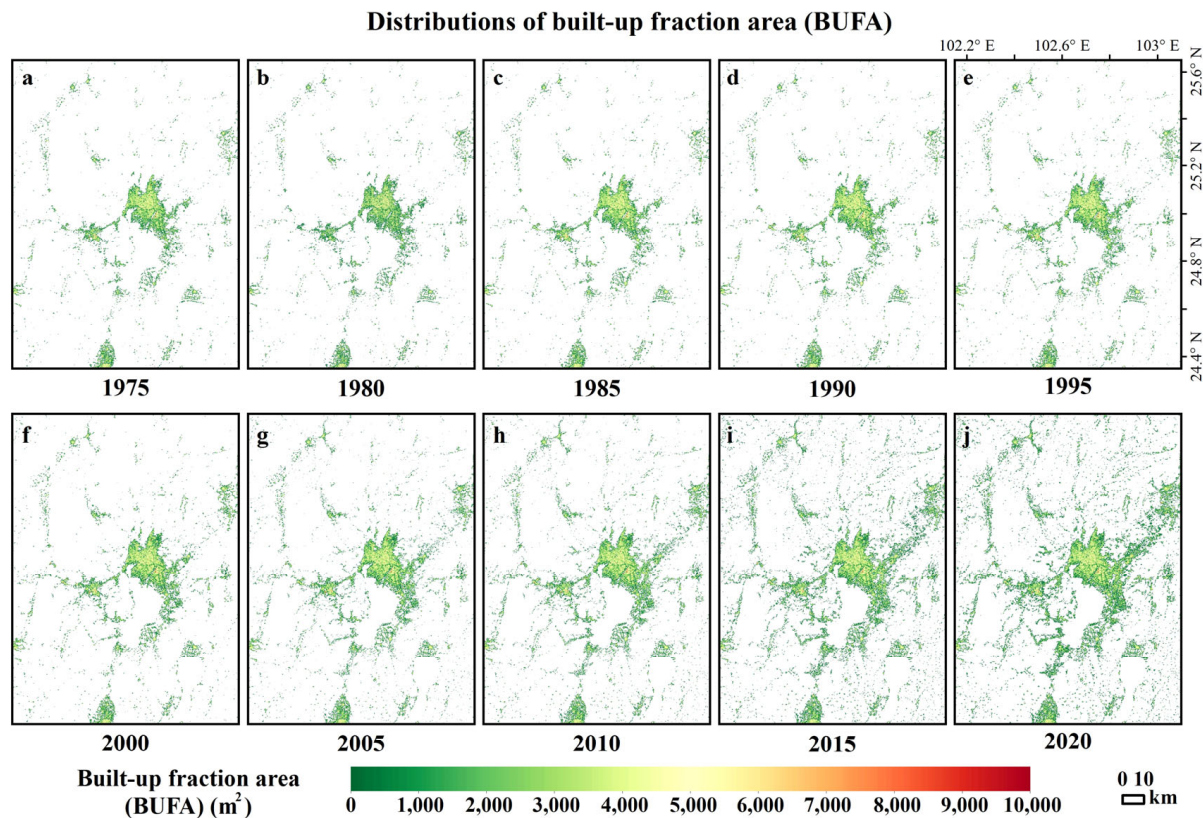


Figure 3. Spatiotemporal evolution of built-up fraction area (BUFA) in the Kunming Core Region (KCR) from 1975 to 2020. Decadal distribution patterns (a–j) showing BUFA dynamics over ten time points (1975, 1980, 1985, 1990, 1995, 2000, 2005, 2010, 2015, 2020) at five-year intervals. BUFA values are represented by a color gradient from dark green (0) to red (10,000 m^2), with white indicating non-built-up areas.

4.1.1. Temporal Evolution Pattern of Urbanization

Figure 4a shows the total built-up area components (BUFA, RA and NRA) from 1970 to 2020, highlighting a pronounced and nonlinear expansion over the study area. Both BUFA and RA exhibit comparable growth trajectories, beginning at approximately 270–280 km^2 in 1970 and rising steadily to more than 650 km^2 and 600 km^2 , respectively, by 2020. This parallel progression indicates that RA contributed the majority of the built-up expansion, while BUFA represents the aggregated footprint of all built-up features. In contrast, NRA remained relatively minor throughout the study period, fluctuating between 5 and 20 km^2 until the mid-2000s before reaching approximately 30 km^2 in 2020. The fitted trend curves in Figure 4b further formalize these observations: BUFA and RA are both well described by an exponential model $y = ae^{bx}$ with high coefficients of determination ($r = 0.97$), capturing the accelerated growth after 2000, while NRA follows a simple linear trend $y = 2.84x + 11.98$ ($r = 0.97$), indicating a slower, more incremental expansion pattern. These aggregated, regional-scale trend models effectively capture the overall temporal trajectory but integrate over all spatial heterogeneity within the KCR. The spatial patterns and sources of variance in urban expansion are examined explicitly in the following sections on spatial differences (Section 4.1.2) and centroid migration (Section 4.1.3).

The temporal increments in urbanized area shown in Figure 4c reveal the dynamic pulses of expansion over five-year intervals. Both BUFA and RA exhibit relatively modest increases (<20 km^2 per five years) before 1990, but thereafter their increments rise sharply, peaking at nearly 130 km^2 in the 2015–2020 interval. This acceleration coincides with the broader economic liberalization and infrastructure investments observed regionally after

the early 2000s. NRA, in contrast, adds only a small fraction (typically $< 5 \text{ km}^2$ per interval), underscoring its marginal contribution to overall urban growth. The stacked bar chart in Figure 4d integrates these increments by visually partitioning the contributions of RA and NRA to each five-year increase, with BUFA superimposed as a cumulative line. The chart shows that RA consistently forms the dominant base of new urban land, while NRA remains a thin layer on top, although its absolute value also rises slightly toward the end of the period.

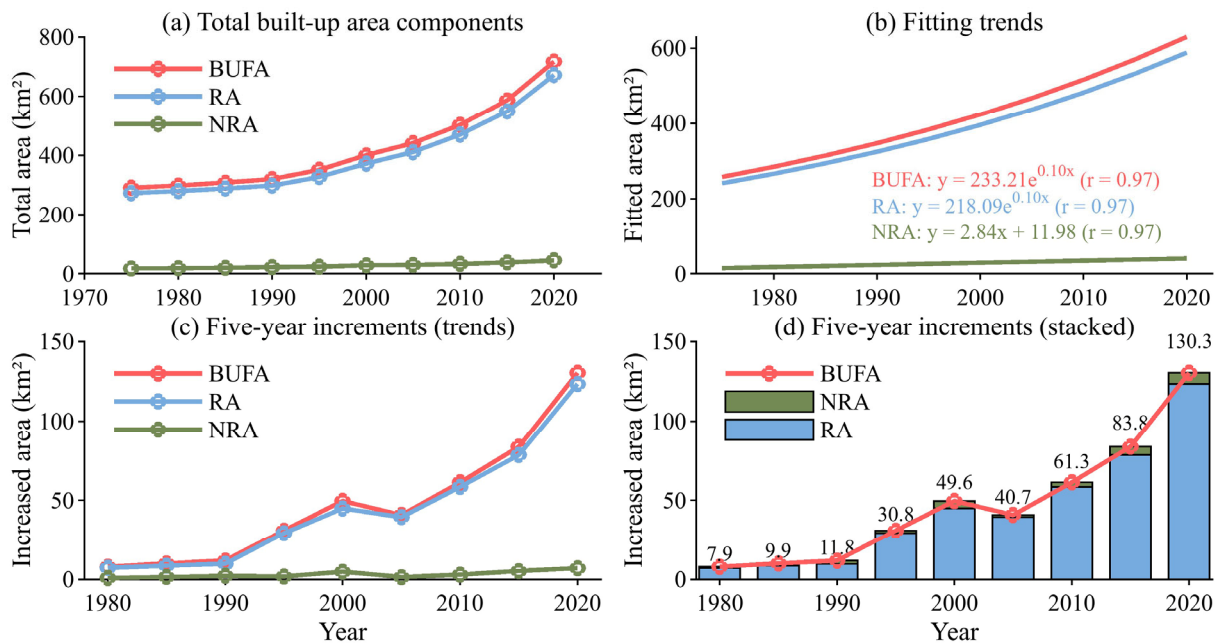


Figure 4. Temporal evolution of urbanized components in the study area: (a) total built-up area components (BUFA, RA, NRA) from 1970 to 2020, showing nonlinear expansion with BUFA and RA dominating; (b) exponential fitting curves for BUFA and RA and linear fitting for NRA; (c) five-year increments; (d) stacked bar chart of five-year increments, with RA and NRA forming the base and BUFA overlaying.

Synthesizing these findings, we found a two-phase evolution of urbanization. The first phase (1970–1995) is characterized by steady but moderate growth in both BUFA and RA, while the second phase (post-2000) marks a rapid, near-exponential expansion dominated by residential development and aggregate built-up area. NRA's linear but low-level growth implies that non-residential activities expanded largely in tandem with, but not at the same scale as, residential and total built-up land. This pattern reflects an urban development trajectory shifting from slow and compact to rapid and expansive, with significant implications for infrastructure demand, land-use planning and the ecological footprint of the metropolitan region.

4.1.2. Spatial Differences in Urbanized Components

Figure 5 presents the spatial differences in BUFA, RA and NRA between 2020 and 1975, as well as frequency distribution histograms of cell value differences for each component, with the x -axis representing cell value difference and the y -axis indicating frequency. BUFA exhibits a mean difference of 819 m^2 , with a standard deviation of 1101 m^2 , ranging from 1 m^2 to $10,000 \text{ m}^2$. RA shows a mean difference of 768 m^2 , a standard deviation of 1005 m^2 , and a range from -130 m^2 to 8633 m^2 . NRA demonstrates a higher mean difference of 1473 m^2 , indicating more substantial changes. BUFA and RA exhibit dispersed patterns

of change across the study area, while NRA displays fewer but larger contiguous areas of difference, suggesting concentrated development.

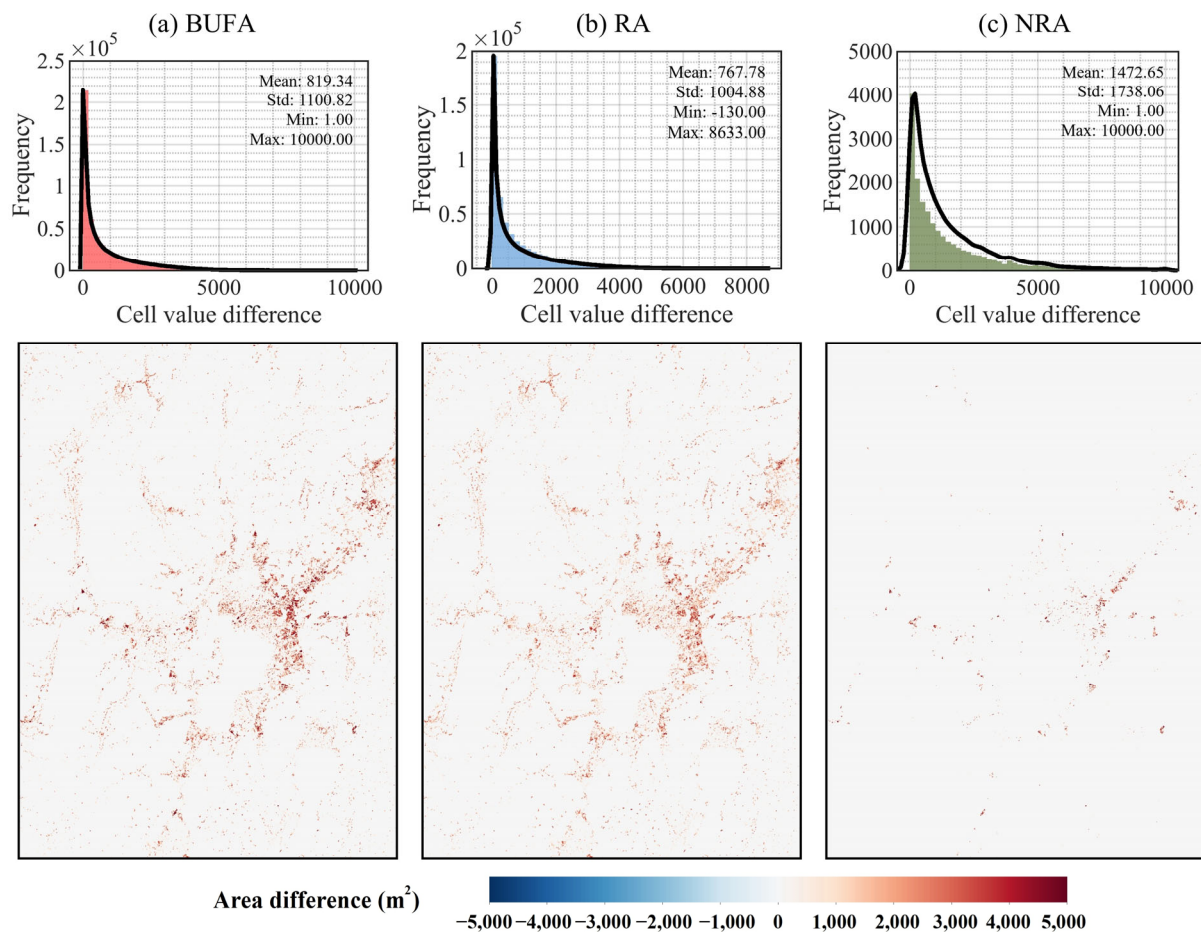


Figure 5. Spatial maps of cell value differences and frequency distribution histograms for built-up fraction area (BUFA), residential areas (RAs) and non-residential areas (NRAs). Sub-figure (a) corresponds to BUFA, (b) to RA, and (c) to NRA, each showing statistical metrics (mean, standard deviation, min, max) and spatial patterns with a blue-to-red color scale indicating negative to positive differences.

Notably, the RA difference map and its histogram demonstrate negative values, indicating localized conversion from residential to other land uses in certain areas between 1975 and 2020, while BUFA and NRA exhibit exclusively positive values, suggesting consistent net expansion throughout the study period. This observed decrease in residential fraction in specific locations, despite the overall net growth, likely reflects complex urban redevelopment processes. A plausible explanatory hypothesis is the in situ densification or functional replacement within older urban cores, where low-density, low-rise residential neighborhoods may have been redeveloped into higher-density residential complexes or converted primarily to non-residential built forms. Such redevelopment would result in a statistical decrease in the “residential fraction” within a grid cell if the new built-up area is classified as NRA or as a denser but smaller footprint RA. Meanwhile, the exclusively positive and spatially concentrated NRA changes suggest that new non-residential development often occurred on previously non-urban land or as large-scale, contiguous projects, rather than through the piecemeal conversion of existing residential areas.

Overall, significant spatial disparities exist among the urbanized components, likely driven by factors such as urban planning policies, economic development priorities and land-use regulations. These differences can profoundly impact urban resource allocation,

infrastructure planning and environmental management, potentially leading to uneven distribution of services and increased pressure on local ecosystems. Understanding these patterns is crucial for sustainable urban development and effective policy-making to balance growth with environmental conservation.

4.1.3. Geographic Centroid Analysis

Figure 6 quantifies the spatial reorganization of urban built-up areas through geographic centroid trajectories of RA and NRA zones from 1975 to 2020. Figure 6a illustrates RA centroid migration using a pink gradient, where each marker represents decadal positions (1975–2020) connected by directional vectors. The trajectory reveals a persistent northeastward shift (ΔLon : $+0.0061^\circ$, ΔLat : $+0.0103^\circ$), reflecting residential expansion toward peri-urban highlands with lower topographic constraints. Meanwhile, Figure 6b traces NRA centroids in green, demonstrating a parallel but spatially distinct migration pattern (ΔLon : $+0.0081^\circ$, ΔLat : $+0.0126^\circ$) toward transportation corridors and economic zones.

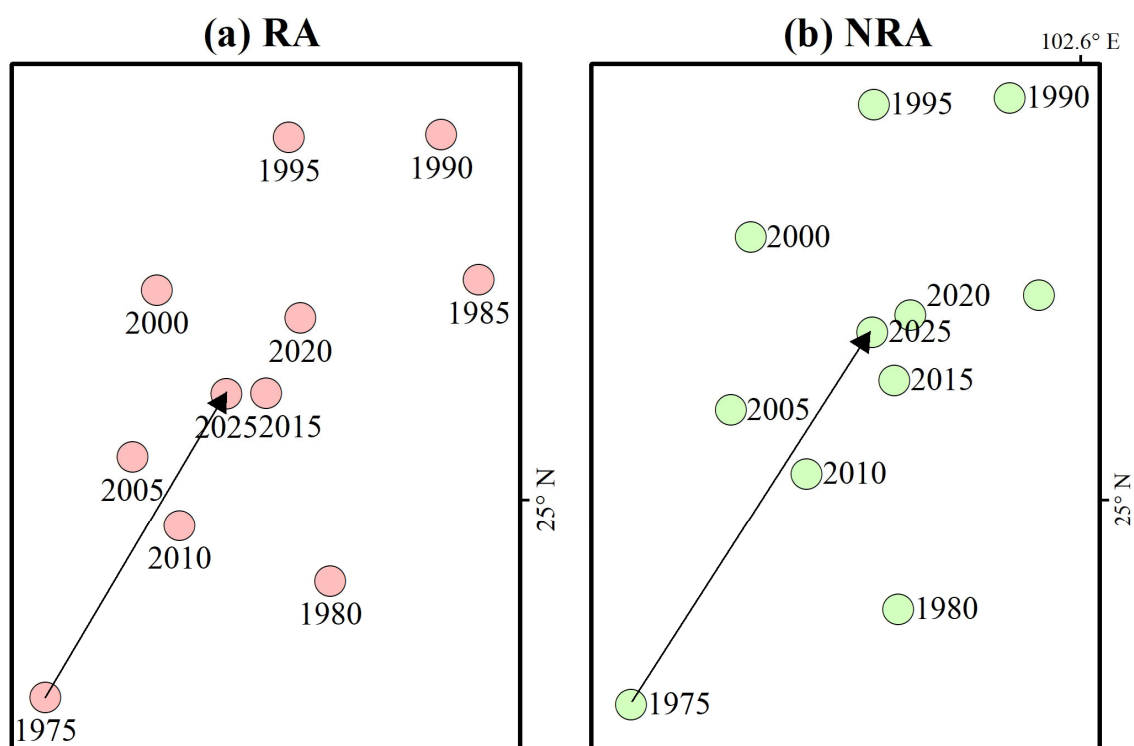


Figure 6. Spatial shift patterns of residential area (RA) and non-residential area (NRA) based on geographic centroid analysis: (a) RA geographic centroid migration from 1975 to 2020; (b) NRA geographic centroid migration from 1975 to 2020.

Notably, both RA and NRA exhibit directional congruence in their macro-scale migration (azimuth: $55\text{--}60^\circ$ NE), indicating coordinated urban growth influenced by regional infrastructure development (e.g., highway networks) and topographical advantages. This centroid co-evolution highlights how shared regional drivers (economic policies, transportation access) synchronize RA and NRA expansion directionality, while distinct sectoral priorities modulate their spatial behaviors [5,9,11]. RA migration reflects incremental residential infill guided by terrain suitability, whereas NRA shifts reveal opportunistic relocation responding to localized economic catalysts, a duality demonstrating how sector-specific adaptations occur within overarching regional development frameworks [34]. The methodology's sensitivity to these nuanced dynamics provides a robust analytical foundation for evaluating multi-scalar urban transformation processes.

4.2. Relationship Between Urbanization and Hydrologic Factors

We further explored the detailed relationships between urban built-up areas (both RA and NRA) and six hydrologic factors (altitude, slope, roughness, DTR, DTWT and VRD). Here, the statistical results for RA and NRA across different values of roughness, DTR, DTWT and VRD, are presented in the main text (Figures 7–10), while those for altitude and slope are provided in the Supplementary Information (Figures S1 and S2).

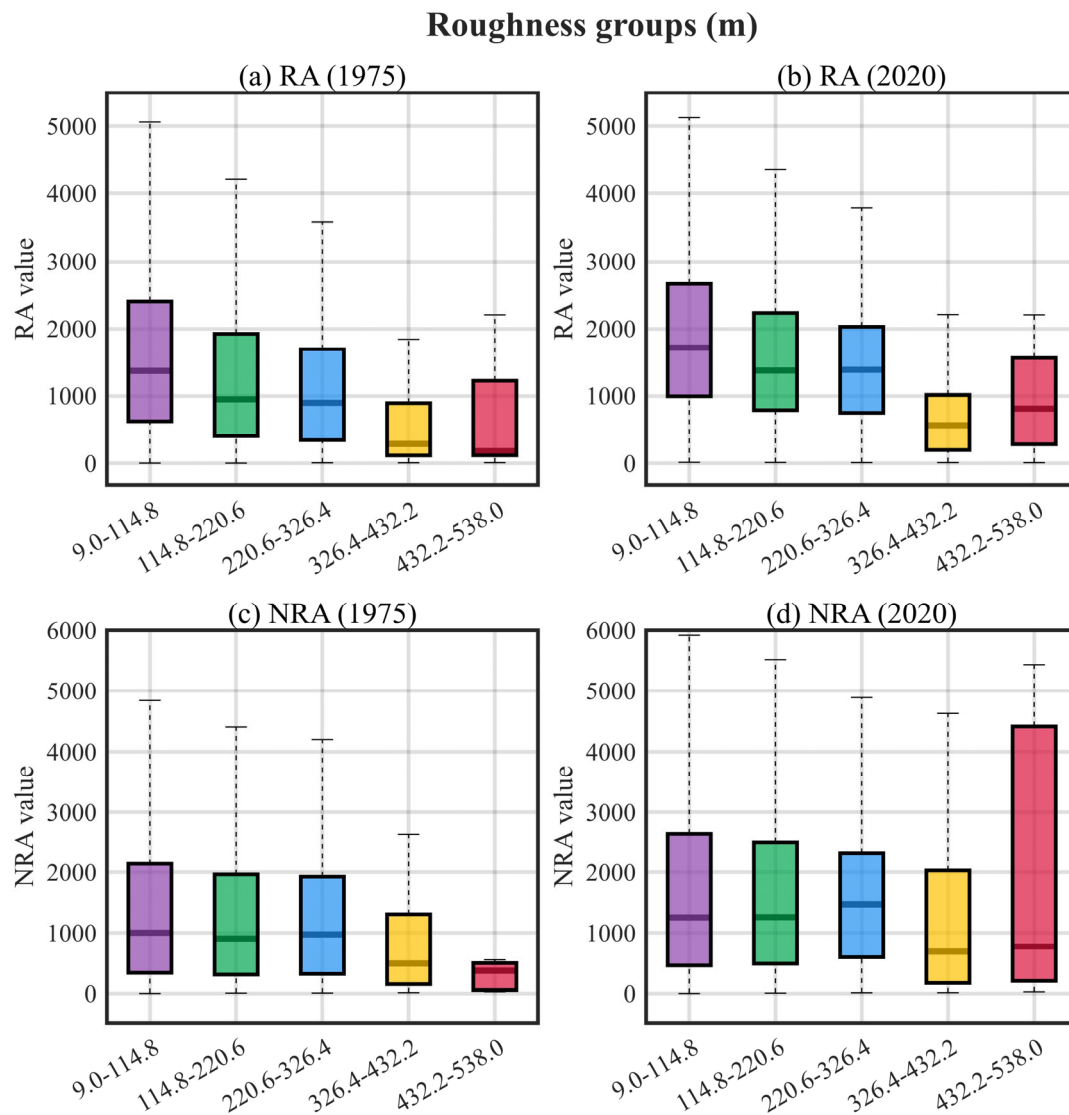


Figure 7. Statistical results of residential area (RA) and non-residential area (NRA) values by roughness groups: (a) RA values in 1975; (b) RA values in 2020; (c) NRA values in 1975; (d) NRA values in 2020. The boxplots display the median (central line), interquartile range (box) and data range (whiskers) for five roughness groups. The unit for roughness is meter (m).

Figure 7a presents a comprehensive statistical analysis of RA and NRA distributions across surface roughness categories during 1975–2020, revealing fundamental shifts in urbanization patterns under hydrologic constraints. The four-panel visualization employs boxplot distributions to quantify urban expansion characteristics across five roughness groups (9.0–114.8, 114.8–220.6, 220.6–326.4, 326.4–432.2 and 432.2–538.0 m), with each boxplot displaying median values (central line), interquartile ranges (box boundaries) and full data ranges (whiskers). Figure 7a,b document RA distributions in 1975 and 2020,

respectively, while Figure 7c,d show parallel NRA distributions, enabling direct temporal and functional comparisons.

The analysis reveals divergent urbanization pathways between residential and non-residential areas. RA distributions demonstrate remarkable stability in lower roughness categories (9.0–220.6 m) with median values maintaining 2000–3000 m², reflecting consistent residential development in topographically favorable zones. Conversely, NRA distributions exhibit significant expansion in higher roughness categories (326.4–538.0 m), where 2020 medians reach 4000–5000 m² compared to 1975 values of 2000–3000 m², indicating preferential non-residential development in topographically complex areas. This functional specialization reflects adaptive urban planning strategies that prioritize residential stability in low-risk zones while permitting commercial/industrial expansion in more variable terrain [35].

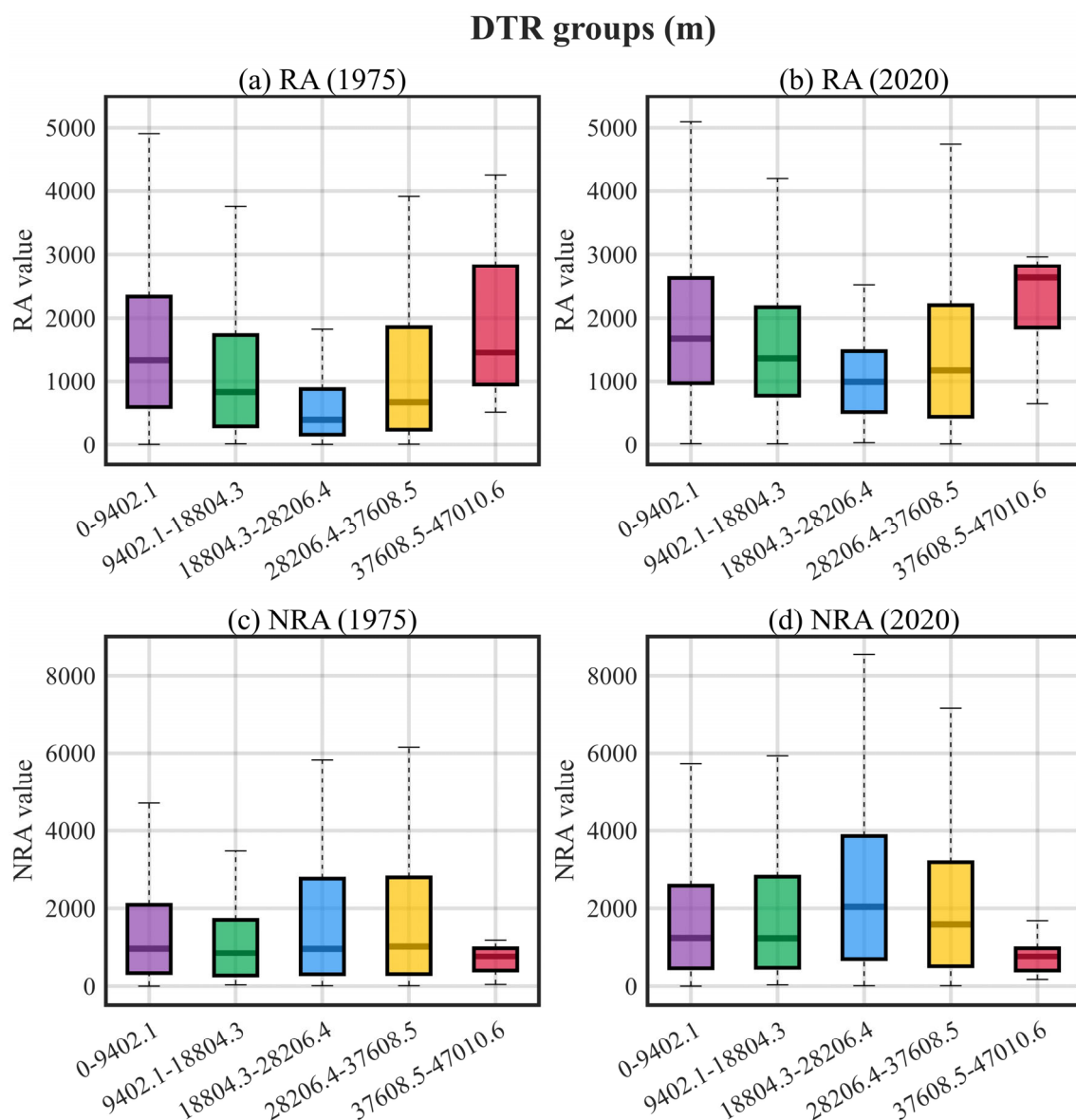


Figure 8. Statistical results of residential area (RA) and non-residential area (NRA) values by distance the river (DTR) groups: (a) RA values in 1975; (b) RA values in 2020; (c) NRA values in 1975; (d) NRA values in 2020. The boxplots display the median (central line), interquartile range (box) and data range (whiskers) for five DTR groups. The unit for DTR is meter (m).

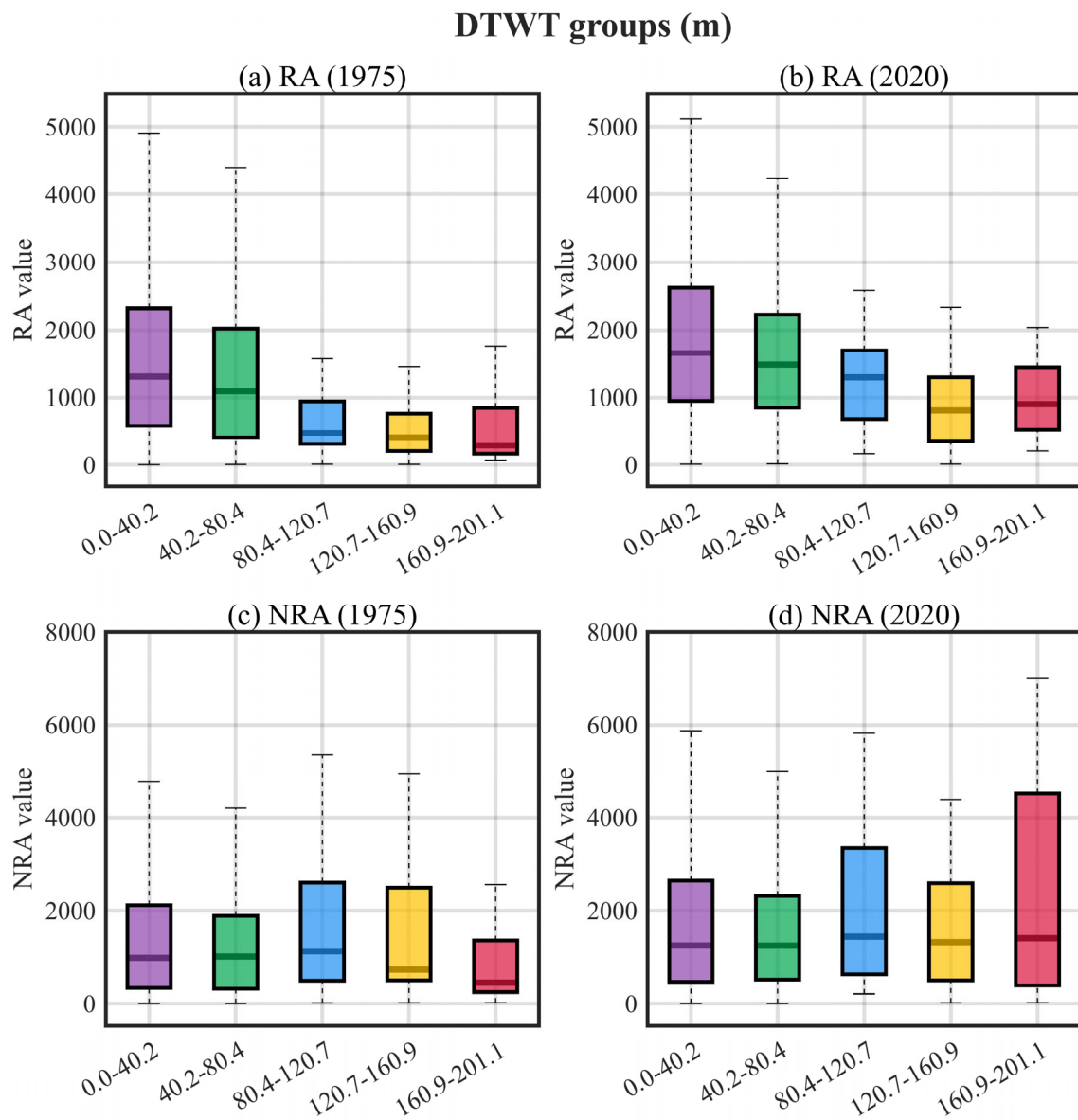


Figure 9. Statistical results of residential area (RA) and non-residential area (NRA) values by depth to water table (DTWT) groups: (a) RA values in 1975; (b) RA values in 2020; (c) NRA values in 1975; (d) NRA values in 2020. The boxplots display the median (central line), interquartile range (box) and data range (whiskers) for five DTWT groups. The unit for DTWT is meter (m).

This analysis reveals that hydrologic factors act as drivers of these differential urbanization patterns. Increased surface roughness directly influences runoff–infiltration dynamics, creating development constraints that disproportionately affect NRAs due to their larger impervious surface footprints [36]. The 45-year progression shows RA values maintaining tighter distributions (1000–1500 m²) across all roughness categories, indicating hydrologic adaptation through improved drainage infrastructure and grading techniques. Meanwhile, NRA distributions show expanding variability (1500–2500 m²) in higher roughness zones, reflecting risk-tolerant development practices that accept greater hydrologic variability for economic gains. These findings align with established urban hydrology principles wherein surface roughness mediates hydrologic responses to urbanization, ultimately shaping spatial patterns of urban growth through complex feedback between terrain characteristics, water movement and development decisions [37,38].

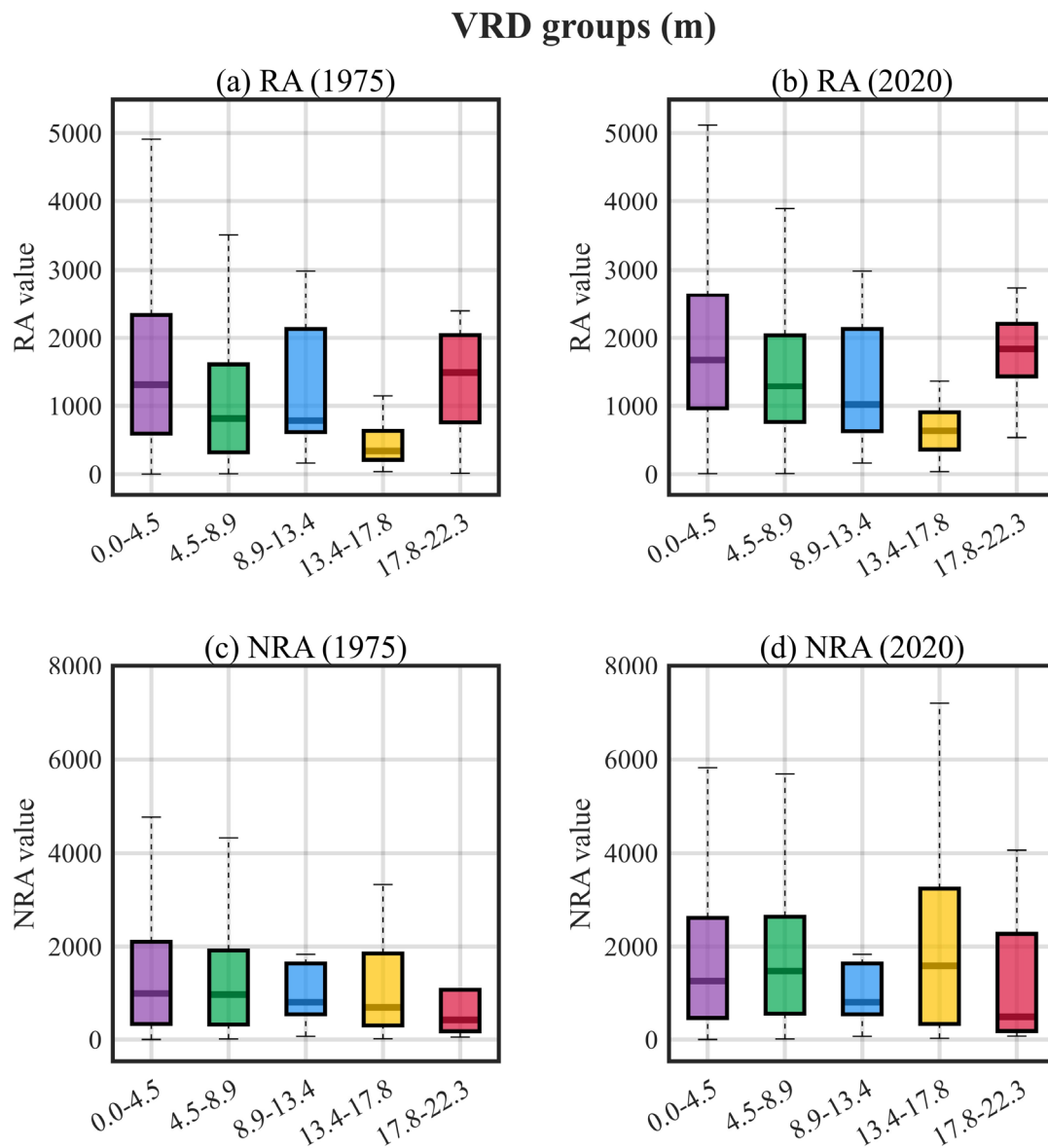


Figure 10. Statistical results of residential area (RA) and non-residential area (NRA) values by vegetation root depth (VRD) groups: (a) RA values in 1975; (b) RA values in 2020; (c) NRA values in 1975; (d) NRA values in 2020. The boxplots display the median (central line), interquartile range (box) and data range (whiskers) for five VRD groups. The unit for VRD is meter (m).

This functional differentiation is further illustrated by the relationship with DTR. In Figure 8, we quantitatively compared the distribution patterns of RA and NRAs across DTR groups spanning 0–47,010.6 m for 1975 and 2020. The boxplot series reveals pronounced temporal and functional differentiation in hydrologic influence: RA distributions show consistently higher values in proximal river zones (0–9402.1 m), with medians exceeding 3500 m² in both epochs, reflecting sustained residential preference for riparian accessibility. Conversely, NRA distributions (Figure 10c,d) exhibit significant spatial expansion toward intermediate DTR ranges (9402.1–28,206.4 m), where 2020 medians increased by 40–60% compared to 1975, indicating strategic decentralization of non-residential functions driven by flood risk mitigation and land availability constraints [39].

The differential response to hydrologic proximity shows distinct urban adaptation mechanisms. RA maintenance of high-density riparian development aligns with historical settlement patterns and water dependency, albeit with improved flood resilience through elevated foundations and drainage infrastructure evident in reduced data variance in

2020 [40]. NRA's shift toward intermediate distances demonstrates how economic activities leverage hydrologic zoning regulations, sacrificing immediate water access for reduced insurance costs and expanded land parcels [41]. This functional segregation, residential permanence versus economic adaptability, illustrates how hydrologic factors spatially mediate urban form through dual channels: biophysical constraints (flood risk) and socio-economic valuations (land value gradients), ultimately producing hydrologically informed urban mosaics where distance to river functions as an organizing principle for land-use allocation [2,7,42].

Figure 9 examines the influence of DTWT on RA and NRA distributions across five water table zones (0.0–40.2 m, 40.2–80.4 m, 80.4–120.7 m, 120.7–160.9 m and 160.9–201.1 m) between 1975 and 2020. The boxplot series reveals divergent temporal trajectories: RA values demonstrate consistent attenuation across all DTWT groups, with median values declining by 25–40% in 2020 compared to 1975, particularly in shallow water table zones (0.0–80.4 m) where values dropped from 3200–3800 to 2100–2600 m². Conversely, NRA distributions exhibit selective expansion in moderate-depth zones (80.4–160.9 m), where 2020 medians increased by 15–30% (from 3500–4200 to 4100–5100 m²), indicating strategic repositioning of economic activities away from hydrologically sensitive areas.

The differential response shows how groundwater depth is associated with distinct urban adaptation patterns. RA's pronounced decline in shallow water table regions aligns with the goal of avoiding areas with high flood and foundation instability risks. Conversely, NRA's greater expansion in intermediate-depth zones (80.4–160.9 m) suggests a different risk calculus, favoring locations that avoid the most severe shallow water table constraints. This functional segregation highlights the role of DTWT as a significant factor in the spatial sorting of urban land uses.

Figure 10 shows the distribution of RAs and NRAs across five VRD groups (0.0–4.5 m, 4.5–8.9 m, 8.9–13.4 m, 13.4–17.8 m and 17.8–22.3 m) for 1975 and 2020, revealing how bio-geophysical factors mediate urban spatial patterns. The boxplot series demonstrates divergent trajectories: RA values show progressive concentration in moderate VRD zones (4.5–13.4 m), where 2020 medians increased by 20–30% compared to 1975 (e.g., from 2800 to 3500 m² in the 4.5–8.9 m group), indicating preferential residential development in areas with balanced soil stability and water retention capacity. Conversely, NRA distributions (Figure 10c,d) exhibit marked expansion in deeper VRD zones (13.4–22.3 m), with 2020 medians surging by 40–50% (e.g., from 3200 to 4800 m² in the 17.8–22.3 m group), reflecting non-residential land-use adaptation to areas with enhanced groundwater access and reduced foundation constraints.

The differential response underscores the role VRD plays as a critical hydrologic proxy influencing urban form through soil–vegetation–water interactions. RA's shift toward moderate VRD zones aligns with residential preferences for stable substrates that minimize infrastructure risks while maintaining adequate water availability [43], evidenced by reduced data variance in 2020 suggesting improved engineering adaptations. NRA's proliferation in deeper VRD zones illustrates how economic activities capitalize on deeper root systems that facilitate stormwater infiltration and reduce drainage costs, particularly for industrial and commercial uses with higher water demands [34,44]. This spatial differentiation demonstrates how vegetation root depth correlates with distinct urban land-use distributions in the study area.

Moreover, impacts of altitude and slope on RA and NRA are provided in the Supplementary Information (see Figures S3 and S4). Figure S3 demonstrates that both residential and non-residential areas show elevated concentrations in mid-altitude zones (1707.6–1985.4 m) with non-residential areas exhibiting greater expansion at higher elevations from 1975 to 2020, reflecting altitude-dependent urbanization preferences. With

Figure S4, we found that both residential and non-residential areas show preferential development in lower slope zones (0–7.9 degrees). Notable values increase in medium slope areas (7.9–23.6 degrees) from 1975 to 2020, showing the role of terrain gradient in shaping urban spatial patterns.

Collectively, across all six hydrologic elements examined (altitude, slope, surface roughness, DTR, DTWT and VRD), our analysis reveals a consistent yet functionally differentiated influence on the spatial allocation of RA and NRA. RA development exhibits strong clustering in hydrologically favorable conditions (low to moderate surface roughness, mid-altitude zones, lower slopes, proximal river corridors, shallow to moderate water table depths and moderate VRD classes), reflecting a sustained emphasis on geotechnical stability, minimized flood and foundation risks, and the general suitability of the hydrologic environment (balancing the avoidance of very shallow water tables with the benefit of accessible water resources). In contrast, NRA shows greater dispersal and expansion into hydrologically variable or marginal environments, including higher roughness terrain, intermediate DTR ranges, deeper DTWT zones, higher elevation bands and deeper VRD categories, indicating risk-tolerant and economically adaptive land-use strategies. This dual pattern underscores how urbanization in the study area has evolved under a hydrologically informed regime where residential land uses prioritize safety, stability and service accessibility, while non-residential uses strategically exploit more hydrologically heterogeneous spaces to optimize land availability, cost and operational requirements. Together, these findings demonstrate that the six hydrologic factors act not merely as background constraints but as active drivers shaping the functional specialization of urban growth, producing a hydrologically mediated mosaic of residential permanence and economic adaptability over the 45-year study period.

4.3. Quantifying the Significance of Hydrologic Factors

In Section 4.2, we explored how six hydrologic factors shape the spatial distribution of RA and NRA through boxplot-based analyses, yet it did not quantify the relative importance of each factor. To address this gap, we employed a contribution-based assessment to weigh each hydrologic variable's influence on RA and NRA distributions. This approach enables a more explicit evaluation of which hydrologic controls dominate urban spatial allocation and how their relative significance has shifted between 1975 and 2020. As shown in Figure 11, we summarized these results for the six factors, expressed as standardized contributions (ranging from 0 to 0.3 for RA and 0 to 0.4 for NRA), with values annotated above each bar. This quantification complements the descriptive patterns outlined in Section 4.2 by revealing the hydrologic hierarchy of urban development drivers.

In Figure 11a, representing RA in 1975, DTR is the most influential factor (0.25), followed by slope (0.20), roughness (0.18), DTWT (0.16), VRD (0.11) and altitude (0.10), indicating a strong early-phase dependency of residential development on riparian proximity and terrain gradients. By 2020 (Figure 11b), the importance of roughness rises to 0.25, while slope and DTR share equal contributions (0.20 each), suggesting a gradual diversification of residential locational drivers beyond river corridors toward terrain-sensitive parameters. VRD and altitude both contribute 0.10–0.15, and DTWT declines to 0.10, reflecting improved engineering adaptations and drainage infrastructure that reduce groundwater-related constraints on RA siting. For NRA, a distinct pattern emerges. In 1975 (Figure 11c), VRD dominates (0.27), followed by roughness and slope (both 0.23), DTWT (0.12), altitude (0.08) and DTR (0.06), indicating non-residential concentration in zones with advantageous vegetation root conditions and moderate topographic complexity rather than river adjacency. By 2020 (Figure 11d), VRD's contribution surges to 0.34, while altitude rises to 0.23, slope remains high at 0.21, and roughness declines slightly to 0.21, whereas DTWT and

DTR fall to 0.10 and 0.04, respectively, demonstrating a pronounced shift in non-residential development toward hydrologically deeper and higher-elevation environments with less dependence on surface water proximity.

Factors contribution to RA/NRA

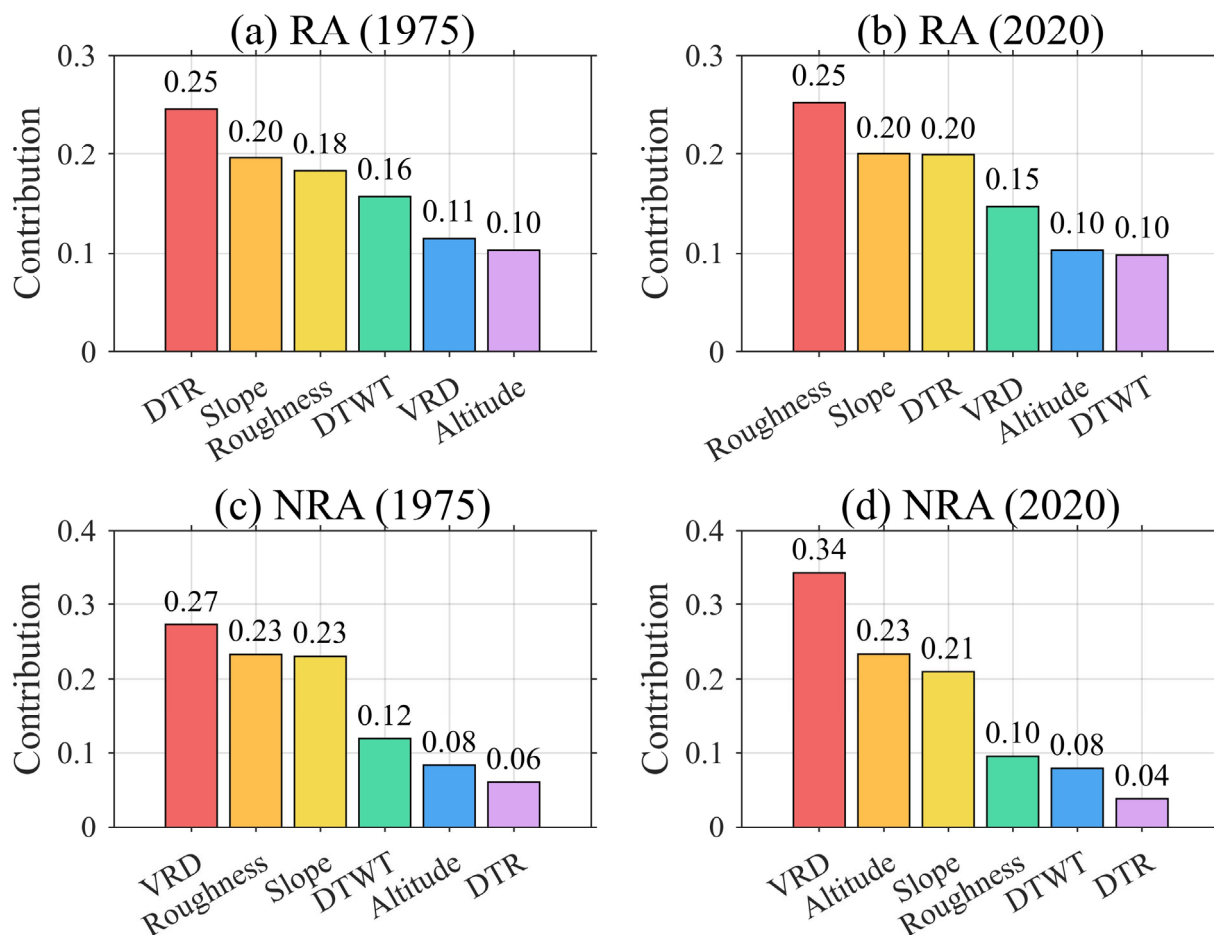


Figure 11. Contribution of various factors to residential area (RA) and non-residential area (NRA) in 1975 and 2020: (a) RA (1975); (b) RA (2020); (c) NRA (1975); (d) NRA (2020). The bar charts display the relative contribution (%) of six factors: VRD (vegetation root depth), Slope, DTWT (depth to water table), altitude, DTR (distance to river), and roughness to RA and NRA distribution. Values above bars indicate the specific contribution percentages. Note the different Y-axis scales: 0–0.3 for RA subplots (a,b) and 0–0.4 for NRA subplots (c,d).

Synthesizing these results, Figure 11 confirms that while RA and NRA are influenced by the same six hydrologic factors, their weightings, and thus their urbanization trajectories, differ fundamentally. Residential development shows an early dominance of DTR and slope but transitions to a more terrain-roughness-centered profile over time, consistent with the expansion of residential zones into more diversified landscapes while maintaining hydrologic safety. Non-residential development, conversely, is persistently and increasingly governed by VRD and altitude, reflecting an economic strategy of exploiting higher-elevation, deeper-root and less flood-prone environments for industrial and commercial uses. These quantified contributions reinforce the narrative established in Section 4.2: hydrologic factors not only constrain but actively direct the spatial specialization of urban growth. The shift in factor dominance from 1975 to 2020 highlights how technological, regulatory and economic adaptations have reshaped the hydrologic determi-

nants of urban form, producing a dual-patterned urban mosaic of residential stability and non-residential adaptability under evolving environmental constraints.

5. Discussion

5.1. Limitations

5.1.1. Limitations of Built-Up Fraction (BUFA), Residential (RA) and Non-Residential (NRA) Data

The GHS-BUILT-S R2022A dataset, while providing valuable multitemporal coverage (1975–2030), exhibits inherent constraints for fine-scale urbanization analysis. Its 100 m spatial resolution may obscure subtle urban features or mixed land-use transitions, particularly in heterogeneous peri-urban zones. The distinction between RA and NRA relies on automated semantic classification of Sentinel-2 imagery, which may misassign functional categories in areas with complex building typologies (e.g., mixed commercial-residential blocks). Temporal interpolation of built-up surfaces between Landsat epochs (1975–2014) and Sentinel-2 (2018) introduces uncertainty, especially during rapid urbanization phases where nonlinear growth may be underrepresented. Finally, the dataset's focus on surface imperviousness does not directly quantify population density or building occupancy, limiting socio-economic inferences.

5.1.2. Limitations of Hydrologic Data

Acknowledging the inherent uncertainties of global-scale geospatial data is essential for a balanced interpretation. The Copernicus DEM (GLO-30), as a Digital Surface Model (DSM), captures surface elevations including vegetation and infrastructure; this provides a realistic representation of the surface topography influencing runoff processes, though it differs from a bare-earth model. The GLOBGM-derived depth to water table (DTWT) estimates offer a valuable regional-scale approximation of groundwater conditions, while acknowledging that local hydrogeological heterogeneity exists. Similarly, the vegetation root depth (VRD) data, derived from a global inverse model, provides a robust macro-scale pattern of rooting constraints, with the understanding that local validation in mountainous regions like the KCR represents an opportunity for future refinement. The Euclidean distance to rivers (DTRs) calculation based on available vector data provides a consistent metric of fluvial proximity, which served as a fundamental and widely used proxy in our analysis. These characteristics of the source data were carefully considered in the interpretation of results. Our data harmonization protocol was designed specifically to ensure an internally consistent analytical basis, allowing a systematic assessment of relative hydrologic constraints across the study area. The identified patterns and their quantified contributions therefore remain valid for the regional-scale, comparative objectives of this study. These considerations also help define the path for future work, notably the development of high-resolution models, which can incorporate more localized data where available.

5.1.3. Methodological Limitations

The analytical framework applied herein faces several constraints. Spatial resampling of all cells to 100 m resolution for integration homogenizes native data scales (e.g., 30 m DEM, 10 m VRD), potentially diluting high-resolution hydrologic signals. Boxplot-based statistical comparisons aggregate spatial heterogeneity, masking local interactions between urbanization and hydrology. The contribution-weighting approach (see Figure 11) quantifies factor dominance but does not account for collinearity among variables, risking overinterpretation of individual drivers. Reliance on Euclidean distance for river proximity oversimplifies hydrologic connectivity, neglecting flow accumulation or floodplain dynam-

ics. The regional focus on KCR limits generalizability to cities with divergent climatic, geological or planning.

Furthermore, the use of simple, lumped-parameter models (exponential and linear) to describe regional urban growth trends (Section 4.1) inherently aggregates all sources of spatial variance. While effective for characterizing the overarching temporal trajectory, these models do not distinguish between the differential growth drivers operating in, for example, lowland urban cores versus peri-urban highlands. This analytical choice was intentional, as the study's design first establishes the aggregated temporal pattern before decomposing the spatial heterogeneity through subsequent mapping and statistical comparisons. However, it remains a simplification that future, spatially explicit predictive modeling could directly address this issue by simulating the localized interactions that generate the observed regional trend.

5.2. Policy Implications

The temporal and spatial analyses (Sections 4.1.1 and 4.1.2) reveal a two-phase evolution of urbanization in the KCR: a steady, compact growth before 1995 and a rapid, near-exponential expansion after 2000, dominated by residential development and aggregate built-up area. RA forms the primary driver of new urban land, while NRA remains a minor but spatially concentrated component, frequently aligned with transport and economic corridors. These findings suggest the need for policies that proactively manage residential growth in newly urbanizing zones by coordinating land supply with infrastructure, ensuring efficient public services, and maintaining environmental buffers [45–47]. Moreover, the detection of RA–NRA conversions and the heterogeneity of spatial change point to potential conflicts between residential stability and commercial expansion [48]. Integrating these insights into zoning frameworks can promote balanced land-use allocation, minimize service disparities and reduce ecological pressures.

The results of Section 4.2 indicate that hydrologic factors actively mediate the location of residential and non-residential areas through dual mechanisms of physical constraints and socio-economic valuation. Residential uses cluster in low-risk hydrologic conditions, whereas non-residential activities expand into hydrologically variable or marginal environments. This functional differentiation underscores the need for policy instruments that integrate hydrologic risk mapping into urban planning to prioritize safe and stable residential zones while guiding industrial and commercial uses toward areas with appropriate drainage, groundwater conditions and terrain stability. Such policies should also promote investments in adaptive infrastructure, particularly in flood mitigation, infiltration systems and slope stabilization, to reduce long-term vulnerability of both RA and NRA.

Moreover, results show that the relative significance of hydrologic factors shifts over time, with RA becoming more terrain-sensitive and NRA increasingly influenced by vegetation root depth and altitude. These quantified contributions highlight the importance of dynamic, factor-based land-use policies that evolve as urban expansion interacts with topography and hydrology [37]. Policymakers should adopt flexible planning thresholds and incentive schemes that respond to changing hydrologic determinants, thereby sustaining safe, efficient and economically viable urban growth [49,50].

The geographic centroid analysis (Section 4.1.3) demonstrates a consistent northeastward migration of both RA and NRA centroids, reflecting coordinated yet sectoral distinct expansion into peri-urban and transport-linked zones. This directional co-evolution implies the need for forward-looking corridor planning and inter-jurisdictional coordination to manage future growth hotspots, avoid over-concentration of infrastructure loads, and preserve ecologically sensitive highland areas [51]. Policies emphasizing transit-oriented

development and greenbelt protection can further mitigate unintended environmental and social consequences of this spatial shift [52].

In summary, these findings reveal that sustainable urban development in the KCR requires an integrated approach linking temporal growth trends, spatial heterogeneity, hydrologic risk and directional migration. Embedding these insights into regulatory, fiscal and infrastructural strategies can enable planners to align residential stability with economic adaptability, balance environmental and development goals, and build resilience against hydrologically mediated risks over the coming decades.

6. Conclusions

In this study, we systematically explored the spatiotemporal dynamics of urbanization in the Kunming Core Region (KCR) from 1975 to 2020 using multi-decadal built-up land distribution data derived from the GHS-BUILT-S dataset. By integrating temporal increments, spatial differences, centroid trajectories and hydrologic factor analyses, we quantified the changing patterns of built-up fraction area (BUFA), residential area (RA) and non-residential area (NRA) at five-year intervals. The research framework combined descriptive mapping with statistical evaluation and contribution-based weighting, enabling us to characterize not only the pace and direction of urban expansion but also the differentiated roles of six hydrologic factors, including altitude, slope, surface roughness, distance to river (DTR), depth to water table (DTWT) and vegetation root depth (VRD), in shaping urban growth. This approach provided a robust, multi-scalar understanding of how physical and hydrologic conditions intersect with socio-economic processes to generate a distinctive urban mosaic in one of China's rapidly transforming mountain-basin regions.

Key findings include the following:

1. RA dominates built-up expansion throughout the study period, whereas NRA remains minor but increasingly spatially concentrated along transport corridors and economic zones.
2. Urbanization follows a two-phase trajectory, shifting from slow, compact growth before the mid-1990s to rapid, near-exponential expansion after 2000.
3. RA and NRA exhibit coordinated but functionally distinct centroid migrations, reflecting simultaneous regional drivers and sector-specific adaptation.
4. Hydrologic factors exert differentiated influences, with RA clustering in low-risk, hydrologically favorable areas, and NRA dispersing into more variable environments.
5. Quantitative contribution analysis reveals temporal shifts in factor dominance, highlighting the evolving hydrologic determinants of urban form.

Specifically, BUFA and RA expanded steadily from 1975 to 1995 and then accelerated markedly after 2000, demonstrating a transition from compact core development to dispersed, polycentric growth. NRA increased only incrementally, yet its expansion became more spatially concentrated in later years, particularly along infrastructure corridors. Geographic centroid analysis showed a persistent northeastward migration of both RA and NRA, indicating coordinated yet sectoral distinct directional growth. These results portray a dual-phase urbanization process, combining rapid residential-driven expansion with selective non-residential relocation under shared regional drivers.

Finally, three avenues need further investigation. First, expanding the hydrologic factor framework to include additional eco-hydrologic indicators (e.g., soil moisture, stormwater retention indices) could refine our understanding of biophysical constraints on urbanization [46]. Second, coupling high-resolution socio-economic data with hydrologic drivers would enable multi-objective optimization of land-use allocation under varying policy scenarios [53]. Third, addressing the critical need for process-based understanding highlighted in this review, establishing high-precision, high-resolution urban-hydrologic

models, is essential. We are currently developing a ParFlow-CLM-City model, building on the ParFlow-CLM platform [54–57]. Such a model would explicitly simulate coupled surface–subsurface processes, including runoff, interflow, and groundwater exchange, under the combined impacts of climate change and anthropogenic pressures. This would directly address the hydrological connectivity in hillslope systems and dramatically improve the predictive capacity and process-based decision support for sustainable urban development in topographically complex regions.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/hydrology13020048/s1>, Text S1: Slope and roughness calculations in ArcGIS; Figure S1: Spatiotemporal evolution of residential area (RA) in the Kunming Core Region (KCR) from 1975 to 2020. Decadal distribution patterns (a–j) showing RA dynamics over ten time points (1975, 1980, 1985, 1990, 1995, 2000, 2005, 2010, 2015, 2020) at five-year intervals. RA values are represented by a color gradient from dark green (0) to red (10,000 m²), with white indicating non-built-up areas; Figure S2: Spatiotemporal evolution of non-residential area (NRA) in the Kunming Core Region (KCR) from 1975 to 2020. Decadal distribution patterns (a–j) showing NRA dynamics over ten time points (1975, 1980, 1985, 1990, 1995, 2000, 2005, 2010, 2015, 2020) at five-year intervals. NRA values are represented by a color gradient from dark green (0) to red (10,000 m²), with white indicating non-built-up areas; Figure S3: Statistical results of residential area (RA) and non-residential area (NRA) values by altitude groups: (a) RA values in 1975; (b) RA values in 2020; (c) NRA values in 1975; (d) NRA values in 2020. The boxplots display the median (central line), interquartile range (box), and data range (whiskers) for five groups; Figure S4: Statistical results of residential area (RA) and non-residential area (NRA) values by slope groups: (a) RA values in 1975; (b) RA values in 2020; (c) NRA values in 1975; (d) NRA values in 2020. The boxplots display the median (central line), interquartile range (box), and data range (whiskers) for five groups.

Author Contributions: Conceptualization, Z.L. and S.M.; methodology, Z.L.; software, C.Q.; validation, D.N.; formal analysis, Z.Z. and Z.L.; investigation, C.S. and Z.L.; resources, Z.L.; data curation, H.T. and Z.L.; writing—original draft preparation, C.S. and Z.L.; writing—review and editing, L.Z. and S.M.; visualization, Y.W. and Z.L.; supervision, C.S. and Z.L.; project administration, C.S. and Z.L.; funding acquisition, C.S. and Z.L. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: All datasets employed in this study are publicly accessible. The GHS-BUILT-S R2023A dataset (Global Human Settlement Built-Up Surface Grid) for the period 1975–2030 was obtained from the Joint Research Centre Data Catalogue of the European Commission (<http://data.europa.eu/89h/9f06f36f-4b11-47ec-abb0-4f8b7b1d72ea>, accessed on 1 August 2025). Digital Elevation Model (DEM) data was acquired from the OpenTopography platform (<https://portal.opentopography.org/dataCatalog>, accessed on 1 August 2025). River network data was provided by the Kunming Water Resources Bureau (<https://shuiwu.km.gov.cn/>). Water table depth data is available from the GLOBGM v1.0 data supplement (<https://public.yoda.uu.nl/geo/UU01/44L775.html>, accessed on 1 August 2025), and vegetation root depth data was accessed from the Earth2Observe portal (<https://wci.earth2observe.eu/thredds/catalog/usc/root-depth/catalog.html>, accessed on 1 August 2025).

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

Abbreviations

The following abbreviations are used in this manuscript:

BUFA	built-up fraction
DEM	Digital Elevation Model
DSM	Digital Surface Model
DTR	distance to river
DTWT	depth to water table
GHS	Global Human Settlement
GHSL	Global Human Settlement Layer
GHS-BUILT-S	Global Human Settlement Layer built-up fraction data
GHS P2022	Global Human Settlement Layer Data Package 2022
GLOBGM	Global Groundwater Mode
KCR	Kunming Core Region
NRA	non-residential area
RA	residential area
SRCi	standardized regression coefficients
VRD	vegetation root depth

Note that single-word factors (e.g., slope, altitude, roughness) are presented in full, while multi-word factors are abbreviated (e.g., DTR for distance to river, VRD for vegetation root depth).

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