Modeling spatial complexity of factors influencing FAR and urban morphological configurations in Isfahan metropolitan

Original Article

Received: 2025/09/29
Revised: 2025/10/19
Accepted: 2025/10/29

COPYRIGHTS

©2025 The author(s). This is an open access article distributed under the terms of the Creative Commons Attribution (CC BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, as long as the original authors and source are cited. No permission is required from the authors or the publishers.

Khalil Askarpour[1], Hossein Hataminezhad[2*], Saeed Zanganeh Shahraki[3]

1. Ph.D. Candidate in Geography and Urban Planning, Department of Geography, Alborz Campus, University of Tehran, Tehran, Iran
2. Professor, Department of Human Geography and Planning, Faculty of Geography, University of Tehran, Tehran, Iran
3. Associate Professor, Department of Human Geography and Planning, Faculty of Geography, University of Tehran, Tehran, Iran

Abstract

The ratio of floor area to built form (FAR) in rapidly developing metropolitan areas, such as Isfahan, results from a complex interplay of morphological, land-use, accessibility, and institutional variables that distorts FAR's regulatory function and generates spatial inequality. This applied study employs a mixed, descriptive-analytical case-study design. The temporal scope spans 2012–2022 and includes census data, density and land-use parcel layers, urban plans, and municipal reports. The study area was divided into an optimized hexagonal grid (3.88 ha cells), producing 695 metric units. The tools analyzed included ArcGIS, Fragstats, EViews, Excel, and Google Earth, based on the extraction of four main metrics (FAR, population density, occupancy percentage, and vertical diversity index), principal component analysis to form a composite CDFI index, spatial autocorrelation test, and spatial modeling (MGWR, SAR/SEM) along with scenario simulation frameworks (EUM/CA and ABM). According to the results, the first two PCA components explained 69.74% of metric variance. The CDFI ranged 0.503–0.900 (max: District 4 = 0.900; min: District 14 = 0.503), displayed significant spatial autocorrelation (Moran's I) and strong spatial heterogeneity driven by accessibility and land-use mixing ($R^2 \approx 0.91$). Findings indicated that road networks, transport accessibility, and land-use mix dominate density structure. Therefore, FAR governance should be decoupled from municipal revenue, reframed as place-based and multi-criteria policies, based on institutionally separating regulatory and fiscal roles, diversifying municipal income, targeting density incentives via CDFI, preserving historic fabric, and reinforcing green infrastructure and public transit.

Keywords

CDFI
Floor area ratio (FAR)
Isfahan metropolitan
Morphological configurations
Spatial metrics

* Corresponding Author: hataminajad@ut.ac.ir

HOW TO CITE THIS ARTICLE

Askarpour Kh. Hataminezhad H. Zanganeh Shahraki S. Modeling spatial complexity of factors influencing FAR and urban morphological configurations in Isfahan metropolitan. *Urban Economics and Planning* 7(5):94-118.

DOI: 10.22034/uep.2025.550126.1725

1. Introduction

The Floor area ratio (FAR), as one of the fundamental indicators of urban planning, plays a pivotal role in determining land-use intensity, building density, and the spatial organization of cities. Beyond regulating the physical structure of urban areas, this indicator entails wide-ranging implications for energy efficiency, social equity, land economic value, and environmental sustainability (Cheshmehzangi, 2021: 45; Lu, 2023: 118). In essence, FAR is not merely a technical regulation or control instrument; rather, it constitutes a complex mechanism for balancing urban growth, quality of life, and the efficiency of urban systems (Moon, 2019: 64).

Despite its fundamental importance, the spatial distribution of FAR emerges from the interaction of multiple variables, including characteristics of the built-up environment, socio-economic conditions, accessibility to transportation infrastructure, and regulatory policies (Yu, 2024: 37; Gao, 2006: 214). These factors do not operate independently; instead, they form an intertwined network that generates synergistic or, at times, contradictory effects on urban density patterns. This complexity is particularly pronounced in developing countries, which are often confronted with rapid urbanization, data limitations, and weak regulatory and monitoring systems. Consequently, the management and optimization of FAR have become a critical and multidimensional challenge in such contexts (Shi, 2013: 76; Liu & Shi, 2022: 53).

From an applied perspective, the central question concerns how, within cities of developing countries and under conditions of limited resources and data availability, an optimal density pattern can be designed and managed that is economically and socially equitable while remaining environmentally sustainable. Challenges such as unbalanced urban expansion, excessive density in city centers, informal settlements, and inefficient energy consumption are among the direct consequences of the absence of an integrated approach to FAR regulation (Cobbinah et al., 2025: 64; Huang et al., 2025: 213). Accordingly, the development and application of novel analytical frameworks—such as Spatial Co-Embedding—can not only enrich urban planning theory but also provide policymakers with effective tools for formulating sustainable, efficient, and balanced development strategies.

Modeling approaches capable of adequately capturing the complexity of spatial factors are therefore essential. The elastic urban morpho-blocks (EUM) approach, which integrates cellular automata (CA), has been proposed as an effective means for simulating urban spatial dynamics. CA-based models are particularly adept at representing the evolutionary nature of urban form and building configurations by accounting for the effects of local interactions and spatial rules. This approach underscores the importance of adopting models that accurately represent the dynamic, complex interactions between the determinants of building density and urban form (Ma et al., 2021: 28).

One of the major shortcomings and research gaps in previous studies is their emphasis on linear and one-dimensional relationships between FAR and explanatory variables. In contrast, recent empirical evidence indicates that these relationships are often nonlinear, heterogeneous, and spatially dependent (Lu, 2025: 92; Cao, 2025: 141). Advanced methods such as multiscale geographically weighted regression (MGWR) and spatial co-embedding frameworks, through the integration of multi-source data and the analysis of complex spatial relationships, enable the identification of patterns and interactions that have remained overlooked in conventional approaches (Zheng, 2023: 205; Huang, 2022: 77). These approaches have gained increasing significance, particularly in urban energy modeling, environmental impact assessment, and the design of sustainable development strategies (Bahu, 2013: 99; Sun, 2018: 53).

Metropolitan Isfahan, despite its rich historical background, substantial economic capacity, and distinctive cultural status, has faced profound challenges in housing provision and building density over recent decades. The housing sector, as one of the principal pillars of the urban economy and physical structure, exerts not only residential functions but also extensive social, economic, and environmental impacts on urban life (Zangeneh-Shahraki et al., 2023: 202). Nevertheless, the uneven distribution of building density, the heavy reliance of municipal revenues on density-related charges, and the unregulated growth of construction activities have diverted urban management in Isfahan away from sustainable development.

The excessive increase in building density across many parts of the city, regardless of environmental, infrastructure, and transportation capacities, has led to consequences such as increased pollution, traffic congestion, pressure on public services, and the degradation of green spaces and historic urban fabrics. This process has not only undermined spatial justice but has also intensified physical and social dualities within the city (upper-city versus lower-city). Moreover, the dominance of short-term economic perspectives in density regulation and the transformation of FAR into a fiscal instrument for municipal financing have severely compromised its strategic function as a tool for regulating and guiding urban development.

At the same time, accelerating urbanization trends, the concentration of industries and services in Isfahan, and the inability of existing policies to adequately respond to real housing needs further intensify the need to rethink density management paradigms. Over the past two decades, urban planning in Isfahan has been driven more by quantitative growth than by the principles of qualitative and sustainable development. As a result, density-related instruments, instead of serving a regulatory role, have become drivers of spatial inequality, stagnation in the housing market, and the erosion of urban livability.

Within this context, the present study, by integrating robust theoretical foundations with advanced methodological approaches, seeks to uncover the latent dimensions of interaction between FAR and environmental, social, and economic variables, providing a scientifically grounded response to the fundamental challenges of density management in metropolitan areas of developing countries.

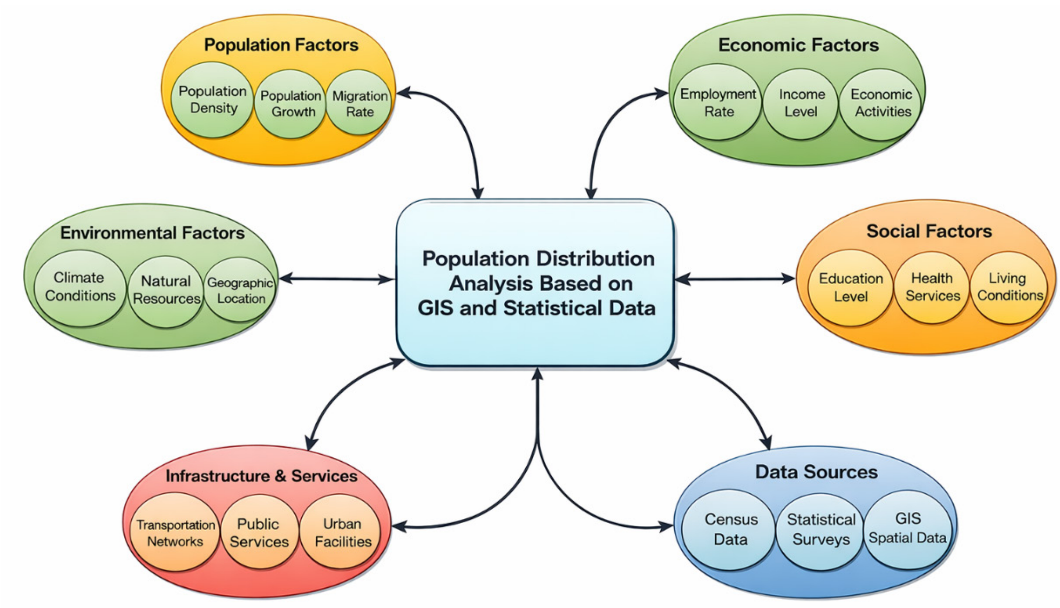

Figure 1. Conceptual framework of the study

2. Theoretical framework and review of the literature

2.1. Spatial complexity of FAR and urban form patterns

The floor area ratio (FAR) is a key indicator for assessing building density, directly influencing urban development patterns, quality of the living environment, access to services, and urban sustainability. In the urban planning literature, FAR is regarded not only as a physical instrument for measuring development intensity but also as a policy and economic tool that affects land prices, spatial justice, and housing market dynamics (Bertaud, 2018). From a theoretical perspective, FAR is closely associated with three principal conceptual frameworks: (1) Compact city, which emphasizes population concentration, efficient land use, and reduced automobile dependency (Jenks & Burgess, 2000); (2) Smart growth, which considers endogenous development, mixed land uses, and appropriate density as core instruments for achieving sustainable cities (Neuman, 2005); and (3) Spatial justice, which addresses the socio-economic consequences of density and demonstrates that unbalanced FAR policies may lead to social exclusion and the formation of spatial dualities (Fainstein, 2014).

From a methodological standpoint, recent studies have increasingly focused on integrating spatial regression models, environmental simulations, and accessibility analyses to reveal the spatial complexity of FAR. Empirical evidence indicates, for example, that increases in FAR may negatively affect natural ventilation patterns and urban temperatures (Huang et al., 2025; Li et al., 2018) or generate strong spatial spillovers on adjacent neighborhoods through spatial autocorrelation (Peng et al., 2021). One of the principal challenges in developing countries is the transformation of FAR from a planning instrument into a municipal revenue-generating mechanism, whereby density selling replaces regulatory urban development tools, and produces adverse outcomes such as uneven urban growth, rising housing prices, and intensified social inequality (Cobbinah et al., 2025; Shatkin, 2017). This is particularly evident in large cities across Asia and Africa, where weak regulatory institutions and land market pressures have exacerbated discretionary implementation of FAR policies.

The relationship among FAR, accessibility indicators, and urban networks is also critical. Studies have shown that proximity to metro systems and public transportation networks positively correlates with FAR, with higher densities typically concentrated in such areas (Liu, 2023; Lu et al., 2016). In addition, building coverage ratio (BCR) and urban morphological patterns interact with FAR and shape vertical versus horizontal growth trajectories (Zheng, 2023; Song et al., 2024). Overall, the literature demonstrates that FAR exhibits a multidimensional and nonlinear relationship with the urban environment, including heat islands and carbon emissions. FAR policies can also function either as effective instruments for promoting sustainable development and spatial justice or as inefficient mechanisms for capital accumulation within urban fabrics. In developing countries, the main challenge is institutional inefficiency and revenue priorities of municipalities that lead to deterioration in the quality of life and urban sustainability. These findings underscore the necessity of adopting complex adaptive system perspectives in FAR modeling and policymaking, as only through multi-layered analyses—environmental, economic, and social—can pathways toward balanced and sustainable urban development be delineated.

A review of recent studies indicates that FAR has consistently been treated in both international and domestic literature as a central indicator in managing building density and organizing urban space. Through research on Chinese cities, Zheng (2023) and Lee (2021) emphasized the importance of access to public transportation infrastructure and green spaces in shaping the heterogeneous distribution of FAR. Their findings aligned with those of Liu (2021) in Shanghai, which demonstrated a strong association between high density and the concentration of public services. Similarly, studies in Guangzhou (Peng et al., 2021) revealed the linkage between FAR, housing vacancy rates, and land values, highlighting the need for balanced development to prevent uneven urban expansion. In Urumqi, Fen (2023) underscored the environmental consequences of high density, particularly reduced airflow and increased carbon emissions, while Karen & Park (2022) showed that FAR incentive mechanisms can provide a foundation for affordable housing provision in informal settlements in Nepal.

At a broader scale, studies by Cheshmehzangi & Dawodu (2022) and Jung & Yoon (2021) pointed to a direct relationship among FAR, energy consumption, and microclimatic quality, reinforcing the imperative to integrate density policies with energy sustainability strategies. Furthermore, Wurm et al. (2021), drawing on citizens' cognitive perceptions, proposed density-based thresholds for identifying urban centers, thereby highlighting the perceptual and social dimensions of density policymaking.

At the national level, domestic research reflects similar challenges. Nikpour et al. (2022) reported clustered, uneven density distributions in Hamedan, leading to population and activity concentration in certain areas and stagnation in others. Mohammadpour Chabaki and Hasanpour (2022) demonstrated in Tehran that the sale of excess density disrupts spatial equilibrium and fuels land and housing speculation, while Hasani and Taban (2022) revealed a direct relationship between building density and increased air pollution in Arak. Studies such as Baghaei et al. (2021) and Nouraei and Shamohammadi (2021) also emphasized the importance of linking density to indoor environmental quality in residential complexes and to sustainable urban design. In Tabriz, Alizadeh et al. (2021) demonstrated that municipal revenue dependence on density selling strips construction practices of their regulatory function, transforming them into fiscal instruments, a trend corroborated by Lalehpour (2021) and Khorramabad and Mokhtari (2021) in Tehran through evidence of excessive horizontal expansion and the climatic inefficiency of high-density typologies.

Theoretically and epistemologically, the principal gap between international and domestic scholarship is that the international literature systematically conceptualizes FAR as part of a complex adaptive system, wherein density, morphology, accessibility, and socio-economic functions interact simultaneously, exhibiting feedback loops and path-dependence. In contrast, domestic studies often analyze FAR as an isolated variable or the outcome of short-term municipal and market decisions, devoting limited attention to overlapping relationships, temporal feedbacks, and institutional mechanisms of density production. This theoretical divergence has resulted in insufficient formulation and testing of fundamental questions—such as the interaction between municipal revenue policies (density selling) and unequal spatial outcomes, or the role of nonlinear thresholds and transition points between urban physical states.

Methodologically, the gaps are even deeper and more multifaceted. Many domestic studies rely on descriptive analyses or linear correlation models and fail to adequately address well-known issues such as spatial endogeneity, spatial spillovers, MAUP, and scale sensitivity. Moreover, limited temporal data and the lack of multi-scale & POI, and multi-source datasets—such as cadastral data, remote sensing, and taxation/building permit records—constrain spatio-temporal dynamic analyses and counterfactual policy evaluation. In terms of advanced methodologies, the application of techniques capable of simultaneously modeling spatial heterogeneity and nonlinearity—such as MGWR, Spatial Durbin/Spatial Panel models, and Bayesian hierarchical spatial models (e.g., INLA) – or the integration of regression constructs with explainable ML with SHAP remain limited in domestic research. Similarly, hybrid modeling and simulation approaches, including spatial co-embedding, cellular automata for morphological simulation (elastic urban morpho- blocks), Agent-based models (ABM) for actor behavior, and CFD for microclimatic impacts, have received insufficient attention.

These theoretical and methodological gaps have two key consequences. First, policy implications derived from local studies often lack generalizability and temporal robustness, suffering from limited external validity and insufficient causal interpretation. Second, the distributive and justice-oriented effects of density across different social groups and historical spaces are inadequately quantified, potentially leading to unintended or counterproductive policy outcomes.

The innovation of the present research lies precisely in addressing these gaps. Theoretically, the study moves beyond a unidimensional view of FAR and conceptualizes it as a relational text linking physical structure, spatial networks, and institutional dynamics, in which temporal feedbacks, dependency trajectories, and distributive consequences are treated as core components. Methodologically, the research adopts an integrated framework encompassing three complementary levels: (1) robust spatio-econometric analysis using spatial, temporal, and spatio-temporal regression models (Spatial Durbin/Spatial Panel) and control instruments for endogeneity (IV's & spatial instruments) to extract causal and spillover effects; (2) modeling local heterogeneity through MGWR and co-embedding techniques for compressing and jointly embedding morphological and social indices; and (3) simulation and scenario-building through the integration of EUM/CA, ABM, and CFD, to estimate the consequences of urban form and patterns development.

This combined theoretical and methodological approach yields three principal scientific and practical outcomes that determine the study's innovation: first, formulating an interdisciplinary theory that explains FAR simultaneously as a physical driver, an outcome of institutional structures, and a distributor of environmental and social effects; second, developing a generalizable and reproducible pipeline analytical–simulation framework capable of quantifying optimal FAR thresholds, nonlinear tipping points, and distributive impacts; and third, providing policy-relevant tools that reveal not only average effects but also their spatial–social distribution, leading to the design of balanced policies (e.g., adjusting credits, targeted incentives, revenue alternatives for municipalities).

Overall, the present study bridges the theoretical gap of linear, single-variable perspectives and addresses the methodological shortcomings of multi-source, nonlinear, and interpretable models through an integrated, policy-oriented approach. Its scientific contribution lies in the synthesis of spatial causal inference, quasi-experimental validation, and scenario-based simulation, offering a directly actionable framework for density management in metropolises of developing countries.

3. Study area

The historic city of Isfahan, the third most populous metropolis in Iran and the capital of Isfahan Province, covers an area of approximately 482 km² and is located in the central Iranian Plateau. Geographically, it lies at 51°29′ east longitude and 32°38′ north latitude, along the Zayandeh Rud River and the Zagros Mountains (Soffeh range). The city is situated on a relatively flat plain with an average slope of about 2%, extending toward the northeast, with an elevation of approximately 1,580 meters above sea level (Dehghani, 2018: 124). Isfahan has a temperate climate with four well-defined seasons. Owing to its strategic position at the crossroads of the north–south and east–west corridors of the country, the city has historically served as a meeting point for diverse ethnic groups and cultures. The establishment of the city is closely linked to the water resources originating from the high Zagros Mountains, particularly Zardkuh-e Bakhtiari, which give rise to the Zayandeh Rud River. Over the centuries, urban development has predominantly expanded toward the southwest, where water availability has been greater and environmental pollution comparatively lower. According to the most recent official Population and Housing Census conducted in 2016, the population of Isfahan was 1,961,260 (Isfahan Municipality Statistical Yearbook, 2016). At present, the city is administratively divided into 15 municipal districts. Given its industrial–service economic structure, the overall level of cultural facilities in this metropolis is relatively favorable. Nevertheless, despite the abundance of facilities, a critical issue remains the unequal distribution of services and infrastructure, which are not equitably allocated across the different districts of Isfahan. Based on the latest census documentation of 2016, the city comprises 15 municipal districts and 198 neighborhoods. Several influential factors, including the topography of the Zagros mountain range and the parallel ridges of the city, shape the city’s spatial development. The prominent intra-urban natural features of Isfahan include the west–east course of the Zayandeh Rud River and surrounding elevations, most notably Mount Soffeh, with an elevation of 2,232 meters. Urban growth directions have been strongly influenced by these factors, with development largely oriented from south to north. The formation of the earliest neighborhoods was primarily driven by the community’s cultural and social characteristics. Neighborhoods were developed after the 1960s, following the urban development plans, based on the physical and spatial divisions envisaged in these plans and influenced by factors such as major transportation corridors, service centers, neighborhood boundaries, and natural features. Table 1 represents the demographic and physical characteristics of Isfahan’s municipal districts in 2016. The population of Isfahan increased from approximately 287,000 in 1956 to nearly 2 million in 2016, representing an almost eightfold increase over a 55-year period. Population growth rate was at its highest during the 1950s–1960s, while remaining at approximately 2.5% over the past two decades.

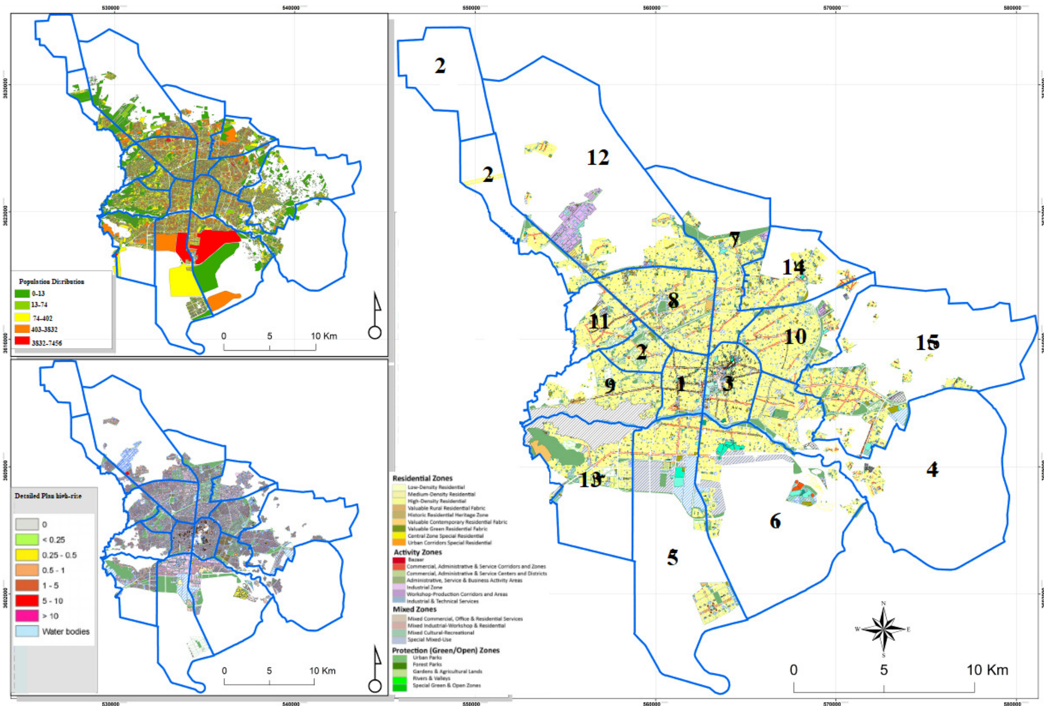

Figure 2. Isfahan municipality districts, land uses, spatial distribution of population, and land use classes

Table 1. Demographic and physical characteristics of the Isfahan municipal districts in 2016 (Source: Statistical Center of Iran, General Population and Housing Census (2016), Isfahan Municipality)

Municipal district	Population	Area (hectares)	Growth Rate (%) 2011–2016
1	79,091	810	0.3
2	69,120	2,145	1.3
3	110,368	1,148	0.1
4	133,731	133,731	1.2
5	150,865	1,702	−1.6
6	112,129	6,600	0.1
7	168,732	1,357	2.6
8	239,756	2,039	0.2
9	75,168	1,054	0.5
10	207,803	2,200	−0.4
11	58,841	1,140	−0.1
12	136,376	1,608	1.6
13	132,469	2,010	2.3
14	164,850	940	−0.3
15	121,961	1,664	1.6
Total	1,961,260	146,385.776	0.5

The city of Isfahan covers an area of 223.34 km² (with an urban administrative boundary of 1,005.67 km²). On this basis, it is the third-largest city in Iran in area, after Tehran and Mashhad. The population of Isfahan increased from 254,708 in 1956 to 1,961,260 in 2016 (with the population within the urban boundary approaching 3 million), and has recently exceeded 2,123,657 inhabitants. If the current trend of horizontal expansion of this metropolis continues, more than the present urban area must inevitably be allocated to residential uses over the next ten years. The consequence of such physical expansion is the conversion of surrounding farmlands, orchards, and ecological areas into residential, service, industrial, and similar land uses.

Challenges such as inadequate housing conditions and low housing quality across extensive parts of Isfahan, the lack of homeownership for a substantial share of urban households, and weaknesses in the equitable allocation of governmental housing-sector credits across different districts of the city constitute some of the principal urban issues. According to statistics from the past decade, the average price per square meter of land varies considerably among different areas of Isfahan. The highest residential land prices are observed in Districts 5 and 6, both located in the southern part of the city. The next highest land prices belong to District 3, situated within the historic and traditional urban fabric, where the presence of bazaars and commercial centers is the primary driver of elevated land values. The average growth rate has been approximately 35%, with the highest growth recorded in Districts 5 and 6 (81%), followed by Districts 1, 3, and 4 (77%).

Under current conditions, municipal revenues in Isfahan are subject to notable fluctuations, and a significant portion of the municipality's income sources (in 15 districts) to finance urban expenditures relies on charges and revenues derived from building density and land-related levies. This excessive dependence on revenues from the housing sector—combined with disproportionate density rates and municipal charges in the housing sector—has contributed to price escalation and its spillover effects on the prices of other goods, while simultaneously leading to stagnation in construction activity and real estate transactions. Boom or recession in the housing sector has, at various times, exposed Isfahan Municipality to acute financial problems and crises.

In particular, recession in construction activity and housing transactions imposes severe financial constraints on district municipalities, whose primary revenues are largely derived from such charges. In many cases, compensating for revenue shortfalls through alternative sources is not feasible in the short term, resulting in density selling becoming entrenched as a legal and structural dilemma within urban management.

Figure 3. (a) The physical urban fabric of a section of Isfahan along the Zayandeh Rud River; (b) A view of the skyline of Isfahan and distant high-rise buildings; (c) The 400-unit Aftab residential towers on Barazandeh Street, Isfahan; and (d) The Sepehr residential towers

4. Materials and methods

Although spatial metrics were historically employed primarily under the "landscape metrics" to quantify the form and pattern of vegetation cover in natural environments, analyzing the spatial structures and configurations is now regarded as an integral component of urban planning. Macro-level concepts such as place, distance, direction, connectivity, and pattern have long constituted the theoretical foundations of spatial analysis in urban studies. Based on a systematic review of the theoretical and empirical literature, this study identifies the principal shortcoming in the modeling of urban form and density as methodological. Specifically, reliance on uniform and, in some cases, inappropriate methods, the use of unreliable data, and the application of constructed indicators lacking a robust scientific foundation have led to reductionism, analytical haste, and ultimately a flawed understanding of the inherent complexity of spatial patterns.

In response to this methodological gap, the present research, for the first time, proposes the use of "spatial base units" as an intermediary and foundational framework for urban spatial planning and analysis. The selection of the scale and type of these base units (metrics) is contingent upon three key principles: the spatial extent of the study area, the research objectives, and the nature of the available data. Nevertheless, the application of this approach offers substantial benefits due to the advantages of accuracy, linkability, and shareability. By joining informational layers across multiple spatial levels from micro scales, such as land parcels and building blocks, to broader scales, such as land-use zones, tracing and examining the interrelationships between urban density and form from the level of individual housing units to neighborhoods, districts, and the entire urban region becomes possible.

This research is applied in terms of purpose, and adopts an analytical–descriptive method with a quantitative approach. To model the spatial complexity of factors influencing building density and urban form in metropolitan Isfahan, first, the effective physical–spatial indicators were extracted and analyzed using reliable documentary data. These sources included census data, statistical block information, detailed and comprehensive urban development plan studies, upstream planning documents, and annual and seasonal reports of the Isfahan Municipality over ten years (2012–2022). Following the operationalization and quantification of these indicators, an accurate map of the spatial metrics related to the physical structure of Isfahan was produced, and its accuracy was validated to assess spatial patterns.

After defining the base unit of analysis (a grid composed of hexagonal cells) and examining spatial autocorrelation, the quantitative data for each indicator were assigned to these spatial base units. By integrating multiple information layers within a geographic information system (GIS) environment, final values were calculated for each cell, and ultimately, a composite metric representing the influential indicators on urban density and form was generated. Throughout this process, specialized software was employed, including ArcGIS for spatial analysis and map production, FRAGSTATS for the calculation of selected advanced spatial metrics, EViews for spatial statistical analyses, Excel for data organization, and Google Earth for preliminary extracting information and verification of spatial accuracy.

Table 2. Components, indexes, and operational variables of the study for modeling the building density status and urban form of the 15 municipal districts of Isfahan

Component/ dimension	Operational indicator	Measurement variables/items	Exact formulas and calculation methods	Source
Physical density and coverage	Building density Floor area ratio (FAR); gross population density (persons/ha); building coverage ratio (CR)	FAR = Σ(GFA_i) / Plot_Area; Population_Density = Population_Count / Area_hectares; Coverage Ratio (CR) = Σ(Building_ Footprints) / Total_Plot_Area × 100	FAR and similar density indexes are standard foundations of urban planning; for example, Angel et al. (2021) present the "anatomy of urban density" with its constituent factors.	Angel et al. (2021)
	Vertical occupancy Mean number of floors (Mean_Floors); coefficient of building heights variation (CV_Height); vertical diversity index (VDI)	Mean_Floors = Σ($Floors_i$) / n; CV_Height = σ(Height) / μ(Height); VDI = −Σ[(h_i / H_total) × ln(h_i / H_total)]	Height-related indexes (e.g., mean floors) are widely used in urban studies to represent vertical density (e.g., Angel et al. examine floor utilization alongside FAR to explain density).	
Land use and mix	Entropy index; distance-based diversity index (DBI); herfindahl–hirschman index (HHI)	Entropy: H = −∑ p_i ln(p_i) / ln(k), where p_i = $Area_i$ / Total_Area; DBI = $\sum_j$ w(d_{ij}) × $Diversity_j$, where w(d_{ij}) = exp(−d_{ij} / σ); HHI = ∑ $(p_i)^2$	Entropy and HHI are commonly used to measure land-use mix. For example, Jiao et al. (2021) report the widespread use of these indexes and explain their formulations in land-use mixing studies.	Jiao et al. (2021)
	Access to services (public) Mean distance to the nearest service (m); number of services within a 500 m radius; accessibility score (2SFCA)	Network Distance: Dist_min = min(NetworkDist(i, j)); Service Count: Count_500m = ∑ ($Services_j$ ∈ radius(500 m)); 2SFCA: Two-Step Floating Catchment Area method with supply–demand allocation within distance thresholds (general formulation provided in the cited source).	Access to services is often assessed using a combination of distance to facilities and the 2SFCA method. Tao et al. (2020) introduce a hierarchical 2SFCA approach; simpler metrics such as mean distance or counts within a buffer are also widely used.	Tao et al. (2020)
Street network and connectivity	Network continuity Intersection density (intersections/km²); percentage of Multi-Leg intersections; connectivity index	Intersection_Density = N_intersections / Area_km²; % Multi-Leg = (N_multi-legged / N_total) × 100; Connectivity: e.g., α, β, or other composite network connectivity indices	Intersection density is commonly used as a measure of network connectivity in traffic planning and urban design. Official planning resources (e.g., EPA databases) list intersection density as an extractable network metric.	EPA (2021)
	Access to public transport Distance to the nearest metro/BRT station; number of lines within a 500 m radius; service frequency index	Network Distance: Transit_Access = min(NetworkDist(i, $station_j$)); Lines_500m = Count(transit_lines within 500 m); Service Frequency: total trips within a specified time interval (fleet-based formulation)	Public transport accessibility is typically measured using minimum network distance or the number of stations/lines within a defined buffer. The EPA also introduces indicators for transit service density (service frequency).	

Component/ dimension	Operational indicator	Measurement variables/items	Exact formulas and calculation methods	Source
Urban fabric and morphology	Fine-grained urban fabric Mean parcel area (m^2); block density (blocks/km^2); grain index (coefficient of variation of parcel areas)	Mean_Parcel = Σ($Area_i$) / n; Block_Density = N_blocks / Area_km²; Grain Index = σ(parcel_areas) / μ(parcel_areas)	"Urban grain" refers to the fine or coarse pattern of parcels and is measured using indicators such as parcel-area variance or block density. Urban morphology studies show that fine-grained neighborhoods are more strongly associated with pedestrian activity.	Lam et al. (2024)
	Density, capacity, and permeability Impervious surface area percentage (ISA%); density of local street network; walkability permeability index	ISA% = (Built_area + Roads_area) / Total_area × 100; Local_Density = Length_local_roads / Area_hectare; Walkability = Pedestrian_network_length / Area	Impervious surface percentage is commonly derived from satellite imagery using land-cover indexes (e.g., NDBI or ISA). Pedestrian-network length and local street density are standard indicators of urban permeability in walkability studies.	
Environmental sustainability and energy	Thermal resilience Impervious surface index (ISA); vegetation density (NDVI); land surface temperature (LST); LST anomaly	NDVI = (NIR − RED) / (NIR + RED); LST (Landsat 8): LST = BT − 273.15, where BT = K2 / ln(K1 / ML + 1); LST_anomaly = LST_local − LST_regional_mean	ISA can be calculated from land-use/land-cover maps. NDVI is a standard index provided in Landsat data. LST is derived from thermal satellite data using established equations (USGS provides detailed explanations for NDVI and LST products).	U.S. Geological Survey (2024)
Urban heritage and identity	Historical form Percentage of valuable historical fabric; density of cultural/religious land uses; fabric cohesion index	Historic% = Historic_area / Total_area × 100; Cultural_Density = N_cultural_POIs / Area_km²; Cohesion (Connectivity) = e.g., ratio of connected links within the network	Conservation and regeneration of historical fabrics are commonly assessed using indicators such as the share of historical areas or the density of cultural land uses. Recent studies highlight the role of historical form in social value (e.g., cases examined in China and Europe).	Zhang et al. (2024)
	Urban deterioration Percentage of deteriorated areas, building age index, and mean physical condition of buildings	Deterioration% = Deteriorated_area / Total_area × 100; Age_Index = Σ(Current_year − Construction_year) / n; Physical_Condition = Σ(Condition_scores) / n	Urban deterioration is often estimated using local inspection or visual-survey data. Building age and structural condition indexes are also widely used in urban studies to assess fabric quality.	
Spatial analysis and modeling	Spatial autocorrelation Global Moran's I; local indicators of spatial association (LISA); Getis–Ord Gi* test	Global Moran's I: $I = (n / W) \times [\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})] / [\sum_i (x_i - \bar{x})^2]$; Local LISA: $I_i = (x_i - \bar{x}) \sum_j w_{ij}(x_j - \bar{x}) / \sigma^2$; Getis–Ord $Gi^* = (\sum_j w_{ij} x_j) / (\sum_j x_j)$	Moran's I and LISA tests are standard methods for measuring spatial autocorrelation. Specialized spatial statistics references describe these formulations in detail (e.g., Anselin, 1995, and subsequent works).	Zhang et al. (2021)
	Regression modeling Geographically Weighted Regression (GWR); Multiscale GWR (MGWR); Spatial Autoregressive Models (SAR/SEM)	GWR: $y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i) x_{ik} + \varepsilon_i$; MGWR: $y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i, bw_k) x_{ik} + \varepsilon_i$; SAR: $y = \rho W y + X\beta + \varepsilon$	Multiscale GWR (MGWR) represents a new generation of GWR in which each variable is associated with a distinct spatial scale. These methods are widely used in contemporary spatial studies to model spatial non-stationarity (Fotheringham and Oshan, 2023).	Fotheringham & Li (2023); Fotheringham et al. (2023)

5. Research findings

The selection of the study area and integration of diverse datasets are critical for accurately modeling the spatial congruence of factors affecting floor area ratio (FAR). This study focuses on urban zones exhibiting significant variations in FAR, population density, and land-use patterns, as these factors are essential for understanding spatial heterogeneity.

To assess spatial patterns of building density (associated with the specific location of each metric) and urban form, and to model the complexity of influencing factors in the metropolitan area of Isfahan, the study area was divided into a network of hexagonal, triangular, and square spatial units with defined dimensions, and the corresponding spatial metrics were computed within these units.

In the first stage of modeling, to determine the most appropriate scale and set of spatial metrics, a method was employed that selected metrics exhibiting minimal spatial autocorrelation while effectively representing various dimensions of building density and form (Google Earth). Accordingly, four key metrics—for example, floor area ratio (FAR), gross population density, building coverage percentage, and vertical diversity index (VDI)—were selected to represent distinctive features of the urban structural form.

Using field data and the city's parcel maps (according to the existing land-use layer), hexagonal units with areas of 3, 5, and 7 hectares were generated in ArcGIS, and spatial analyses were conducted on these units. After calculating the selected metrics for each spatial unit, variation curves of each metric relative to zone area were plotted and analyzed. Zones exhibiting the highest correlation in these curves were considered units with stable spatial patterns and were selected for further analysis.

Finally, four selected metrics were calculated across 15 zones for metropolitan Isfahan (sampling units). Following spatial analysis at the class level, the output values were exported as text (TXT) and Excel files and prepared as input data for subsequent modeling stages in Fragstats.

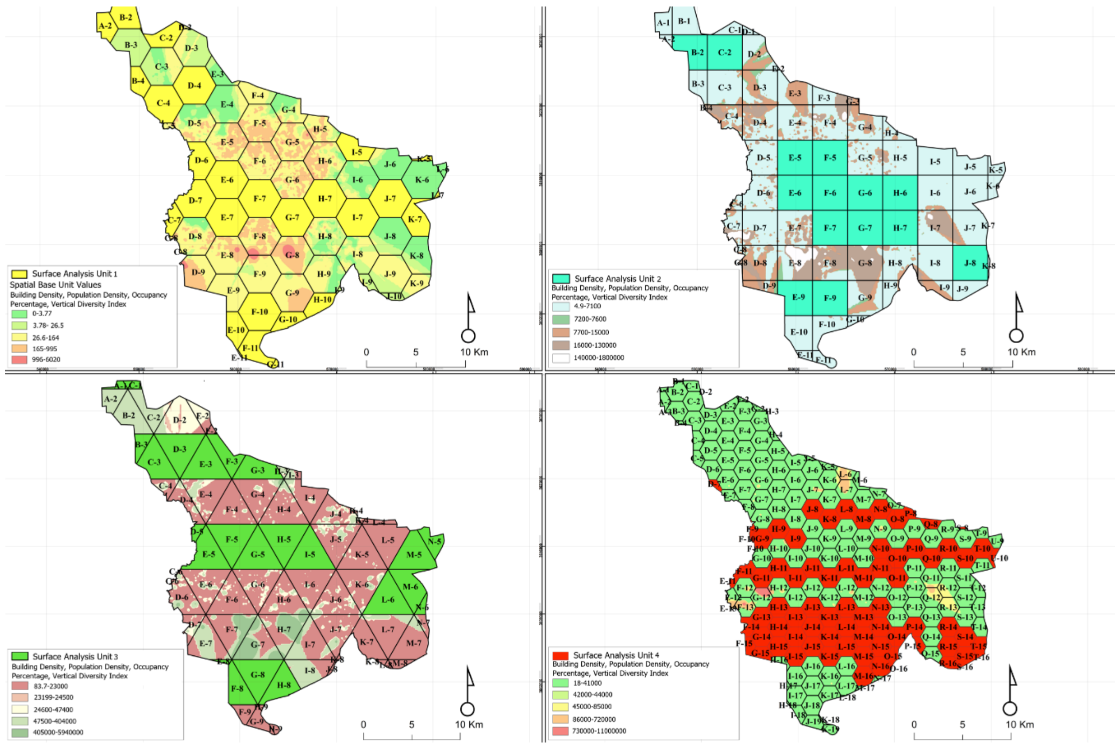

Figure 4. Processing and integrating the operational indicators and the method of assigning each indicator to the basic spatial unit (metric)

5.1. Integration of spatial metrics and principal component analysis (PCA) for modeling building density and urban form

Given the necessity of integrating spatial metrics for a comprehensive modeling of building density patterns and urban form, the principal component analysis (PCA) approach was adopted as the methodological framework. Since individual spatial metrics alone cannot fully capture the complex dimensions of spatial interdependence, a multivariate combination of these metrics with optimized weighting coefficients is essential.

In this study, after extracting the values of the four spatial metrics within the principal analytical units, PCA was employed to determine the optimal weighting structure. The mathematical basis of PCA relies on computing the covariance matrix to identify directions of maximum variance in the dataset, defined by new axes called principal components. To eliminate bias arising from differing ranges of metric values and ensure balanced contributions from each variable, the data were first standardized using z-score normalization, which transforms each variable to have a mean of zero and a variance of one. Subsequently, the covariance matrix was computed, and its eigenvalues and eigenvectors were extracted. Eigenvectors indicate the main directions of data dispersion, while eigenvalues represent the significance of each component. Finally, eigenvalues, representing the proportion of variance explained by each component, were used as the basis for assigning weighting coefficients to the original metrics in the final composite model. This statistically grounded approach allows the construction of a robust composite index that maximizes the representation of spatial interdependence among factors influencing building density and urban form in metropolitan Isfahan.

Table 3. Characteristics of principal analytical units for each spatial metric

Feature	Unit of analysis	Abbreviation	Formula/relationship	Unit	Range
Level/density/ margin	Number of metrics	NP	–	NP > 0	NP > 0
	Metric density	PD	Count / Percent	PD > 0	PD > 0
	Metric area	AREA_MN	–	hectares	AREA ≥ 0
	Metric percentage	PLAND	–	%	0 ≤ PLAND ≤ 100
	Disaggregation index	MESH	Total patch area ≤ MESH ≤ Patch area	m^2	–
	Division	DIVISION	–	Relative	0 ≤ DIVISION < 1
Shape	Mean shape index	SHAPE_MN	–	Unitless	SHAPE ≥ 1
Contiguity/ proximity	Mean Euclidean distance to nearest neighbor	ENN_MN	–	Metric	ENN > 0

(ni: number of metrics by type; A: metric area; a_{ij}: individual metric area; p_{ij}: metric perimeter; h_{ij}: distance to nearest metric; c_{ijr}: adjacency value; V: total values per metric)

Based on the findings of the PCA, the most influential metrics in modeling building density and urban form were categorized according to their respective eigenvalues. Using the factor loadings of each metric as weighting coefficients, a composite density and form index (CDFI) was developed for various zones across metropolitan Isfahan.

The general formula of this index, presented in Equation (1), is based on the linear weighted combination of standardized metrics, incorporating the statistical significance of each principal component. In this formula, eigenvalues (E) serve as the weights for each principal component, and factor loadings (L) represent the contribution of each metric to its corresponding component. Mathematically, the final index is calculated as the weighted sum of linear combinations of standardized metrics (M) for each principal component, where each component is multiplied by its eigenvalue.

This approach allows the multidimensional integration of spatial metrics while preserving the underlying structure of data dispersion, providing a comprehensive representation of the spatial complexity of factors affecting building density and urban form.

Equation (1): Composite density and form index (CDFI)

CDFI=E1×[i∑(L1i×Mi)]+E2×[i∑(L2i×Mi)]+⋯+En×[i∑(Lni ×Mi)]

Where:

- CDFI: Composite Density and Form Index
- N: Number of metrics
- E_n: Eigenvalue of the nth principal component
- L_{ni}: Factor loading of the ith metric in the nth component
- M_i: Standardized value of the ith metric

This formulation enables the calculation of a unified index capturing the complex interactions of spatial factors influencing urban density and form, providing a reliable basis for spatial complexity analyses in metropolitan Isfahan.

Table 4. Results of spatial metrics processing in relation to analytical units (PCA)

Component/ dimension	Operational metric	Measured variables	Formula/calculation method	a1 (NP)	a2 (Division)	a3 (PD)	a4 (LPI)	R^2	Prob.	St.d
Building density and occupancy	Building density	FAR, population density, coverage ratio	FAR = Σ(GFA)/Plot_Area; CR = Σ(Footprint)/ Total_Area ×100	3.024	0.009	2.001	1.220	0.441	0.001	2.003
	Vertical occupancy	Mean floors, CV height, VDI	Mean_Floors = Σ(Floors)/n; VDI = -Σ[(h/H) ln(h/H)]	2.014	0.007	0.333	0.258	0.369	0.005	4.001
Land use and mixing	Land use mix	Entropy, HHI, distance-based diversity	H = -Σ p_i ln(p_i)/ln(k); HHI = Σ(p_i²)	4.018	0.025	0.411	5.068	0.441	0.000	0.369
	Access to public services	Dist_min, Count_500m, SFCA2	Dist_min = min(NetworkDist); 2SFCA = Supply/Demand within 500 m radius	1.036	1.054	0.371	0.170	0.258	0.000	1.369
Road network and connectivity	Network connectivity	Intersection density, connectivity index	Intersection_Density = N_intersections / Area_km²; Connectivity: α, β indices	0.971	0.068	1.042	0.336	0.147	0.000	6.214
	Access to public transport	Distance to station, number of lines	Transit_Access = min(NetworkDist); Lines_500m = Count(lines within 500 m)	3.330	0.147	3.014	2.021	0.874	0.000	2.314
Morphology and urban fabric	Fine-grained fabric	Mean parcel area, block density	Mean_Parcel = ΣArea/n; Block_Density = N_blocks / Area_km²	1.009	0.258	0.448	4.140	1.250	0.005	0.669
	Density/ permeability	ISA%, local road density, walkability	ISA% = (Built_area + Roads_area)/Total_area ×100; Walkability = Ped_network_length / Area	2.480	0.095	2.220	1.820	0.680	0.001	1.820
Environmental sustainability and energy	Thermal resilience	NDVI, LST, ISA, LST anomaly	NDVI = (NIR-RED)/(NIR+RED); LST (Landsat 8) = BT-273.15; LST_anomaly = LST_local - LST_regional_mean	2.900	0.120	2.700	1.950	0.720	0.0005	1.500
Urban heritage and identity	Historic form	Historic%, cultural density, POI density	Historic% = Historic_area / Total_area ×100; Cultural_Density = N_cultural_POIs / Area_km²	3.520	0.030	0.600	4.500	0.520	0.000	0.420
	Urban fabric deterioration	Deterioration%, age index, physical condition	D% = Deteriorated_area / Total ×100; Age_Index = Σ(CurrentYear-ConstructionYear)/n	1.180	0.950	0.520	0.210	0.330	0.002	1.100
Spatial analysis and modeling	Spatial autocorrelation	Moran's I, LISA, Gi*	Moran's I: I = (n/W) Σ_i Σ_j w_ij (x_i - x̄)(x_j - x̄) / Σ(x_i - x̄)²	3.800	0.150	2.900	3.200	0.910	0.000	0.800

* a1/NP; a2/Division; a3/PD; a4/LPI.

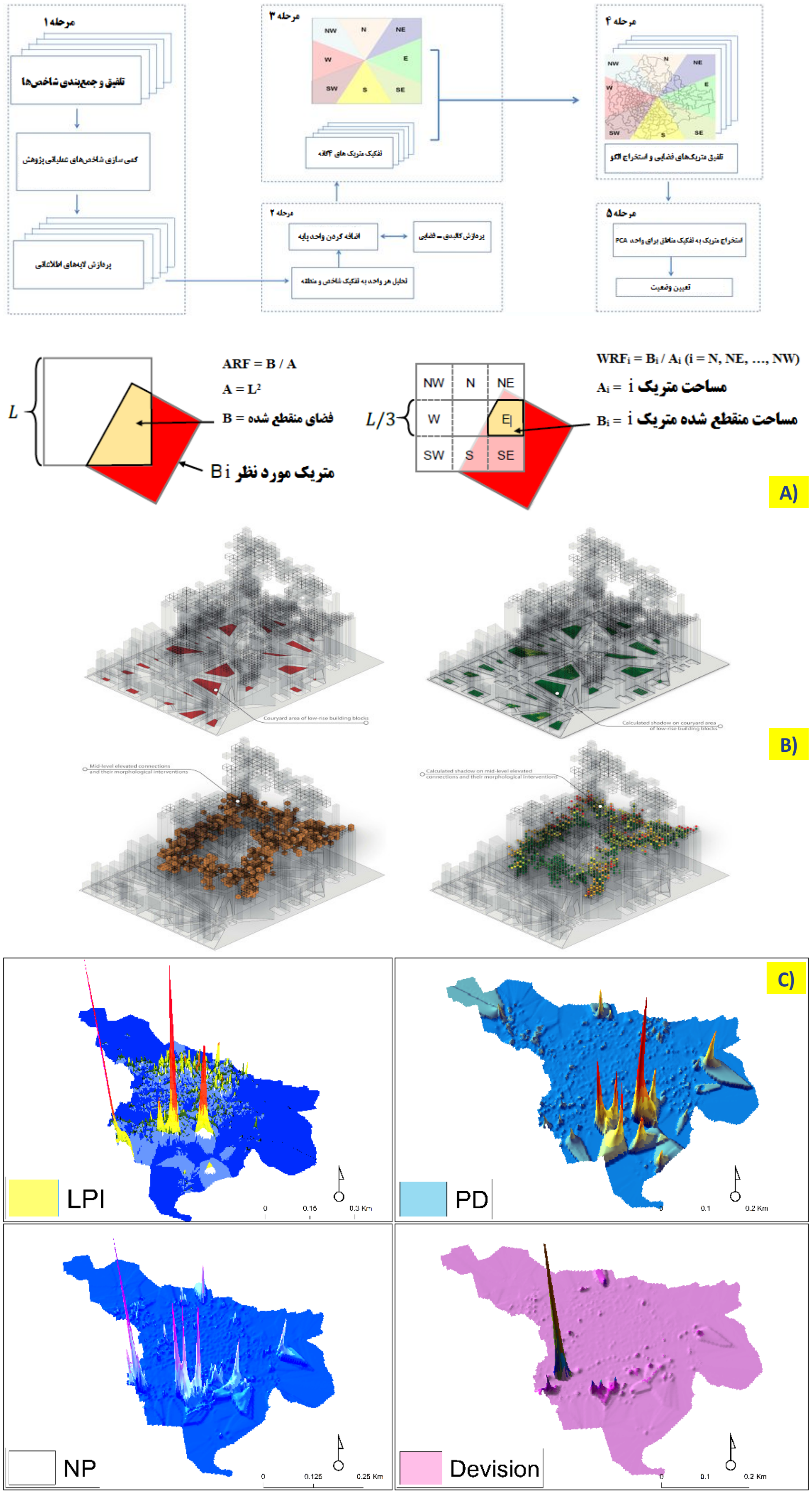

Figure 5. (a) Calculation process b) Adding instrumental variables to c) Spatial base unit based on the 4 metrics studied

The developed model was systematically applied across all metrics extracted from the study zones, and the composite density and form index (CDFI) was computed for each spatial unit. Accordingly, the final spatial pattern map was generated by integrating the outputs from all units.

To improve model accuracy, zones with lower-than-expected NP (number of patches) values were identified in ArcGIS as “Zones exhibiting no significant spatial pattern” and segregated. These zones, lacking a clear spatial pattern, were treated as neutral areas in the final predictive map. This approach enhanced the analytical precision of the model by enabling a clear distinction between zones with significant spatial patterns and those with unstructured spatial organization.

The final output was produced as a continuous raster layer, representing the graded spatial distribution of the CDFI across metropolitan Isfahan.

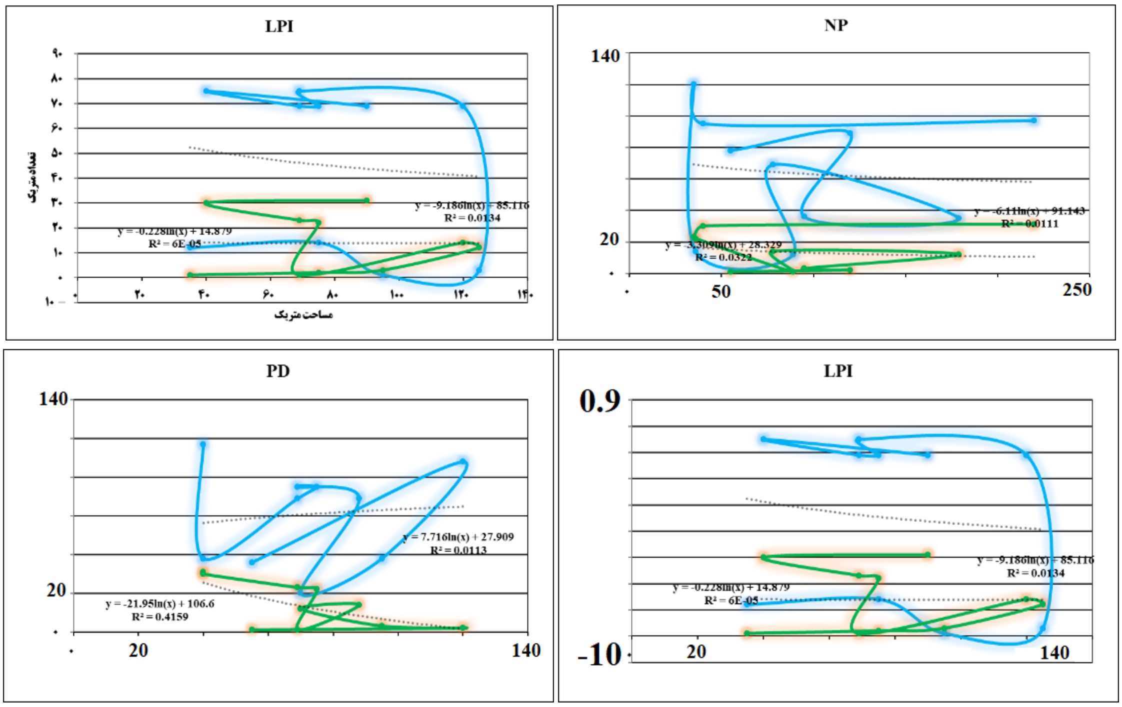

Figure 6. Results of PCA of instrumental variable values in sample metrics with the designated areas and the degree of correlation with the state of building density and form in each spatial metric, along with the communication network of concepts

Based on the findings from the validation process of the selected metrics, using sample units of predetermined sizes and analyzing their correlation with spatial quality conditions within each assessment unit, the visual interpretation, combined with correlation coefficient evaluation, indicates that zones with an area of 3.88 hectares are optimal for metric calculation and regional segmentation.

According to Figure 6 and Table 5, the PCA results on standardized metric values indicate that density and land-use dispersion indexes explain 69.74% of the total variance of the four metrics examined. This validation, based on spatial correlation analysis and efficiency evaluation of different metrics, confirms that selecting a 3.88-hectare unit not only aligns with statistical criteria but also corresponds to the actual spatial distribution of urban patterns. These findings are consistent with previous studies regarding the determination of optimal scales for spatial analysis in urban environments.

The application of PCA on standardized spatial metrics has demonstrated high capability in identifying and extracting dominant patterns of building density and land-use distribution. The significant variance explained by the first two components (69.74%) highlights the crucial role of building density and activity distribution in determining the overall spatial structure of metropolitan Isfahan. This variance proportion falls within the acceptable range for quantitative urban-spatial analysis and demonstrates the model’s ability to consider structural complexities in the study area. Furthermore, the evaluation confirms that an integrated approach combining PCA with spatial validation is a suitable tool for analyzing the complexity of factors influencing building density and urban form. This approach allows the simultaneous identification of complex relationships between various spatial variables and has sufficient generalizability for application in other metropolises.

Table 5. Results of variance analysis for instrumental variables of spatial metrics

Principal component (PCI) / wij	Number of zones	Number of metrics	Mean	Variance	Min	Max	Variance % (Var.Per)
Building density and urban occupancy	15	4	2.021	3.0020	1.3300	3.6697	13.35
Land use, mixing, and functional diversity	15	4	3.014	1.0180	0.5520	7.2581	26.41
Access to urban service centers at the regional scale	15	4	5.021	2.2200	1.0014	3.2587	11.86
Open space, spatial concentration and isolation, and physical growth	15	4	1.180	0.7410	1.0087	3.8541	14.02
Access, density, and land-use distribution	15	4	2.036	1.0258	1.3670	3.3258	12.10
Road network, connectivity, and access	15	4	2.369	0.8851	1.8740	4.3690	15.90
Urban fabric, morphology, and environmental sustainability	15	4	1.257	0.9614	0.9842	1.7452	6.35

The results in Table 5 show that the variance, minimum and maximum ranges, and means of each component represent the extent and range of variations across zones, providing a more precise understanding of the optimal spatial scales for urban planning interventions. The variance percentage for each component indicates how much information and interpretation that component extracted from the multidimensional dataset. Consequently, selecting these dimensions for modeling spatial complexity is validated and provides effective guidance for urban policy and design.

The component "Access, density, and land-use distribution", with a 26.41% variance share, accounts for the highest explanatory power of spatial variation, emphasizing the fundamental role of these parameters in shaping and altering urban spatial structures. The high variance contribution indicates that the spatial distribution and accessibility of land uses directly affect urban density and physical structure. Its mean value of 3.014 indicates significant variations among the study zones, reflecting high functional diversity and dispersion in metropolitan Isfahan.

Conversely, the component "Urban fabric, morphology, and environmental sustainability", with only 6.35% variance, has the least influence on total variance, suggesting either relatively uniform characteristics across zones or lower importance in structural variation compared to other components. Its mean of 1.257 confirms the lack of substantial fluctuations in this dimension.

The component "Access to urban service centers at regional scale" has the highest mean of 5.021 and a variance of 2.220, highlighting the importance of this variable in the urban service network and spatial differentiation of zones. It serves as a key indicator reflecting significant variations in urban physical dynamics and activity distribution.

Additionally, components such as "Road network, connectivity, and access" (15.90% variance) and "Building density and urban occupancy" (13.35% variance) underscore the critical role of connectivity and physical density in shaping urban spatial conditions. These results highlight the mutual importance of physical elements and spatial organization in urban spatial analyses.

In summary, the findings indicate that to understand and influence building density and urban form in metropolitan Isfahan, special attention should be given to parameters related to density, land-use distribution, and accessibility, while other dimensions, despite their importance for understanding the overall structure, play a reduced role in actual spatial variations.

Accordingly, the final model for the composite density and form index (CDFI) of metropolitan Isfahan was constructed using Equation 2, integrating the eigenvalues of all instrumental variables and the factor loadings of metrics as coefficients for the 15 regional units. The results are illustrated in Figures 7–10.

Equation (2):

CDFI = ((Outdoor index, Spatial concentration and isolation index, Physical growth index of regions, FAR, Index of density and distribution of land uses and access to municipal service centers on a regional scale)) N1 × (L1 × NPi × L2 × PDi + L3 × SHAPEMNI + L4 × FRACMNI + L1 × CONTIGMNI + L2 × ENNMNI + L3 × DIVISIONi +E1 × (L4 × PLANDi + L2 × LPIi + L3 × AREA_MNIi + L1 × MESHi) + E2 × (L1 × SPLITi)

This formulation allows the calculation of a comprehensive index that captures the complex interactions among spatial factors affecting building density and urban form, and serves as a foundation for spatial complexity analysis in metropolitan Isfahan.

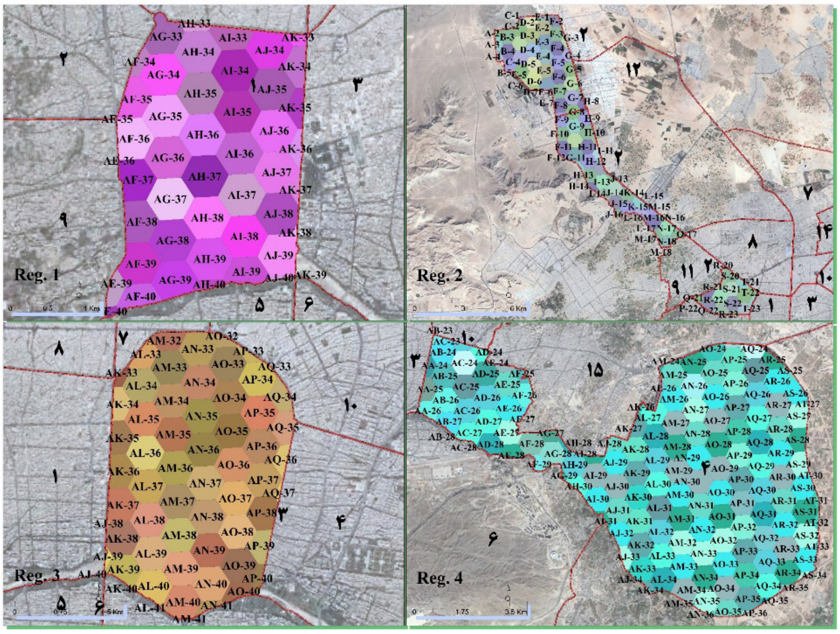

Figure 7. Final results of CDFI patterns for areas 1 to 4 based on the integration of spatial metrics

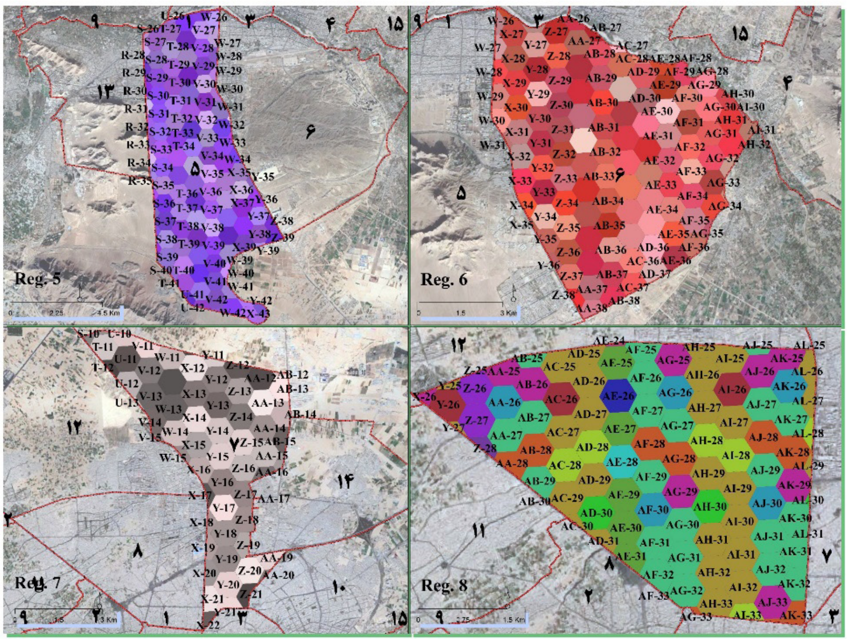

Figure 8. Final results of CDFI patterns for areas 5 to 8 based on the integration of spatial metrics

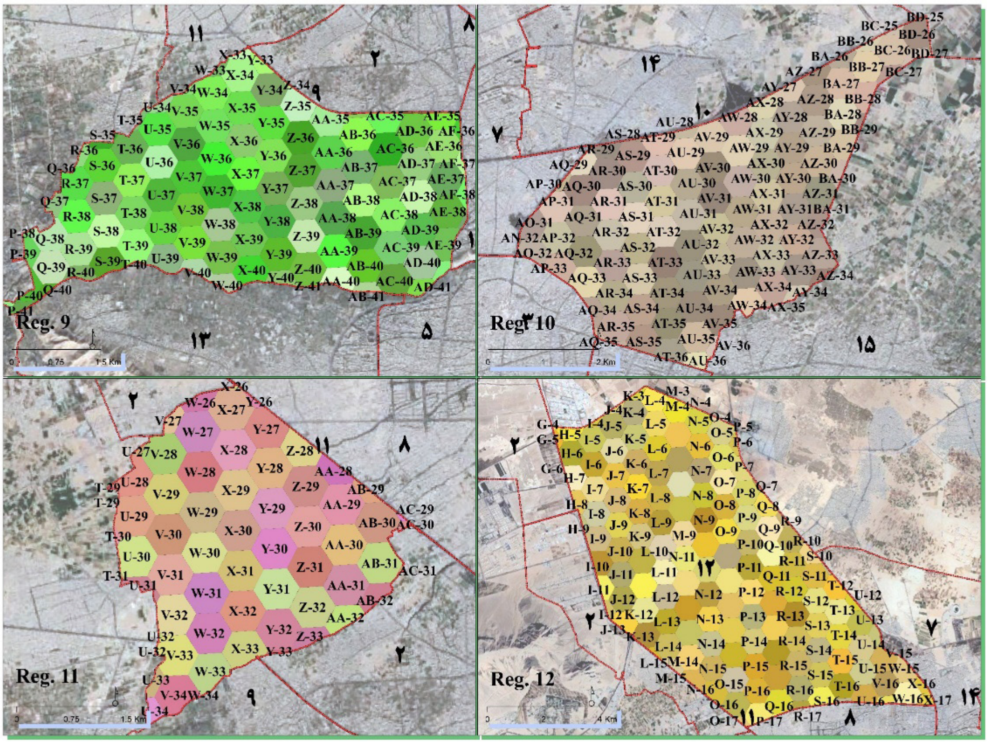

Figure 9. Final results of CDFI patterns for areas 9 to 12 based on the integration of spatial metrics

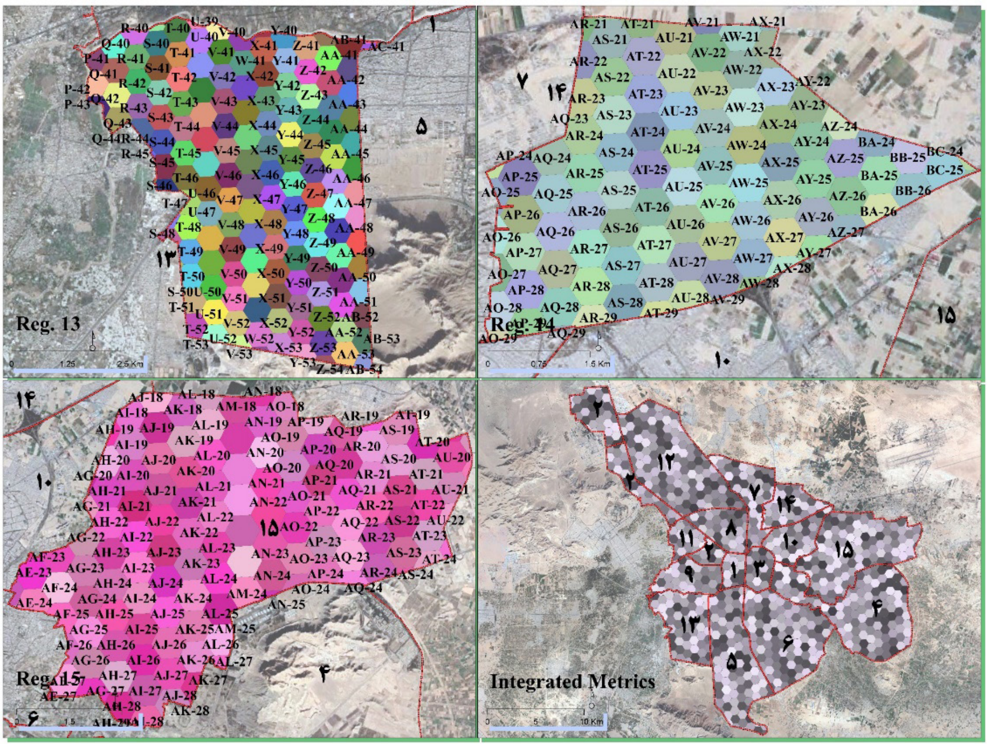

Figure 10. Final results of CDFI patterns for areas 13 to 15 based on the integration of spatial metrics

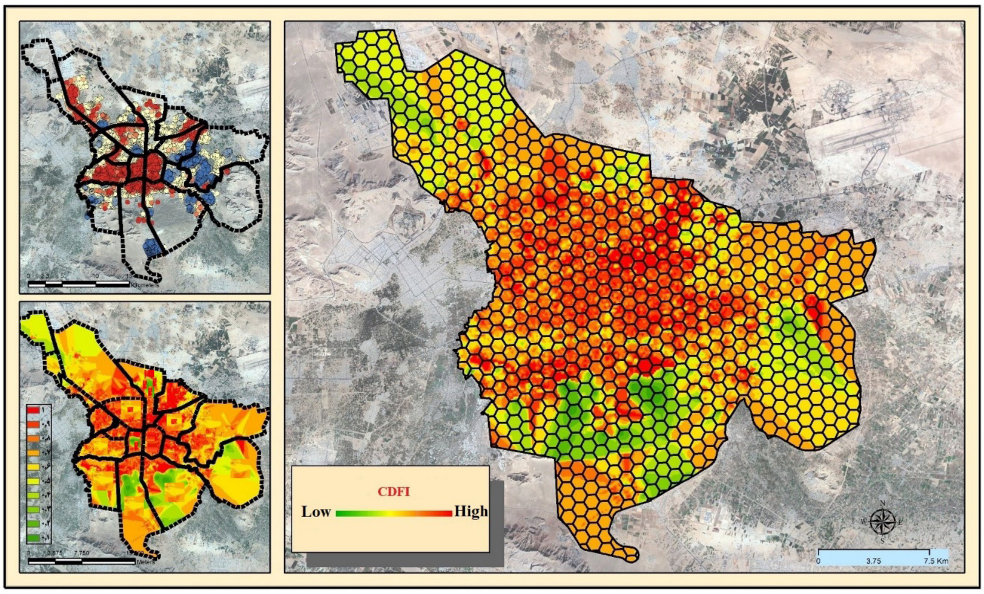

Figure 11. Final results of density and urban form patterns for Isfahan Metropolitan and the map of final spatial metrics based on the CDFI index

According to the results presented in Table 6, using the components of the density and form model (Equation 2), and as illustrated in Table 6 and Figure 11, among all 695 generated metrics, 46.3 zones were classified based on the histogram and distribution range of the CDFI, which ranges from 0 to 1. The classification was performed into 10 classes, ranging from low density and disproportionate form (0.1) to optimal density and proportionate form (1), and a unified class map was prepared.

Table 6. Density and form index of zones based on metric type and area

Metric type	Zone	Number of metrics	Area (ha)	Total area (%)	S.Met	F.Met (ratio of CDFI metrics to total metrics in each zone)	CDFI	r
LPI	1	31	810	0.553	3612.950	4.46	0.648	8
LPI	2	42	2,145	0.001	12.963	6.04	0.726	4
PD	3	59	1,148	0.784	9,745.612	8.49	0.681	7
Division	4	70	133,731	91.355	1,346,930.935	10.07	0.900	1
LPI	5	61	1,702	1.163	14,938.417	8.78	0.762	3
Division	6	65	6,600	0.005	61.727	9.35	0.808	2
NP	7	51	1,357	0.001	9.958	7.34	0.719	5
PD	8	32	2,039	1.393	9,388.201	4.60	0.606	10
LPI	9	47	1,054	0.720	7,127.770	6.76	0.606	11
LPI	10	41	2,200	1.503	12,978.417	5.90	0.579	13
LPI	11	39	1,140	0.779	374	5.61	0.537	14
Division	12	56	1,608	1.098	6,397.122	8.06	0.699	6
PD	13	36	2,010	0.001	12,956.547	5.18	0.590	12
PD	14	46	940	0.642	10.412	6.62	0.503	15
LPI	15	19	1,664	0.001	6,221.583	2.73	0.635	9
Total		695	146,385.776	100	14,638,577.600	100	1	–

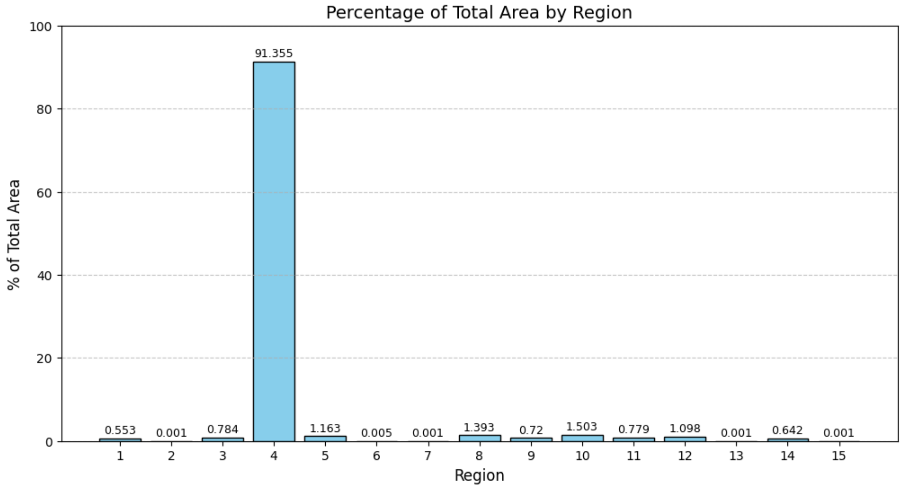

Figure 12. Status of the final CDFI index with the number of metrics (area in hectares) for each of the 15 municipal districts

Based on the analyzed data, the status of building density and urban form in metropolitan Isfahan can be interpreted and modeled in an integrated and scientific manner, focusing on the spatial complexity of influential factors across 15 urban districts. The CDFI, along with the metrics NP, Division, PD, and LPI, serves as the primary modeling criterion, quantitatively representing the complex interactions and interdependencies among density, spatial coherence, and urban form across the city.

The analysis indicates that District 4, with a CDFI of 0.900 and 70 Division metrics covering 133,731 hectares, exhibits the highest spatial complexity. This index not only reflects the concentration of optimal metrics but also indicates uniform distribution and extensive scale, demonstrating high spatial coherence and controlled urban form at the regional level. District 6, with 65 Division metrics and a CDFI of 0.808, ranks second. Similar to District 4, it clearly shows a harmonious pattern of density and form. Districts 5, 7, and 12, with CDFI values ranging from 0.762 to 0.719, are classified as areas of relatively high coordination, although the scale and dispersion of metrics are smaller than in Districts 4 and 6.

In other districts, such as 3, 8, 13, and 14, PD metrics with variable densities (32–59 metrics) and areas ranging from 940 to 1,148 hectares indicate relative metric dispersion and lower coherence in urban form. Nevertheless, the effect of dispersion on CDFI remains notable, and Districts 3 and 8, with CDFI values of 0.681 and 0.606, maintain a moderate level of spatial coordination. LPI metrics are more prevalent in Districts 1, 2, 5, 9, 10, 11, and 15, where metric densities are low to moderate, and CDFI values range from 0.537 to 0.726, indicating reduced metric concentration and limited influence of continuous form on metropolitan coherence. District 15, with only 19 LPI metrics and a CDFI of 0.635, exhibits the lowest metric density and the smallest coverage area, reflecting limited spatial cohesion and relative form dispersion.

Indicator component analysis reveals that density and physical occupancy components (FAR, population density, and coverage ratio), with a1=3.024 and R^2=0.441, alongside vertical occupancy, average number of floors, and VDI index, with a2=2.014 and R^2=0.369, play a primary role in shaping density patterns and volumetric space. In the functional dimension, land-use mixing, with entropy and HHI indexes (a1=4.018, R^2=0.441), exerts the greatest influence on metric coherence and spatial combination, while access to public services (a1=1.036, R^2=0.258) shows supplementary effects.

The road network and urban connectivity, including public transport accessibility indexes (a1=3.330, R^2=0.874) and network connectivity (a1=0.971, R^2=0.147), play a key role in facilitating urban flows and metric distribution, particularly in Districts 4, 6, and 12, which exhibit high spatial correlation and superior CDFI values. Morphology and permeability indexes, including ISA% and walkability indexes (a1=2.480, R^2=0.680), demonstrate the districts' ability to maintain structural cohesion and facilitate urban permeability, most evident in Districts 4, 6, and 5.

Urban heritage and identity components, including historic form and fabric deterioration (a1=3.520, R^2=0.520 for historic form), play a decisive role in preserving cultural and morphological characteristics in central and historic districts, with their effect on spatial coherence observable in Districts 1 and 5. Moran's I spatial correlation index (a1=3.800, R^2=0.910) confirms that metric distribution is neither random nor uniform but exhibits complex, clustered spatial patterns across the city.

In the final analysis, districts with the highest CDFI values (4, 6, 5, 7, and 12) feature coordinated metric densities, extensive area coverage, and high spatial cohesion, reflecting the complex interplay between building density, land-use mix, street network accessibility, and morphological characteristics. Conversely, districts with lower CDFI values (10, 11, 13, 14, and 15) show dispersed metrics and reduced form coherence, representing relative disharmony in density and urban form. This integrated technical analysis provides a scientific framework for managing density, optimizing urban form, and planning based on spatial data in Isfahan, enabling accurate prediction, control, and enhancement of spatial coherence at various urban scales.

6. Discussion and conclusion

The key findings of this study, including the prominent role of the road network and transportation accessibility, the importance of land-use mixing in explaining FAR distribution and urban form patterns, strong spatial heterogeneity (confirmed by Moran's I and LISA indexes), and the dominance of density-occupation and land-use distribution components in explaining spatial variance, are aligned with much of the international and domestic literature. Specifically, the positive correlation between proximity to transport networks and higher density mirrors findings reported in Liu (2023) and Lu et al. (2016), indicating that Isfahan exhibits the same link between access structure and vertical/horizontal development selection, theoretically supporting compact city and smart growth frameworks (Jenks & Burgess, 2000; Neuman, 2005).

The role of land-use mixing as a high-loading PCA component aligns with literature emphasizing the functional impact of activity distribution on density (Jiao et al., 2021), indicating that FAR policies cannot be designed independently of functional and networked urban structures. The findings on density and land-use distribution components, which explain the largest share of variance, are consistent with Peng et al. (2021) and Zheng (2023), showing that spatial land-use distribution and network structures are primary drivers of density inequalities. Heterogeneous-spatial analysis (MGWR/SAR) further demonstrates that explanatory variable effects are heterogeneous and location-dependent, supporting theoretical expectations regarding nonlinear, scale-dependent behavior of spatial variables (Lu, 2025; Cao, 2025) and justifying the use of localized models such as MGWR.

This study not only confirms previous observations but also methodologically deepens them by introducing the CDFI, which integrates multiple spatial metrics into a single measure, enabling identification of thresholds and density classes —an element often missing in prior single-variable studies. However, the results reveal some discrepancies with environmental and microclimatic literature. For instance, while Huang et al. (2025) and Li et al. (2018) highlight the significant impact of density on microclimatic parameters (LST and NDVI), "fabric, morphology, and environmental sustainability" in this study demonstrate low variance share (≈6.35 percent). This variance can be explained as follows: first, spatial inconsistency and relative uniformity of vegetation cover and impervious surfaces in certain Isfahan zones have reduced the spatial variability of these parameters. Second, in the local context, the priorities of municipal revenue generation and housing development pressures (density selling) may direct spatial decisions in a way that effectively mitigates the potential environmental impacts of density. This is consistent with the findings of Cobbinah et al. (2025) and Shatkin (2017), which introduce density selling as the driver of inequality and unsustainability in developing countries. Thus, apparent disagreements with certain environmental studies mostly result from the significance of policy-institutional interventions and differences in variables' scale/dispersion, rather than real theoretical conflict.

Another prominent contribution is the strong CDFI's capacity to reveal "coherent" and "incoherent" zones in density distribution, consistent with theoretical studies on heterogeneity and historical feedback loops in urban densification (Bertaud, 2018; Zheng, 2023). Comparisons with domestic studies confirm the decisive role of Districts 4 and 6 in producing high CDFI values and spatial cohesion, aligning with findings from Nikpour et al. (2022) and Alizadeh & Asghari Zamani (2021). They also revealed that the concentration of policies and markets in certain zones produces densely clustered patterns. The findings of the present study confirm and support this literature; it allows policy thresholds to be extracted by proposing the weighted, integrated CDFI formulation, which previous studies seldom addressed.

Causally, Isfahan's density pattern results from three overlapping reasons: network-accessibility capacity (road and transit network), spatial function and composition of activities (land-use mix), and institutional-economic incentives (density selling and municipal revenue structure). This causal combination aligns with existing theoretical evidence in urban governance, land economics, and spatial studies, explaining why environmental considerations often fail to decisively shape developmental decisions, as economic and structural drivers dominate (Shatkin, 2017; Cobbinah et al., 2025).

Methodologically, the integrated approach (spatial econometrics + MGWR + PCA + EUM/CA-ABM simulation) demonstrates a clear capacity to reveal spatial heterogeneity and nonlinear thresholds, overcoming limitations of linear macro-scale models. It supports literature emphasizing multi-source, multi-scale methodologies (Zheng, 2023; Fotheringham & Li, 2023) and highlights that policy-oriented analyses must consider both spatial heterogeneity and cross-sector interactions.

Overall, the findings demonstrate that building density and urban form cannot be understood through linear, one-dimensional, or cross-sectional relationships. Quantitative and qualitative evidence indicate that spatial dynamics in Isfahan are the result of a complex adaptive system, where physical, socio-economic, institutional, and environmental indicators operate in an intertwined network with strong interdependencies. Formulating and calculating the CDFI, which explains 69.74% of total data variance, confirms this hypothesis and highlights the limitations of conventional urban modeling approaches.

Comparisons with prior studies in Iranian cities (Tehran, Tabriz, and Hamedan) reveal similar spatial mismatches, rooted in institutional inertia and knowledge gaps between planning systems and dynamic urban realities. Theoretically, this study reveals that the FAR concept in developing cities, like Isfahan, is multifaceted and contradictory: technically a tool for regulating physical development, yet practically a mechanism for short-term revenue accumulation. This duality produces a "flawed spatial logic," where density distribution prioritizes market pressures and municipal budget constraints over sustainability, spatial justice, or functional efficiency. Quantitative findings reflect this flawed logic, demonstrating strong spatial heterogeneity in CDFI across the 15 districts (0.503 in District 14 to 0.900 in District 4).

District 4, with the highest spatial complexity (CDFI=0.900), exemplifies relatively successful integration of density, land-use mix, and accessibility, whereas peripheral districts with lower CDFI values indicate planning failures in achieving balanced development. Methodologically, this research innovates through an integrated analytical-simulation pipeline covering three domains: spatial econometrics for causal inference, spatial heterogeneity modeling for local differences, and dynamic scenario-building for policy outcome prediction. This integrated framework addresses methodological gaps in domestic literature, which often suffer from descriptive, linear, and spatially blind approaches. The successful application of MGWR and PCA confirms that spatial dependence and scalability are not abstract concepts but concrete realities to be incorporated into urban decision-making models.

Practically, the findings advocate a new doctrine for urban management in Iran: moving from "centralized, homogenized planning" toward "context-sensitive smart policies". The final CDFI map of Isfahan clearly demonstrates that each urban district possesses a unique spatial signature, requiring tailored policy packages. High CDFI areas (e.g., Districts 4 and 6) should prioritize cohesion maintenance and quality improvement, whereas low CDFI areas (e.g., Districts 14 and 15) should focus on structural regeneration and remediation of deficits. Addressing density-sale issues requires municipal revenue diversification and institutional separation between regulatory and revenue-generation functions.

The insights from this study extend beyond Isfahan, providing guidance for other Iranian cities: (1) transition from cross-sectional data to spatio-temporal databases to track urban dynamics; (2) integrate quantitative analyses and qualitative methods to capture social and perceptual dimensions of density; and (3) develop AI-based decision-support platforms capable of real-time policy scenario simulation and evaluation. Ultimately, this study emphasizes that the sustainable future of Iranian metropolises depends on embracing urban complexity and replacing "islanded rationality" with "systemic rationality". Only through this paradigm shift can building density become an opportunity for creating more equitable, resilient, and human-centered cities.

Authors' Contributions

The first author contributed 70%, the second author 15%, and the third author 15% to this research.

Acknowledgments

This article is derived from the first author's doctoral dissertation entitled "Explanation and Presentation of an Appropriate Building Density Model in the City of Isfahan," conducted under the supervision of the second and third authors at the Alborz Campus of the University of Tehran. The authors express their sincere gratitude to all individuals who assisted in conducting this study, particularly those who contributed to the evaluation of the manuscript's quality.

Conflict of Interest

The authors declare that they have no conflicts of interest regarding the authorship or publication of this article.

References

Abrego, N., & Ovaskainen, O. (2023). Evaluating the predictive performance of presence–absence models: Why can the same model appear excellent or poor? *Ecology and Evolution*, 13(12), e10784. https://doi.org/10.1002/ece3.10784

Ahmed, Z. U., Sun, K., Shelly, M., & Mu, L. (2021). Explainable artificial intelligence (XAI) for exploring spatial variability of lung and bronchus cancer (LBC) mortality rates in the contiguous USA. *Scientific reports*, 11(1), 24090. https://doi.org/10.1038/s41598-021-03198-8

Ahn, Y., Leyk, S., Uhl, J. H., & McShane, C. M. (2024). An integrated multi-source dataset for measuring settlement evolution in the United States from 1810 to 2020. *Scientific data*, 11(1), 275. https://doi.org/10.1038/s41597-024-03081-x

Alizadeh S., & Asghari-Zamani A. (2021). Investigation of Changes in Construction Density in Iranian Metropolitan Cities (Case Study: Zafaraniyeh Neighborhood, Tabriz Metropolis). *Economic Geography Research*, 2(5): 15–31. https://dor.isc.ac/dor/20.1001.1.27173747.1400.3.2.2.3 [In Persian].

Angel, S., Lamson-Hall, P., & González-Blanco, Z. (2021). Anatomy of density: Measurable factors that constitute urban density. *Buildings & Cities*, 2(1), 264–282. https://doi.org/10.5334/bc.91 journal-buildingscities.org

Asghari Zamani A., & Alizadeh S. (2021). Investigating the Relationship between Decreasing Building Life and Increasing Regional Value in Tabriz Metropolis (Case Study of Zafaranieh Town). *Urban Environmental Planning and Development*, 1(4): 41-56. https://dorl.net/dor/20.1001.1.27833496.1400.1.4.4.8 [In Persian].

Baqaei M., Ziyari Y., Zarabadi Z., Sadat S., & Majedi H. (2021). Evaluation and Explanation of a Sustainable Urban Design Model Based on a Density-Oriented Approach in Urban Fabric (Case Study: District 2 of Tehran). *Geographical Studies (Regional Planning)*, 11(4): 261–285. https://www.jgeoqeshm.ir/article_136682.html [In Persian].

Bertaud, A. (2018). Order without design: How markets shape cities. MIT Press. https://doi.org/10.7551/mitpress/10671.001.0001

Bueno, M., Macera, B., & Montoya, N. (2023). A comparative analysis of machine learning techniques for national glacier mapping: Evaluating performance through spatial cross-validation in Perú. *Water*, 15(24), 4214. https://doi.org/10.20944/preprints202310.0862.v1

Cao, Q., Chen, J., Zhao, J., & Stouffs, R. (2025). From Heuristics to Data: Quantifying Site Planning Layout Indicators with Deep Learning and Multi-Modal Data. *arXiv preprint arXiv*:2508.11723. https://doi.org/10.48550/arXiv.2508.11723

Cheshmehzangi, A., & Dawodu, A. (2021). Towards a sustainable energy planning strategy: The utilisation of floor area ratio for residential community planning and design in China. *Frontiers in Sustainable Cities*, 3, 687895. https://doi.org/10.3389/frsc.2021.687895

Christen, P., & Churches, T. (2005, April). A probabilistic deduplication, record linkage, and geocoding system. In *Proceedings of the Australian Research Council Health Data Mining Workshop: Canberra, AU*. https://www.semanticscholar.org/paper/70a4d632a60edbcec6e7cc787812e7e425995552

Cobbinah, P. B., & Finn, B. M. (2025). On Pedestrian Accessibility: Spatial Justice and Progressive Planning in African Cities. *Journal of Planning Literature*, 40(2), 170-184. https://doi.org/10.1177/08854122241240071

Dehqani H. (2019). Typology of 15 Urban Districts of Isfahan with Emphasis on Social Problems in Extremely Vulnerable Neighborhoods. *Applied Sociology*, 30(2): 117–136. https://dor.isc.ac/dor/20.1001.1.20085745.1398.30.2.8.2 [In Persian].

Edwards, S. E., Strauss, B., & Miranda, M. L. (2014). Geocoding large population-level administrative datasets at highly resolved spatial scales. *Transactions in GIS*, 18(4), 586-603. https://doi.org/10.1111/tgis.12052

Fainstein, S. S. (2014). The just city. *International journal of urban Sciences*, 18(1), 1-18. https://doi.org/10.1007/s10901-011-9243-8

Fan, C., Yang, Y., & Mostafavi, A. (2021). Neural embeddings of urban big data reveal emergent structures in cities. *arXiv preprint arXiv*:2110.12371. https://doi.org/10.48550/arXiv.2110.12371

Fauzi, C. (2020). Pengembangan Sistem Informasi Geografis Menggunakan YWDM Dalam Perencanaan Tata Ruang. *J-SAKTI (Jurnal Sains Komputer dan Informatika)*, 4(2), 598-607. https://doi.org/10.30645/J-SAKTI.V4I2.252

Fotheringham, A. S., & Li, Z. (2023). Measuring the unmeasurable: models of geographical context. *Annals of the American Association of Geographers*, 113(10), 2269-2286. https://doi.org/10.1080/24694452.2023.2227690

Fotheringham, A. S., Oshan, T. M., & Li, Z. (2023). Multiscale geographically weighted regression: Theory and practice. CRC Press. https://doi.org/10.1201/9781003435464

Gao, X., Asami, Y., & Katsumata, W. (2006). Evaluating land-use restrictions concerning the floor area ratio of lots. *Environment and Planning C: Government and Policy*, 24(4), 515-532. https://doi.org/10.1068/c0531

Goldberg, D. W., Wilson, J. P., & Knoblock, C. A. (2007). From text to geographic coordinates: The current state of geocoding. *URISA journal*, 19(1), 33-46. https://www.semanticscholar.org/paper/26f64bcacac4a64693ffe76d2e894ae6bfc88e36

Ha, J., Lee, S., & Park, C. (2016). Temporal effects of environmental characteristics on urban air temperature: The influence of the sky view factor. *Sustainability*, 8(9), 895. https://doi.org/10.3390/SU8090895

Hassani K., & Taban M. (2022). The Importance of Building Density in Reducing Urban Air Pollution (Case Study: Arak City). *Geography and Urban Space Development*, 9(1): 93–108. https://dor.isc.ac/dor/20.1001.1.25383531.1401.9.1.6.7 [In Persian].

Huang, Y., Li, S., Lin, J., Zheng, L., Zhuang, C., Guan, C., & Zhuang, Y. (2025). Nonlinear and threshold effects of urban building form on carbon emissions. *Energy and Buildings*, 329, 115243. https://doi.org/10.1016/j.enbuild.2024.115243

Isfahan Municipality, Statistical Yearbook of Isfahan City (2016). Deputy for Planning, Research, and Information Technology of Isfahan Municipality, Cultural and Recreational Organization of Isfahan Municipality. https://www.isfahan.ir/ [In Persian].

Isfahan Provincial Governor's Office. (2012–2022). *Statistical Yearbook of Isfahan Province*. Isfahan: Office of Statistics and Information. https://ostan-es.ir/ [In Persian].

Jenks, M., & Burgess, R. (2000). Compact cities: Sustainable urban forms for developing countries. Routledge. https://doi.org/10.4324/9780203478622

Jiao, J., Rollo, J., & Fu, B. (2021). The hidden characteristics of land-use mix indices: An overview and validity analysis based on the land use in Melbourne, Australia. *Sustainability*, 13(4), 1898. https://doi.org/10.3390/su13041898

Jr, s., & Xm, z. (2013). A quantification analysis of suburban land use and construction intensity based on AFAR: A case of the land development around Zijingang campus, Zhejiang University. *Lowland Technology International*, 15(2), 56-65. https://doi.org/10.14247/LTI.15.2_56

Jung, S., & Yoon, S. (2021). Analysis of the effects of floor area ratio change in urban street canyons on microclimate and particulate matter. *Energies*, 14(3), 714. https://doi.org/10.3390/en14030714

Karn, P. L., & Park, J. (2022). Affordable housing for low-income households through floor area ratio incentive: the case of Manohara settlement in Kathmandu, Nepal. *International Journal of Urban Sustainable Development*, 14(1), 304-318. https://doi.org/10.1080/19463138.2022.2103823

Lalehpour M., Esmaeilpour M., & Pahlevani F. (2021). Analysis of the Physical Development of Khorramabad City with Emphasis on Indicators of Inner-City Development. *Journal of Human Settlement Planning Studies*, 16(4): 919–934. http://jshsp.iaurasht.ac.ir/article_684070.html [In Persian].

Lam, C. J., Schram, R. J. C., & Vennemann, F. B. (2024). A walk across Europe: Development of a high-resolution walkability index. Preprint. (Arch. Pub. Data Sci.) arxiv.org

Li, L., Yang, X., & Qian, Y. (2018). CFD simulation analysis of the influence of floor area ratio on the wind environment in residential districts. *Journal of Engineering Science & Technology Review*, 11(5). 185-192. https://doi.org/10.25103/jestr.115.24

Li, Z., Jiao, L., Zhang, B., Xu, G., & Liu, J. (2021). Understanding the pattern and mechanism of spatial concentration of urban land use, population, and economic activities: A case study in Wuhan, China. *Geo-Spatial Information Science*, 24(4), 678-694. https://doi.org/10.1080/10095020.2021.1978276

Liu, D., & Shi, Y. (2022). The influence mechanism of urban spatial structure on urban vitality based on geographic big data: A case study in downtown Shanghai. *Buildings*, 12(5), 569. https://doi.org/10.3390/buildings12050569

Liu, T. (2023). Explaining China's housing vacancies: A theory based on the incentives of local government officials. *Journal of Government and Economics*, 10, 100077. https://doi.org/10.1016/j.jge.2023.100077

Lu, Q., Ning, J., You, H., & Xu, L. (2023). Urban intensity in theory and practice: Empirical determining mechanism of floor area ratio and its deviation from the classic location theories in Beijing. *Land*, 12(2), 423. https://doi.org/10.3390/land12020423

Lu, Z., Zhang, H., Southworth, F., & Crittenden, J. (2016). Fractal dimensions of metropolitan area road networks and the impacts on the urban built environment. *Ecological indicators*, 70, 285-296. https://doi.org/10.1016/j.ecolind.2016.06.016

Ma, R., Li, X., & Chen, J. (2021). An elastic urban morpho-blocks (EUM) modeling method for urban building morphological analysis and feature clustering. *Building and Environment*, 192, 107646. https://doi.org/10.1016/j.buildenv.2021.107646

Mahoney, M. J., Johnson, L. K., Silge, J., Frick, H., Kuhn, M., & Beier, C. M. (2023). Assessing the performance of spatial cross-validation approaches for models of spatially structured data. *arXiv preprint arXiv*:2303.07334. https://doi.org/10.48550/arXiv.2303.07334

Mishra, U., Gautam, S., Riley, W. J., & Hoffman, F. M. (2020). An ensemble machine learning approach improves predicted spatial variation of surface soil organic carbon stocks in data-limited northern circumpolar regions. *Frontiers in Big Data*, 3, 528441. https://doi.org/10.3389/fdata.2020.528441

Mohammadpour-Chabaki H., & Hassanpour R. (2022). Analysis of the Consequences of Selling Surplus Building Density in District 2 of Tehran. *Human Settlement Planning Studies*, 18(17): 829–842. https://dorl.net/dor/20.1001.1.25385968.1401.17.3.4.8 [In Persian].

Mokhtari L., Karimi-Nia Sh., & Kian-Arthi M. (2021). Typology of General Form and Relative Density of Residential Buildings in Tehran from the Perspective of Climatic Performance and Energy-Consumption Optimization. *Naghsh-e-Jahan—Journal of Architecture and Urbanism*, 11(4): 60–78. https://dor.isc.ac/dor/20.1001.1.23224991.1400.11.4.5.4 [In Persian].

Neuman, M. (2005). The compact city fallacy. *Journal of Planning Education and Research*, 25(1), 11–26.

Nikpour A., Mohammadiyari B., & Soleimani M. (2022). Spatial Modeling of Factors Influencing Building Density (Case Study: Hamedan City). *Spatial Planning*, 12(2): 27–46. https://dor.isc.ac/dor/20.1001.1.22287485.1401.12.2.1.3 [In Persian].

Nouraei H., & Shamohammadi M. (2021). Exploring the Relationship between Housing Unit Density and Indoor Environmental Quality in Residential Complexes (Case Study: Sepahan Shahr, Isfahan). *Soffeh*, 31(1): 53–68. https://doi.org/10.29252/soffeh.31.1.53 [In Persian].

Peng, Y., Liu, J., Zhang, T., & Li, X. (2021). The relationship between urban population density distribution and land use in Guangzhou, China: A spatial spillover perspective. *International journal of environmental research and public health*, 18(22), 12160. https://www.mdpi.com/1660-4601/18/22/12160#

Pohjankukka, J., Pahikkala, T., Nevalainen, P., & Heikkonen, J. (2017). Estimating the prediction performance of spatial models via spatial k-fold cross-validation. *International Journal of Geographical Information Science*, 31(10), 2001-2019. https://doi.org/10.1080/13658816.2017.1346255

Reba, M., Reitsma, F., & Seto, K. C. (2016). Spatializing 6,000 years of global urbanization from 3700 BC to AD 2000. *Scientific data*, 3(1), 1-16. https://doi.org/10.1038/sdata.2016.34

Shatkin, G. (2017). *Cities for profit: The real estate turn in Asia's urban politics*. Cornell University Press.

Shebek, N., & Mayer, V. (2025). Technologies of geoinformatic modelling for spatial objects. *Urban Development and Spatial Planning*. https://doi.org/10.32347/2076-815x.2025.89.286-301

Shi, Z., Fonseca, J. A., & Schlueter, A. (2021). Floor area density and land uses for efficient district cooling systems in high-density cities. *Sustainable Cities and Society*, 65, 102601. https://doi.org/10.1016/j.scs.2020.102601

Sonderman, J. S., Mumma, M. T., Cohen, S. S., Cope, E. L., Blot, W. J., & Signorello, L. B. (2012). A multi-stage approach to maximizing geocoding success in a large population-based cohort study through automated and interactive processes. *Geospatial health*, 6(2), 273. https://doi.org/10.4081/GH.2012.145

Song, C., Deng, Z., Zhao, W., Yuan, Y., Liu, M., Xu, S., & Chen, Y. (2024). Developing urban building energy models for Shanghai City with multi-source open data. *Sustainable Cities and Society*, 106, 105425. https://doi.org/10.1016/j.egypro.2016.06.035

Statistical Center of Iran. (2016). General Census of Population and Housing: Urban Areas Results of Isfahan Province. [In Persian].

Stock, A. (2025). Choosing blocks for spatial cross-validation: lessons from a marine remote sensing case study. *Frontiers in Remote Sensing*, 6, 1531097. https://doi.org/10.3389/frsen.2025.1531097

Tao, Z., Cheng, Y., & Liu, J. (2020). Hierarchical two-step floating catchment area (2SFCA) method: Measuring the spatial accessibility to hierarchical healthcare facilities in Shenzhen, China. *International Journal for Equity in Health*, 19, 164. https://doi.org/10.1186/s12939-020-01280-7 equity/healthj.biomedcentral.com

U.S. Environmental Protection Agency. (2021). Smart Location Database: Sample variables. https://www.epa.gov/smart-growth/smart-location-mapping epa.gov

U.S. Geological Survey. (2024). Landsat Normalized Difference Vegetation Index. https://www.usgs.gov/landsat-missions/landsat-normalized-difference-vegetation-index usgs.gov

Wurm, M., Goebel, J., Wagner, G. G., Weigand, M., Dech, S., & Taubenböck, H. (2021). Inferring floor area ratio thresholds for the delineation of city centers based on cognitive perception. *Environment and Planning B: Urban Analytics and City Science*, 48(2), 265-279. https://doi.org/10.1177/2399808319869341?urlappend=%3Futm_source%3Dresearchgate

Yu, X. (2024). Low-rise buildings in big cities: Theory and evidence from China. *Real Estate Economics*, 52(2), 366-400. https://doi.org/10.1111/1540-6229.12476

Zangeneh-Shahraki S., Hamidi A., & Ghorbani R. (2023). Analyzing the Impact of Sanctions on the Urban Housing Sector of Rentier Governments (Case Study: Iranian Cities). *IUESA*, 11(44): 199-225. http://iueam.ir/article-1-2072-fa.html [In Persian].

Zhang, R., Casanovas, M. M., González, M. B., & Sun, S. (2024). Revitalizing heritage: The role of urban morphology in creating public value in China's historic districts. *Land*, 13(11), 1919. https://doi.org/10.3390/land13111919 mdpi.com

Zheng, S. (2023). FAR, BCR, and urban energy modeling in Jinan. *Energy and Buildings*, 285, 112951.