



UDC 528.94:711.14

SPATIAL PATTERN ANALYSIS OF BUILT-UP LAND USE AND ZONING CONFORMITY USING POLYGON-BASED STATISTICS: A CASE STUDY OF TEGAL CITY, INDONESIA

Rifqiya LUTHFIYANI^{1,2✉}, Parluhutan MANURUNG¹, Adi WIBOWO¹

¹Department of Geography, Faculty of Mathematics and Natural Sciences, Universitas Indonesia, 16424 Depok, Indonesia

²Directorate of Topographic Mapping of Marine and Coastal Areas, Geospatial Information Agency (Badan Informasi Geospasial), 16911 Cibinong, Indonesia

Article History:

- received 10 April 2026
- accepted 5 May 2026

Abstract. Rapid urban expansion in coastal cities increasingly challenges the effectiveness of spatial planning enforcement. Tegal city, located on Java's northern coast, is experiencing intensive built-up land development accompanied by growing spatial clustering. This study analyses polygon-level built-up land patterns using Ripley's K-function to identify multi-scale clustering, Global Moran's I to assess spatial autocorrelation, and Local Moran's I (LISA) to detect local clusters. Built-up Land Use/Land Cover (LULC) polygons derived from OpenStreetMap (2024) were compared with the official Spatial Plan (RTRW 2021–2031). The objectives are to identify the clustering behaviour of built-up areas and assess conformity between actual land development and planned zoning. The results reveal a concentric-clustered spatial structure and localized zones of spatial non-conformity with the official spatial plan. Transitional areas exhibit significant land-use mismatches, indicating weaknesses in spatial-use control. A Global Moran's I value of 0.145 ($p < 0.05$) indicates weak but statistically significant positive spatial autocorrelation. These findings highlight the importance of strengthening zoning enforcement and updating detailed spatial plans (RDTR). The study demonstrates how integrated polygon-based spatial statistics can support routine spatial planning evaluation and zoning enforcement in rapidly developing coastal cities.

Keywords: spatial pattern analysis, Ripley's K-function, global Moran's I, Local Moran's I (LISA), built-up land, land-use clustering, spatial plan conformity, coastal city, Tegal city, GIS.

Online supplementary material: Supporting information for this paper is available as online supplementary material at <https://doi.org/10.3846/gac.2026.25842>

✉Corresponding author. E-mail: rifqiya.luthfiyani@ui.ac.id

1. Introduction

Urban land-use change is a global trend characterised by rapid urbanisation and economic transformation, where expanding built-up areas reshape urban socio-ecological systems (Seto et al., 2012). In many cities, intensive conversion of agricultural land to residential, commercial, industrial, and infrastructural uses triggers spatial conflicts, environmental degradation, and governance challenges related to sustainable spatial planning (Lambin & Meyfroidt, 2011). These pressures are exacerbated in coastal cities, where economic opportunity, accessibility, and high population density intensify competition for limited land resources (Neumann et al., 2015). Land-use change can now be detected with increasing spatial and temporal precision using multi-source data, such as Google Earth time-series imagery, which enables fine-scale mapping of land transformation (Wibowo et al., 2016). Overall, these

conditions underscore the importance of analysing land-use patterns not only as physical transformations but also as indicators of spatial governance effectiveness.

Built-up land refers to areas dominated by human-made structures and impervious surfaces, including residential buildings, commercial establishments, industrial facilities, transportation infrastructure, and other urban utilities. In Land-Use/Land-Cover (LULC) classification, "built-up" is commonly defined as any polygon representing permanent or semi-permanent constructed features that replace natural or agricultural surfaces with artificial materials (Brovelli & Zamboni, 2018; Li et al., 2017). Built-up areas serve as proxies for urban expansion, spatial intensity, and land-development pressure, making them crucial indicators in spatial pattern analysis and urban planning evaluation.

Tegal city is strategically located along the northern coastal corridor of Central Java. It lies within the main

Pantura (Trans-Java North Coast) transport network, which connects major regional economic centres (Badan Pusat Statistik, 2024). The city, covering 39.68 km² and administratively divided into four districts and 27 sub-districts, has undergone rapid spatial transformation characterised by the conversion of arable land and green open spaces into urban uses (Priyomarsono & Surya, 2020). Despite the regulatory guidance provided by the Spatial Plan (RTRW 2021–2031), recent assessments have revealed continuing deviations between planned and actual land use (Abbas et al., 2026), indicating weaknesses in zoning enforcement. Studies of other coastal port cities reinforce this pattern: port activity has been associated with the expansion of urban construction land in coastal port cities in China (Li et al., 2025). More broadly, coastal densification can intensify ecological and socio-economic vulnerabilities when spatial governance does not adapt to rapid land-use change (Neumann et al., 2015). Much of the previous literature, however, relies on raster-based, macro-scale analysis and does not evaluate zoning conformity at the polygon level, where spatial planning decisions are most directly implemented.

Spatial pattern refers to the arrangement, distribution, and structural relationships of land-use elements across geographic space. It describes whether urban development forms clustered, dispersed, linear, or mixed configurations, and whether these patterns reflect planned or unplanned growth dynamics (Tsai, 2005). Spatial pattern analysis is fundamental in geography because it reveals how urban morphology evolves, how socio-economic processes shape land use, and how planning regulations influence or fail to influence real development trajectories. In coastal cities such as Tegal, spatial patterns are shaped by accessibility, economic corridors, and environmental constraints, making them powerful diagnostic tools for assessing spatial planning performance and identifying emerging urban pressures.

Spatial governance refers to the institutional frameworks, regulatory instruments, and enforcement mechanisms through which public authorities manage land-use change and ensure that development aligns with formally adopted spatial plans (Shi et al., 2019). In rapidly urbanizing contexts, governance effectiveness is measured not only by the existence of planning documents but by the degree to which those documents translate into observable spatial outcomes on the ground, a concept operationalized as planning conformity or plan compliance (Gharibreza et al., 2025). Conformity-based evaluation examines whether actual land development corresponds to designated zoning categories, and where systematic deviations occur, it reveals institutional gaps in regulatory enforcement and monitoring capacity (Shi et al., 2019).

In Indonesia, spatial governance operates through a hierarchical planning system consisting of national spatial plans (RTRWN), provincial plans (RTRWP), city/district plans (RTRW), and detailed spatial plans (RDTR). Each level carries legally binding zoning designations, yet implementation effectiveness varies considerably across municipalities,

particularly in small and medium-sized cities where monitoring capacity and enforcement resources are limited (Abbas et al., 2026). Coastal cities face additional governance challenges, as competing land demands from fisheries, aquaculture, tourism, and urban expansion frequently generate development pressures that exceed the adaptive capacity of static zoning frameworks (Gharibreza et al., 2025; Neumann et al., 2015).

Spatial statistics offer a quantitative pathway for evaluating planning performance by translating land-use patterns into measurable indicators. Clustering methods such as Moran's I and Ripley's K-function have been applied to detect the spatial concentration of urban development (Roest et al., 2023; Tsai, 2005), while overlay analysis between observed land use and zoning maps enables the identification of non-conforming areas (Shi et al., 2019). Spatial autocorrelation and hotspot statistics have also been applied to a wide range of urban and regional questions, including burned-area detection (Lanorte et al., 2024), metro vibrancy (Tu et al., 2022), and internal migration (Pregi & Novotný, 2025). Ripley's K-function has also been used to relate urban fires to urban functional spaces (Xiong & Li, 2025), while GIS-based clustering has been used to detect urban heat islands (Cafaro et al., 2024). However, most existing studies apply these techniques descriptively, without explicitly linking statistical outputs to governance diagnostics or enforcement priorities. This study addresses that gap by integrating multi-scale spatial clustering analysis with a polygon-level conformity assessment framework, thereby operationalizing spatial statistics as a tool for planning performance evaluation rather than purely morphological description.

2. Research gap and objectives

Few studies have integrated Ripley's K-function (multi-scale clustering), Global Moran's I (global spatial autocorrelation), and Local Moran's I (LISA; local clustering and spatial outliers) within a polygon-based framework for evaluating spatial-plan conformity in small coastal cities such as Tegal. This limits the ability to relate multi-scale spatial structure to localized development pressure and zoning conformity. Accordingly, this study has two objectives: (1) to investigate the multi-scale clustering of built-up land in Tegal city and (2) to assess the conformity of observed development with the RTRW 2021–2031 and identify spatial pressure zones requiring closer planning attention. These objectives are addressed through three research questions: RQ1: To what extent do built-up land polygons in Tegal city exhibit statistically significant spatial clustering across multiple distance scales, and how does clustering intensity vary among land-use categories? RQ2: Does the spatial distribution of built-up land in Tegal city exhibit significant global and local spatial autocorrelation, and which areas contain the strongest High-High and Low-Low cluster concentrations? RQ3: To what degree does observed built-up development conform to the zoning structure designated in the RTRW 2021–2031, and

where are High-Low and Low-High spatial outliers associated with potential planning non-conformity? By integrating Ripley's K-function, Global Moran's I, Local Moran's I, and polygon-level zoning overlay, the study moves beyond purely descriptive spatial-pattern analysis and applies spatial statistics as a planning-monitoring framework. The approach provides a practical basis for identifying locations that warrant field verification, zoning review, and adaptive spatial-planning intervention in rapidly changing coastal urban environments.

3. Materials and methods

This study employs a quantitative spatial methodology with a descriptive and inferential polygon-based analytical design to identify, quantify, and map land-use patterns in Tegal city. The approach analyses spatial structure at the level of land-use polygons while retaining polygon

geometry for zoning-conformity assessment. The analysis consists of two complementary components:

- Descriptive spatial analysis: describes the distribution and spatial characteristics of land use.
- Spatial pattern and conformity analysis: assesses the spatial structure of built-up land and its relationship with the Tegal City Spatial Plan (RTRW 2021–2031).

The study area comprises the entire administrative domain of Tegal city in Central Java Province and was delineated from official boundary datasets collected from the Geospatial Information Agency and the Tegal City Development Planning Agency. Tegal city's geographic boundaries lie between 109°08'–109°10' E and 6°50'–6°55' S, covering an area of about 39.68 km². The city consists of four districts: West Tegal, East Tegal, South Tegal, and Margadana, together with 27 urban villages (Figure 1).

This research incorporates both spatial and non-spatial information gathered from official and geospatial sources.

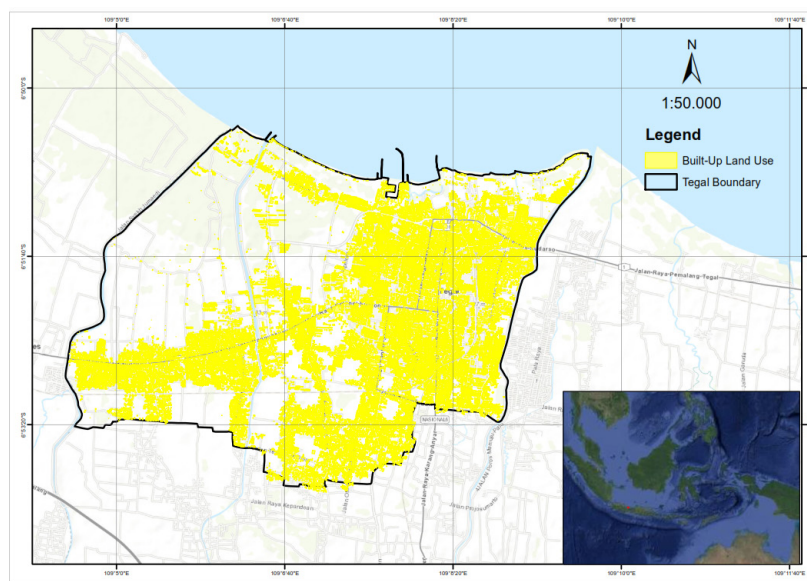


Figure 1. Map of Tegal city

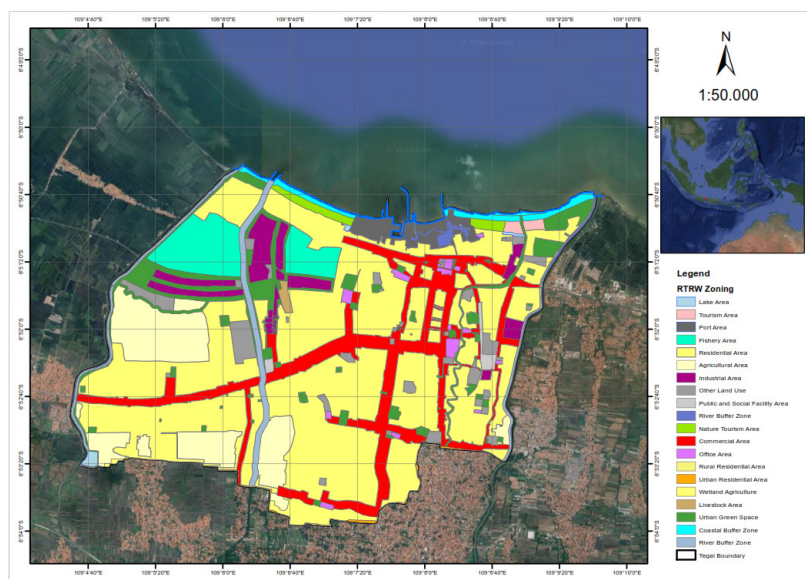


Figure 2. Map of spatial plan zoning of Tegal city (RTRW 2021–2031)

The Spatial Plan of Tegal City (RTRW 2021–2031) defines the official zoning structure used as the regulatory framework for spatial conformity analysis. The zoning categories include residential, industrial, agricultural, coastal protection, and public facility areas distributed across the city (Figure 2). The main datasets utilized include administrative boundary shapefiles, Land-Use/Land-Cover (LULC) polygons, and the Spatial Plan map of Tegal City. Administrative boundaries at the city, district, and sub-district (kelurahan) levels were sourced from the Geospatial Information Agency, which serves as the foundational reference for all mapping and spatial analysis tasks. OpenStreetMap data were used under the Open Database License (ODbL), which allows free use, redistribution, and modification provided that proper attribution is given to OpenStreetMap contributors. All datasets have been projected to the UTM Zone 49S coordinate system based on the WGS 84 datum.

3.1. Spatial pattern analysis

Spatial pattern analysis combines four complementary spatial-statistical techniques: the Nearest Neighbour Index (NNI), Ripley's K-function, Global Moran's I, and Local Moran's I (LISA). NNI was first used to determine whether the distribution of built-up polygon centroids was clustered, random, or dispersed (Clark & Evans, 1954), providing a baseline measure of the overall spatial structure. Ripley's K-function was then applied to assess clustering across multiple distance bands (Diggle, 2014; Fang et al., 2023; Kiskowski et al., 2009; Roest et al., 2023). Monte Carlo simulations and edge correction were used to generate confidence envelopes and reduce boundary bias (Diggle, 2014). Mathematical formulations are provided in Supplementary Material S1. Global Moran's I was calculated using a first-order Queen contiguity spatial weights matrix (Chen, 2023) to measure overall spatial autocorrelation. Positive values indicate that polygons with similar values tend to occur near one another, whereas negative values indicate spatial dispersion. Local Moran's I (LISA) was used to identify statistically significant local clusters and spatial outliers classified as High-High, Low-Low, High-Low, and Low-High (Anselin, 1995). Significant polygons ($p < 0.05$) were mapped in GIS and interpreted in relation to RTRW zoning. Together, these methods provide multi-scale and local evidence of spatial structure that can be related to formal spatial planning.

3.2. Spatial analysis workflow

The spatial analysis workflow consists of six sequential stages integrating built-up land pattern analysis with spatial planning conformity assessment (Figure 3). First, the administrative boundaries of Tegal city, polygon-based land-use data from OpenStreetMap (OpenStreetMap contributors, 2024), and zoning data from the Spatial Plan (RTRW 2021–2031) were assembled. Second, the datasets were harmonized geometrically and thematically. All spatial layers were projected to UTM Zone 49S (EPSG:32749), topological errors were checked, and attribute structures

were standardized. Third, built-up polygons were converted to centroid points for point-pattern analysis. Fourth, NNI and Ripley's K-function were used to assess clustering and dispersion across distance scales. Fifth, Global Moran's I and Local Moran's I (LISA) were applied to evaluate global spatial autocorrelation, local clusters, and spatial outliers. Finally, statistically significant spatial patterns were overlaid with RTRW zoning to identify areas of conformity, development pressure, and potential conflict between observed land development and formal planning regulations.

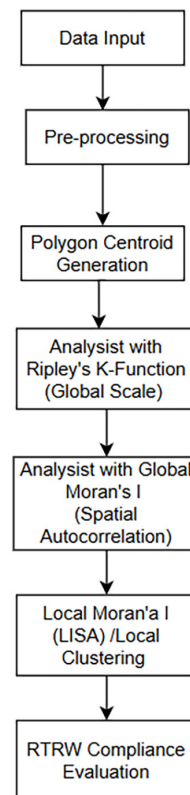


Figure 3. Spatial analysis workflow from data preprocessing to spatial pattern interpretation against RTRW

3.3. Analytical parameters and reproducibility

Spatial statistical analyses were conducted using ArcGIS Pro version 3.2 and GeoDa version 1.20 to ensure computational consistency and reproducibility. All spatial datasets were projected into the Universal Transverse Mercator (UTM) Zone 49S coordinate system (EPSG:32749) prior to analysis. Ripley's K-function analysis was performed using a maximum search radius of 2,000 meters with incremental distance steps of 50 meters. Edge correction was applied using the isotropic correction method to minimize boundary bias. The statistical significance of clustering patterns was evaluated using 999 Monte Carlo simulations to generate confidence envelopes.

Global Moran's I and Local Moran's I (LISA) analyses were conducted using a first-order Queen contiguity spatial weights matrix. Spatial autocorrelation significance was tested at the 95% confidence level ($p < 0.05$). Cluster classification followed the standard four-category typology:

High-High, Low-Low, High-Low, and Low-High spatial associations. All preprocessing procedures, including topology repair, centroid generation, and attribute harmonization, were implemented using ArcGIS Pro geoprocessing tools. Data validation was conducted through visual comparison with high-resolution satellite basemaps to ensure spatial completeness and classification consistency.

3.4. Data quality and limitations

Data quality is critical when volunteered geographic information such as OpenStreetMap (OSM) is used for spatial statistical analysis (Goodchild & Li, 2021). Several cleaning and validation procedures were applied. First, topological inconsistencies, including self-intersections, sliver polygons, and duplicates, were identified and repaired or removed. Second, land-use attributes were harmonized to standardize OSM tags and exclude vague or incomplete classifications. Only polygons clearly representing built-up land (e.g., building = *, landuse = residential, landuse = commercial, and landuse = industrial) were retained to reduce thematic noise. Because OSM coverage may vary spatially and between contributors, mapped coverage was visually cross-checked against recent high-resolution satellite basemaps. Where necessary, minor omissions in under-mapped neighbourhoods were digitised to improve spatial completeness. The reference year 2024 was selected for two reasons:

- It is sufficiently close to the current RTRW planning period (2021–2031) to support an assessment of contemporary planning conformity; and
- 2024 provides sufficiently comprehensive OSM coverage for a municipal-scale analysis of Tegal city. Nevertheless, OSM classification remains coarser than a detailed cadastral database.

The analysis is therefore limited to polygon geometry and distribution and does not include finer building

attributes, such as height or detailed functional subclasses, which are inconsistently available. Converting polygons to centroids also introduces geometric abstraction because complex polygon forms are represented by single points. This limitation was addressed by retaining the original polygon geometry for zoning overlays and policy interpretation, while centroid-based representations were used only for the spatial-statistical analyses that require point features. Spatial completeness and classification consistency were further assessed through comparison with recent high-resolution satellite imagery and official spatial planning datasets. These safeguards reduce, but do not eliminate, uncertainty associated with crowdsourced geographic data.

Future studies may improve robustness through sensitivity testing using alternative land-use datasets, such as official cadastral maps or high-resolution remote sensing classifications. Nevertheless, the current dataset provides sufficient spatial consistency for detecting clustering patterns and evaluating planning conformity at the municipal scale.

4. Results

4.1. Spatial pattern of land use in Tegal city

The built-up land distribution is concentrated primarily in the central and southern parts of Tegal city, with additional concentrations along major roads and the northern coastal corridor (Figure 4). The centroid pattern is spatially uneven, with higher densities near the city centre, industrial areas, and major transport corridors. In contrast, the western and eastern peripheral areas contain more agricultural land, fish ponds, green space, and lower-density development. This pattern indicates a transition from a compact urban core to less intensively developed peripheral areas.

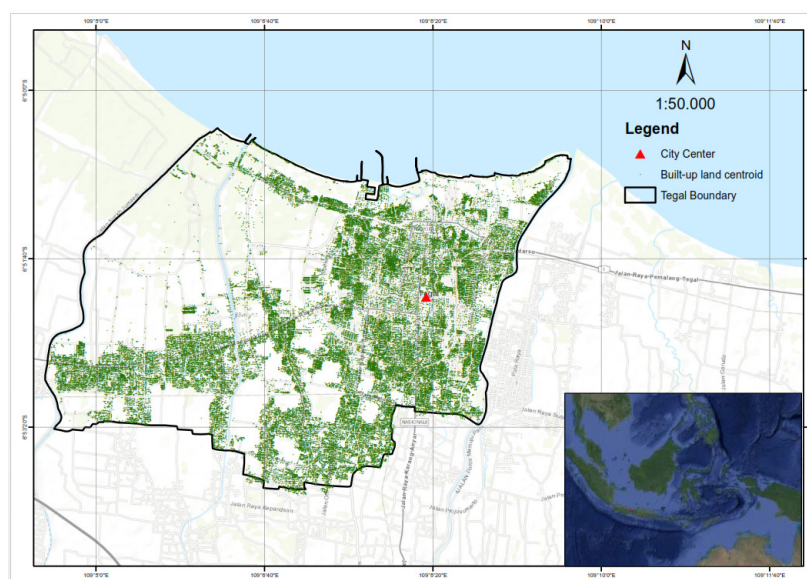


Figure 4. Spatial distribution of built-up land centroids in Tegal city

Each point represents the centroid of a built-up land polygon used as the spatial unit for statistical analysis, including Ripley's K-function and Moran's I. The city center is indicated to provide spatial reference for interpreting clustering patterns.

The Ripley's K-function transformation, $L(r)-r$, remains positive over short to medium distances and crosses the zero line at approximately 1,800–2,000 m (Figure 5). Positive values indicate clustering relative to complete spatial randomness, while negative values indicate a tendency toward spatial regularity. The strongest clustering occurs at approximately 700–900 m, and clustering remains evident to about 1,500 m before weakening toward larger distance bands.

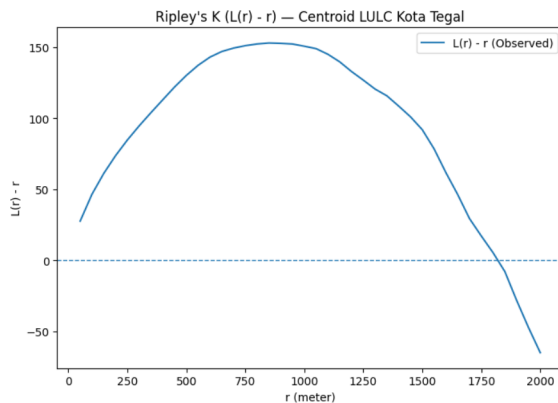


Figure 5. Ripley's K-function ($L(r)-r$) analysis of land-use centroid points

The maximum $L(r)-r$ value exceeds 150 m at a radius of approximately 700–900 m, indicating the strongest clustering at the neighbourhood scale. This pattern is consistent with dense concentrations of built-up polygons within compact residential and mixed-use areas. Beyond approximately 1,800 m, the $L(r)-r$ curve becomes negative, indicating a transition from local clustering to greater spatial regularity at broader scales. The centroid distribution therefore suggests a hierarchical spatial structure: strong clustering in the urban core and development corridors, followed by weaker clustering toward the periphery. This spatial gradient is consistent with the concentration of economic activities and accessibility in central Tegal, together with the persistence of larger agricultural and open-space areas at the urban fringe. Overall, the results indicate a concentric-clustered urban structure, with the highest built-up density near the city centre and more dispersed development toward peripheral areas. Comparison with the RTRW zoning pattern suggests broad macro-scale correspondence while also identifying transitional areas where localized development pressure requires closer planning control.

4.2. Spatial pattern index analysis

Global and local spatial autocorrelation analyses were used to evaluate the spatial structure of built-up polygon area.

Global Moran's I was 0.145 ($p < 0.05$), with the Moran scatterplot regression line $wx = 0.145x - 0.047$ and $R^2 = 0.125$ (Figure 6). The positive Moran's I indicates weak but statistically significant positive spatial autocorrelation: polygons with similar built-up area values tend to occur near one another more often than expected under spatial randomness. The scatterplot contains observations in both the High-High and Low-Low quadrants, reflecting local concentrations of larger and smaller built-up polygons. Larger, more homogeneous parcels occur mainly in industrial and peripheral areas, whereas smaller and more closely spaced parcels are characteristic of dense residential areas in the urban core. These results indicate that Tegal's built-up spatial structure is organized rather than random, but the strength of global autocorrelation is limited.

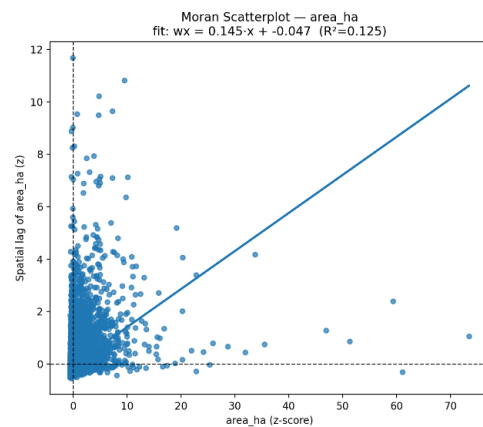


Figure 6. Moran Scatterplot showing the relationship between standardized built-up land values and spatially lagged values, illustrating the global spatial autocorrelation structure of land-use distribution in Tegal city

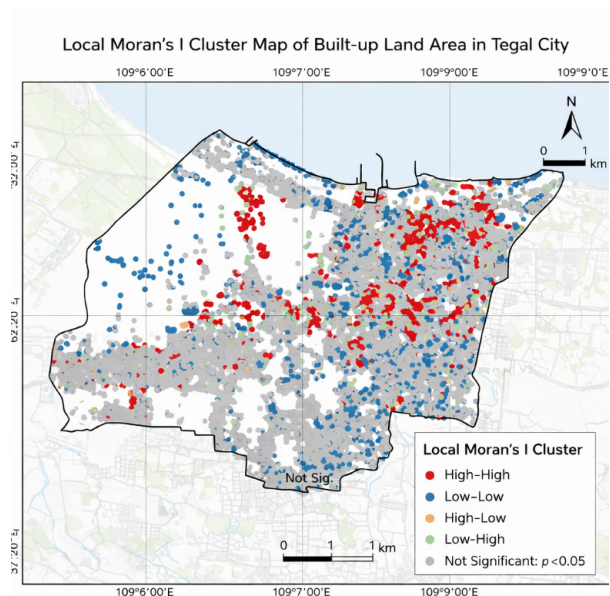


Figure 7. Local Moran's I cluster map of built-up land area (hectares) in Tegal city, illustrating spatial autocorrelation patterns based on parcel area values and their neighboring spatial units

Local Moran's I (LISA) identifies the locations of statistically significant local clusters and spatial outliers (Figure 7). The analysis relates the built-up area of each polygon to the values of neighbouring polygons and classifies significant observations into High-High, Low-Low, High-Low, and Low-High associations. In this study, the analysed variable is built-up polygon area (ha). The LISA results complement the global statistic by showing where positive spatial association and spatial outliers occur within Tegal city.

Red areas represent High-High clusters, while blue areas represent Low-Low clusters. High-Low and Low-High categories indicate spatial outliers. Grey locations are not statistically significant at $p < 0.05$.

Table 1. Data from Local Spatial Autocorrelation Pattern Analysis (LISA / Local Moran's I) (source: author's analysis, 2025)

Color	Indicator	Description
Red	High-High	Spatial units with high built-up land area values surrounded by neighboring units with similarly high values, indicating clusters of large built-up parcels.
Blue	Low-Low	Spatial units with low built-up land area values surrounded by neighboring units with similarly low values, indicating clusters of small built-up parcels.
Orange	High-Low	Spatial units with high built-up land area values surrounded by neighboring units with low values, indicating spatial outliers of large parcels.
Green	Low-High	Spatial units with low built-up land area values surrounded by neighboring units with high values, indicating spatial outliers of small parcels.

The LISA map identifies four principal types of spatial association (Table 1):

1. High-High (Red). Spatial units with high built-up land area values surrounded by neighboring units with similarly high values. This pattern is particularly evident in the southern and southeastern parts of Tegal city, where clusters of large built-up parcels

form areas of concentrated development intensity.

2. Low-Low (Blue). Spatial units with low built-up land area values surrounded by neighboring units with similarly low values. These areas are commonly observed in densely populated residential zones near the city center and along the northern coastal corridor, where small built-up parcels are closely distributed.
3. High-Low (Orange). Spatial units with high built-up land area values are surrounded by neighboring units with low values. These spatial outliers typically occur in transitional zones, particularly between industrial and residential areas, and may indicate emerging areas of land-use pressure or spatial imbalance.
4. Low-High (Green). Spatial units with low built-up land area values are surrounded by neighboring units with high values. This pattern may indicate localized fragmentation or the presence of smaller parcels embedded within areas dominated by larger built-up units.

The LISA results show that statistically significant High-High and Low-Low clusters are concentrated in distinct parts of the city, while High-Low and Low-High observations occur mainly in transitional areas. The local patterns are consistent with the positive Global Moran's I value of 0.145 ($p < 0.05$), confirming that the spatial distribution of built-up polygon area is not random. LISA therefore provides the spatial detail that is not captured by the global statistic and supports identification of locations requiring closer spatial-planning attention. These local patterns are also consistent with the multi-scale clustering detected by Ripley's K-function: dense urban areas exhibit strong local-scale clustering, whereas peripheral areas become more spatially regular at broader scales. The combined results provide the analytical basis for evaluating spatial conformity with the official RTRW zoning structure (Table 2).

Taken together, Ripley's K-function, Global Moran's I, and LISA indicate that Tegal's built-up development has a clear spatial structure at both local and broader scales. Broad correspondence between development concentrations and

Table 2. Spatial clustering characteristics and spatial planning (RTRW) relevance across major land-use classes in Tegal city (source: author's analysis, 2025)

Land-use class	Moran's I	p-value	LISA cluster distribution (% of class area)	Dominant cluster radius (Ripley's K)	Key spatial interpretation
Residential	0.162	0.002	HH: 41.3; LL: 34.8; HL: 11.2; LH: 5.6; NS: 7.1	700–900 m	Compact settlement intensification concentrated in the urban core; expansion governed by accessibility corridors.
Industrial	0.271	0.001	HH: 58.4; LL: 22.6; HL: 9.1; LH: 4.5; NS: 5.4	800–1000 m	Strong clustering aligned with designated economic zones, reflecting partial adherence to RTRW development corridors.
Agricultural	−0.018	0.641	HH: 14.9; LL: 43.7; HL: 9.4; LH: 10.8; NS: 21.2	No statistically dominant radius	Fragmentation in peri-urban transition zones suggests sprawl risks and weakening spatial protection in food-production areas.

Note: HH = High-High, LL = Low-Low, HL = High-Low, LH = Low-High LISA clusters; NS = not significant. Values in the LISA column are shares of class area (%) and sum to 100% for each land-use class.

major planned urban and economic corridors suggests that the RTRW has influenced macro-scale spatial organization. However, High-Low and Low-High transition zones reveal localized spatial discontinuities that warrant closer monitoring. In the coastal and peri-urban context, continued conversion of agricultural, aquaculture, green-space, or environmentally sensitive land may increase ecological and socio-economic pressures. Regular integration of updated geospatial data into RTRW and RDTR monitoring can therefore improve the identification of emerging land-use conflicts and support adaptive spatial planning.

4.3. Spatial conformity with the Spatial Plan (RTRW)

To evaluate the alignment between actual land development and the Spatial Plan of Tegal City (RTRW 2021–2031), an overlay analysis was conducted between the built-up land distribution and the designated zoning categories defined in the spatial plan. This step enables the identification of areas where observed spatial development conforms to planning regulations and areas where spatial deviations occur. The results indicate that a substantial proportion of built-up land development remains consistent with the spatial planning framework. Approximately 92.83% of the built-up land area was classified as conforming to the designated zoning regulations, particularly within established residential, commercial, and service corridors in the southern and central parts of Tegal city (Table 3; Figure 8). These areas demonstrate effective spatial control and reflect the influence of planned development patterns guided by the RTRW.

Table 3. Spatial conformity of built-up land with the RTRW zoning structure (source: author's analysis, 2025)

Category	Percentage (%)
Conforming	92.83
Non-conforming	7.17

However, the analysis also reveals that approximately 7.17% of the built-up land area exhibits spatial deviations from the planned zoning structure. These deviations are primarily observed in transitional urban-agrarian zones and coastal fringe areas, where built-up expansion has encroached into agricultural land, green open space, and environmentally sensitive zones. Such mismatches indicate localized weaknesses in zoning enforcement and highlight the presence of emerging development pressures beyond formally designated growth areas. Spatially, the High-Low and Low-High clusters identified in the Local Moran's I (LISA) analysis correspond closely to these deviation zones, suggesting that spatial outliers serve as early indicators of planning conflicts. These transitional clusters represent areas where urban expansion interacts directly with rural or environmentally sensitive land uses, creating potential risks for land-use sustainability and spatial governance.

Overall, the spatial conformity analysis demonstrates that while the RTRW has successfully structured macro-scale urban development, localized deviations remain evident in specific locations. These findings emphasize the importance of continuous spatial monitoring, adaptive zoning control, and periodic updates to the Detailed Spatial Plan (RDTR) to ensure that spatial policies remain responsive to dynamic urban growth.

5. Discussion

5.1. Comparison of spatial patterns between Tegal city and other coastal cities

The spatial pattern of built-up land in Tegal city is predominantly concentric-clustered, with the highest intensity in the urban core and along major economic and transport corridors. Peripheral areas to the west and east contain more agricultural and open-space land and lower built-up density. Research on coastal port cities in China has similarly linked port and industrial activity with urban construction land

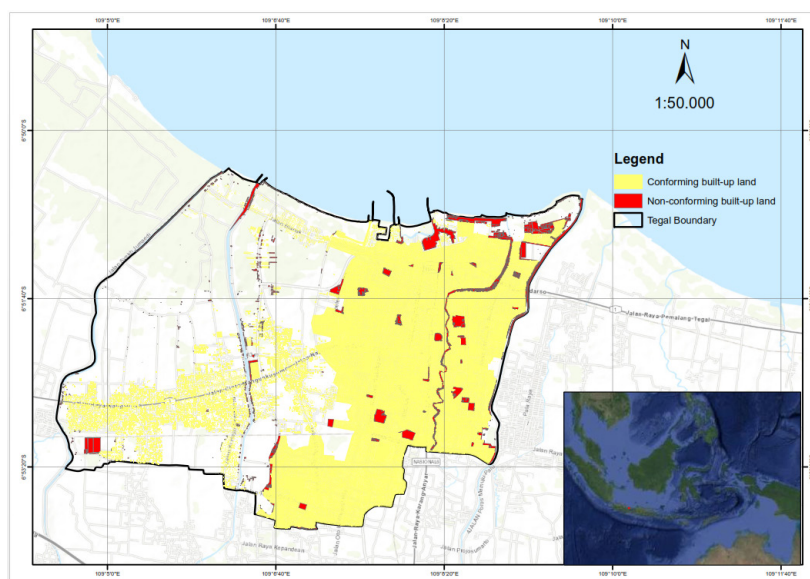


Figure 8. Spatial conformity of built-up land with the Spatial Plan (RTRW) of Tegal city

expansion (Li et al., 2025). In Tegal, however, the mapped pattern is shaped not only by coastal functions but also by the compact historical urban core and the Pantura transport corridor. This produces a spatial structure in which strong local clustering is concentrated in central and southern parts of the city, while broader-scale regularity increases toward the periphery. The comparison should therefore be interpreted as contextual rather than as evidence of identical urban-development processes across cities.

Compared with other rapidly urbanizing coastal settings, Tegal exhibits characteristics of a transition between compact urban growth and emerging peri-urban expansion. The results show strong clustering around established urban and economic areas together with localized development pressure in transitional zones. This combination reinforces the need for continuous spatial monitoring so that land-use fragmentation can be detected before it becomes entrenched.

5.2. Factors driving the emergence of spatial clusters

The integrated results of Ripley's K-function, Global Moran's I, and LISA indicate that spatial clustering in Tegal city reflects the combined influence of economic activity, accessibility, urban development pressure, and spatial planning. The principal factors are discussed below.

Economic growth and economic zones. Industrial and commercial activity in the southern and eastern parts of the city, including South Tegal and Margadana, is associated with concentrations of larger built-up parcels and High-High local clusters. These areas function as focal points of development and can attract adjacent residential and service uses.

Accessibility and transportation connectivity. Major clusters coincide with the Pantura Road and Ahmad Yani corridor, which provide regional connectivity across the northern coast of Java (Janur et al., 2025). The strongest Ripley's K clustering at approximately 700–900 m is consistent with neighbourhood-scale concentration around accessible urban corridors; however, the analysis identifies spatial association rather than a direct causal effect of road distance.

Population and development pressure. Population growth increases demand for housing, services, and urban infrastructure, thereby intensifying development pressure in established urban areas. The spatial-statistical results show where this pressure is expressed as clustered built-up development, but they should not be interpreted as a direct estimate of demographic causation.

Spatial planning and zoning policy (RTRW). The RTRW provides the regulatory framework for directing development and protecting designated land uses. The LISA results show that High-Low and Low-High transition zones coincide with locations where built-up development is more spatially heterogeneous and where zoning conflicts may emerge. These areas are therefore appropriate priorities for monitoring and for adaptive updates to the Detailed Spatial Plan (RDTR).

The persistence of spatial clustering in the southern and central districts is consistent with structural urban processes rather than random growth. Economic activity and transportation accessibility can attract residential and commercial uses to nearby areas, while planning regulations influence where development is permitted. The observed pattern should therefore be understood as the spatial outcome of interacting development pressures and regulatory controls rather than as the product of a single driver.

5.3. Regional implications and scientific novelty

The contribution of this study lies in integrating established spatial-statistical techniques into a practical framework for evaluating spatial planning. High-Low and Low-High clusters are interpreted as transition zones where neighbouring built-up polygons differ markedly in area and where land-use conflicts may warrant closer examination. These spatial outliers can therefore be used as screening indicators for planning monitoring rather than as direct evidence of regulatory failure. A polygon-based conformity indicator was derived from the overlay between observed built-up land and RTRW zoning. The analysis shows that 92.83% of built-up land area conforms to the designated zoning, while 7.17% is classified as non-conforming (Table 3). The non-conforming areas are concentrated in selected transitional urban-agrarian and coastal-fringe locations. Integrating conformity mapping with multi-scale clustering analysis provides a spatially explicit basis for prioritizing field verification, regulatory review, and RDTR updates in locations where development pressure and zoning mismatch coincide.

The novelty of this study therefore lies not in the isolated use of individual spatial-statistical techniques, but in their operational integration with polygon-level zoning conformity assessment. This framework links multi-scale clustering, local spatial association, and plan conformity to support evidence-based monitoring of rapidly developing coastal cities.

6. Conclusions

The spatial distribution of built-up land in Tegal city is clustered at local scales and exhibits weak but statistically significant positive global spatial autocorrelation (Global Moran's I = 0.145, $p < 0.05$). Ripley's K-function identifies the strongest clustering at approximately 700–900 m, while LISA distinguishes significant High-High, Low-Low, High-Low, and Low-High local patterns. Overlay with the RTRW 2021–2031 shows that 92.83% of built-up land area conforms to designated zoning and 7.17% is non-conforming. The non-conforming areas are concentrated mainly in transitional urban-agrarian and coastal-fringe zones, indicating locations where planning monitoring should be strengthened. Together, these findings show that Tegal's macro-scale development broadly corresponds with the

spatial plan, while localized deviations remain important for RDTR evaluation and spatial-use control.

For implementation, municipal authorities should maintain routine geospatial monitoring using updated land-use data and spatial clustering analysis to detect emerging development-pressure zones. High-Low and Low-High transition areas should be prioritized for field verification and zoning review because they represent spatial outliers rather than automatically confirmed violations. Polygon-based conformity indicators can be integrated into periodic RDTR evaluation to support adaptive zoning. Continued coordination between planning agencies and geospatial data providers is also important for maintaining consistent, up-to-date spatial datasets. Future research should extend the analysis with multi-temporal land-use data and sensitivity testing using alternative datasets to evaluate how stable the observed spatial patterns are over time.

Acknowledgements

The authors would like to acknowledge the Geospatial Information Agency of Indonesia (Badan Informasi Geospasial, BIG) for providing official administrative boundary datasets used in this study. The availability of open geospatial data from BIG is gratefully acknowledged and supports spatial research and planning applications in Indonesia.

Funding

This research received no external funding.

Author contributions

Conceptualization, R.L. and P.M.; methodology, R.L. and P.M.; validation, P.M., and A.W.; formal analysis, R.L.; data curation, R.L.; writing – original draft preparation, R.L.; writing, review and editing, P.M. and A.W.; visualization, R.L.; supervision, P.M. and A.W.; project administration, R.L. All authors have read and agreed to the published version of the manuscript.

Disclosure statement

The authors declare no competing financial, professional, or personal interests that could have influenced the work reported in this paper.

References

- Abbas, J., Baja, S., & Neswati, R. (2026). Assessment of spatial dynamic and land use conflicts within the Nature Tourism Park of Malino, Indonesia. *International Journal of Sustainable Development and Planning*, 21(3), 1225–1242. <https://doi.org/10.18280/ijstdp.210322>

- Anselin, L. (1995). Local indicators of spatial association – LISA. *Geographical Analysis*, 27(2), 93–115. <https://doi.org/10.1111/j.1538-4632.1995.tb00338.x>
- Badan Pusat Statistik. (2024). *Kota Tegal dalam angka 2024* [Tegal municipality in figures 2024]. BPS Kota Tegal.
- Brovelli, M. A., & Zamboni, G. (2018). A new method for the assessment of spatial accuracy and completeness of OpenStreetMap building footprints. *ISPRS International Journal of Geo-Information*, 7(8), Article 289. <https://doi.org/10.3390/ijgi7080289>
- Cafaro, R., Cardone, B., D'Ambrosio, V., Di Martino, F., & Miragliola, V. (2024). A new GIS-based framework to detect urban heat islands and its application on the city of Naples (Italy). *Land*, 13(8), Article 1253. <https://doi.org/10.3390/land13081253>
- Chen, Y. (2023). Spatial autocorrelation equation based on Moran's index. *Scientific Reports*, 13, Article 21525. <https://doi.org/10.1038/s41598-023-45947-x>
- Clark, P. J., & Evans, F. C. (1954). Distance to nearest neighbor as a measure of spatial relationships in populations. *Ecology*, 35(4), 445–453. <https://doi.org/10.2307/1931034>
- Diggle, P. J. (2014). *Statistical analysis of spatial and spatio-temporal point patterns* (3rd ed.). CRC Press. <https://doi.org/10.1201/b15326>
- Fang, Z., Shu, H., Song, C., Chen, J., Liu, X., Jiang, J., Jiang, L., Liu, T., & Pei, T. (2023). Length-squared L-function for identifying clustering pattern of network-constrained flows. *International Journal of Digital Earth*, 16(2), 4191–4211. <https://doi.org/10.1080/17538947.2023.2265882>
- Gharibreza, M., Salehpourjam, A., Nasrollahi, A., & Mosaffaie, J. (2025). Spatial zoning of shoreline management plan of the Northern Persian Gulf. *Ocean & Coastal Management*, 270, Article 107925. <https://doi.org/10.1016/j.ocecoaman.2025.107925>
- Goodchild, M. F., & Li, L. (2021). Volunteered geographic information and the future of spatial data infrastructure. *International Journal of Geographical Information Science*, 35(1), 1–19.
- Janur, A., Harintaka, H., & Suhadha, A. G. (2025). Uneven land subsidence patterns along Java's northern urban corridor (Pantura Route) from 2.5D SBAS InSAR approach. *Indonesian Journal on Geoscience*, 12(2), 281–300. <https://doi.org/10.17014/ijog.12.2.281-300>
- Kiskowski, M. A., Hancock, J. F., & Kenworthy, A. K. (2009). On the use of Ripley's K-function and its derivatives to analyze domain size. *Biophysical Journal*, 97(4), 1095–1103. <https://doi.org/10.1016/j.bpj.2009.05.039>
- Lambin, E. F., & Meyfroidt, P. (2011). Global land use change, economic globalization, and the looming land scarcity. *Proceedings of the National Academy of Sciences*, 108(9), 3465–3472. <https://doi.org/10.1073/pnas.1100480108>
- Lanorte, A., Nolè, G., & Cillis, G. (2024). Application of Getis–Ord correlation index (Gi) for burned area detection improvement in Mediterranean ecosystems (Southern Italy and Sardinia) using Sentinel-2 data. *Remote Sensing*, 16(16), Article 2943. <https://doi.org/10.3390/rs16162943>
- Li, X., Li, H., Zhang, Y., & Yang, L. (2017). Spatial patterns and the regional differences of rural settlements in Jilin Province, China. *Sustainability*, 9(12), Article 2170. <https://doi.org/10.3390/su9122170>
- Li, Z., Tian, C., Zhang, Z., & Zhao, H. (2025). *Ports on urban construction land expansion: A case study of coastal port cities in China*. SSRN. <https://doi.org/10.2139/ssrn.5093099>
- Neumann, B., Vafeidis, A. T., Zimmermann, J., & Nicholls, R. J. (2015). Future coastal population growth and exposure to sea-level rise and coastal flooding – a global assessment. *PLoS ONE*, 10(6), Article e0118571. <https://doi.org/10.1371/journal.pone.0118571>

- OpenStreetMap contributors. (2024). *OpenStreetMap* [Data set]. OpenStreetMap Foundation. <https://www.openstreetmap.org>
- Pregi, L., & Novotný, L. (2025). Spatial autocorrelation methods for identifying migration patterns: Case Study of Slovakia. *Applied Spatial Analysis and Policy*, 18, Article 12. <https://doi.org/10.1007/s12061-024-09615-5>
- Priyomarsono, N. W., & Surya, R. (2020). Perkembangan tata ruang Kota Juwana dan peningkatan ketahanan budaya lokal menghadapi globalisasi [Development of Juwana city spatial planning and increasing local cultural resilience in the face of globalization]. *RUANG-SPACE: Jurnal Lingkungan Binaan*, 7(1), 43–52. <https://doi.org/10.24843/jrs.2020.v07.i01.p05>
- Roest, A. H., Weitkamp, G., van den Brink, M., & Boogaard, F. (2023). Mapping spatial opportunities for urban climate adaptation measures in public and private spaces using a GIS-based decision support model. *Sustainable Cities and Society*, 96, Article 104651. <https://doi.org/10.1016/j.scs.2023.104651>
- Seto, K. C., Güneralp, B., & Hutyra, L. R. (2012). Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. *Proceedings of the National Academy of Sciences*, 109(40), 16083–16088. <https://doi.org/10.1073/pnas.1211658109>
- Shi, Y., Ren, C., Lau, K. K.-L., & Ng, E. (2019). Investigating the influence of urban land use and landscape pattern on PM2.5 spatial variation using mobile monitoring and WUDAPT. *Landscape and Urban Planning*, 189, 15–26. <https://doi.org/10.1016/j.landurbplan.2019.04.004>
- Tsai, Y.-H. (2005). Quantifying urban form: Compactness versus 'sprawl'. *Urban Studies*, 42(1), 141–161. <https://doi.org/10.1080/0042098042000309748>
- Tu, W., Zhu, T., Zhong, C., Zhang, X., Xu, Y., Li, Q. (2022). Exploring metro vibrancy and its relationship with built environment: A cross-city comparison using multi-source urban data. *Geo-Spatial Information Science*, 25(2), 182–196. <https://doi.org/10.1080/10095020.2021.1996212>
- Wibowo, A., Salleh, K. O., Frans, F. T. R. S., & Semedi, J. M. (2016). Spatial temporal land use change detection using Google earth data. *IOP Conference Series: Earth and Environmental Science*, 47, Article 012031. IOP Publishing. <https://doi.org/10.1088/1755-1315/47/1/012031>
- Xiong, Y., & Li, G. (2025). Correlation characteristics between urban fires and urban functional spaces: A study based on POI data and Ripley's K-function. *ISPRS International Journal of Geo-Information*, 14(2), Article 45. <https://doi.org/10.3390/ijgi14020045>