Spatial Analysis of Urban Decay: Spillover Effects and Significant Patterns for the City of Rome (Italy)

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Abstract. Contemporary cities face multiple complex challenges, including those related to the social, environmental, and economic aspects of urban decay. This phenomenon represents a critical issue for both built and non-built environments, potentially compromising the achievement of sustainable urban development goals. The spatial patterns of urban decay contain valuable information for developing targeted policies and understanding the causes and effects of its territorial distribution, revealing how urban areas interact and influence each other. The aim of this study is to identify the spillover effects and the most significant spatial patterns of urban decay in the city of Rome (Italy). The application of spatial correlation techniques, such as the bivariate Moran's index, enables the identification of significant relationships between key aspects of urban decay, using a set of indicators capable of representing the social, environmental, and economic dynamics of the phenomenon in Rome.

The results confirm the necessity of considering the spatial dimension of phenomena such as urban decay in urban planning, taking into account the interactions between different areas. Specifically, within the Grande Raccordo Anulare (GRA), which includes the historic center and consolidated residential areas of the city, the analysis has shown that some critical issues are concentrated in specific areas but generate spillover effects in adjacent zones. These findings support the implementation of priority urban regeneration strategies, providing an objective and comprehensive framework to facilitate the achievement of sustainable urban development goals.

Keywords: Urban decay · spatial analysis · spatial correlation · GIS-based decision support system · sustainable planning · socio-spatial inequalities

1 Introduction

With the intensification of urbanization, the quality of the urban environment is becoming increasingly important in ensuring people's well-being and promoting sustainable development. However, contemporary cities face significant challenges related to the

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geographic concentration of economic, social, and environmental distress [1]. These phenomena, often localized in specific urban areas, pose a growing threat to social cohesion and the balanced development of metropolitan regions [2].

In particular, urban decay represents one of the most critical manifestations of these dynamics, emerging as a multidimensional phenomenon that affects both consolidated urban areas and peripheral zones [3]. The presence of abandoned buildings [4, 5], declining property values [6], and rising crime rates [7] are interconnected issues that can further marginalize specific urban areas, following well-defined spatial patterns [8].

A particularly relevant aspect is its spillover effect [9]: decay tends to spread to adjacent areas, generating a negative spiral that progressively affects larger portions of the territory. This process amplifies social and economic inequalities, with effects extending beyond the most affected areas, compromising the overall balance of the urban fabric [10].

The assessment of complex issues such as urban decay, in which geographic space plays a fundamental role, must necessarily consider the spatial dimension [11]. Economic, social, and environmental factors contributing to decay are not uniformly distributed across the territory [12]. To fully understand the spread dynamics of urban decay and their impact on urban areas, it is essential to identify significant patterns that describe the spatial association among the different components of the phenomenon. Analyzing spatial dynamics is crucial to identifying critical areas where multiple issues coexist, enabling the development of targeted strategies to mitigate the phenomenon [13].

Spatial correlation analysis represents a key tool for this type of investigation, allowing for the detection of non-random patterns in the territorial distribution of urban decay indicators. Through spatial correlation techniques, such as the bivariate Moran's index, it is possible to analyze relationships between physical-environmental, social, and economic indicators, assessing both global associations across the study area and local patterns in specific zones [14].

These analyses not only facilitate the understanding of the mechanisms driving urban decay but also provide operational tools to support the planning of effective urban regeneration interventions. Such interventions can counteract the negative effects of urban decay and reverse detrimental trends in the territory [15].

2 Aim

Urban decay is not randomly distributed but follows spatial patterns that influence its spread and impact. However, the spatial relationships between indicators remain largely unexplored, limiting the ability to identify significant patterns and cause-effect relationships useful for urban planning.

This research analyzes urban decay in the city of Rome through a spatial approach, with the primary objective of identifying and interpreting spatial relationships between different indicators of decay using spatial correlation techniques.

In particular, the local bivariate Moran's index will be used to:

- Identify significant clusters of urban decay.
- Explore how the spatial distribution of decay varies depending on the analyzed component (physical-environmental, economic and social).

- Assess the influence of the number of contiguous elements (urban zones) on the stability and reliability of the final outputs.

The analysis will be conducted on the 106 urban zones within Rome's Grande Raccordo Anulare (GRA), using updated territorial data related to the three main components of urban decay.

The results will provide an objective framework to support urban planning, facilitating the identification of priority areas for regeneration interventions and offering valuable insights for sustainable development strategies.

The remainder of the research is structured as follows: Section 3 provides an overview of studies that employ spatial analyses in different thematic areas; Section 4 describes the proposed methodology; Section 5 presents the selected case study. Section 6 discusses the obtained results, including specific examples, while Sect. 7 contains the conclusions and future developments.

3 Background

Spatial analysis, particularly spatial correlation analysis, are widely used in various research fields, including territorial, economic, environmental and social sciences, thanks to the development of advanced methodologies and the integration of GIS tools.

These techniques are extensively applied in real estate market studies to understand the spatial dynamics of housing prices and identify residential submarkets [16].

Bor-Ming, H [17]. employes spatial analysis to examine the housing market in the Tainan Metropolis, using Moran's index to assess the spatial correlation of house prices and Local Indicators of Spatial Association (LISA) to define submarkets by analyzing the spatial concentration of higher and lower prices. Similarly, Yang et al. [18] evaluate the spatial correlation between accessibility to urban vibrancy centers and housing prices in Chengdu, China. This study first identifies urban vibrancy spaces based on social media data and calculates dynamic accessibility over time, subsequently analyzing its spatial correlation with housing prices using the local bivariate Moran's index.

In Italy, Barreca et al. [19] study the relationship between urban vibrancy and the real estate market in the city of Turin. The study uses a neighborhood service index as a proxy for urban vibrancy and investigates the presence of spatial correlation by calculating Moran's index and LISA to reveal different types of spatial correlations. Another study by Barreca et al. [13] focuses on the relationship between social and territorial vulnerability and the real estate market, combining a hedonic approach with spatial analysis techniques to measure the correlation between vulnerability indicators and property values using the local Moran's index.

Spatial analyses are also applied in urban planning. García-Ayllón and Franco [20] use Moran's index to analyze the spatial correlation between urban growth planning models and the increased flood risk in the city of Murcia, in southeastern Spain. Mi et al. [21] employ the local bivariate Moran's index to examine the interaction between topographic gradients and habitat quality within the Chang-Zhu-Tan urban agglomeration.

Murgante et al. [14] measure urban shrinkage phenomena and their effects in the deindustrialized city of Taranto by assessing key urban shrinkage indicators. In this study, Moran's index is used to evaluate global spatial correlation, while LISA statistics

identify local patterns of the phenomenon. Additionally, the same authors have applied various spatial correlation techniques, including Kernel Density, Moran's index, and Getis-Ord index, to identify priority intervention areas in urban regeneration programs. These studies were conducted in the city of Bari, with particular attention to social indicators [22], and in both Bari and Taranto, focusing on urban renewal strategies [23].

4 Methodology

To examine the dependence and spatial association between urban decay indicators, spatial correlation analysis was employed, a statistical technique that identifies non-random spatial patterns in the distribution of one or more variables. This analysis allows for determining whether the examined variables exhibit a random, clustered, or dispersed spatial arrangement.

The principle underlying this technique is that geographic phenomena are often not randomly distributed but follow a spatial logic linked to the physical proximity of geographic units. This concept, known as Tobler's First Law of Geography, states that "*everything is related to everything else, but near things are more related than distant things*" [24]. To analyze such spatial relationships, specific measures such as Moran's Index [25] and Geary's Index [26] are used to calculate global spatial correlation across the entire dataset and local correlation to detect patterns in specific areas.

In this study, Moran's Index was chosen as one of the most widely used tools for spatial analysis. This index measures spatial association by comparing the value of a variable in a given area with the weighted average of values in neighboring areas, using a spatial weight matrix to define proximity relationships [27]. To explore the relationship between two variables, the bivariate Moran's Index was applied, allowing verification of whether the values of a variable X in one area are spatially correlated with the values of another variable Y in surrounding areas [28].

The index ranges from -1 to $+1$, where a value close to $+1$ indicates a strong positive correlation (high values of X in an area are associated with high values of Y in neighboring areas), while a value close to -1 indicates a strong negative correlation (high values of X in an area are associated with low values of Y in neighboring areas). A value close to 0 indicates no correlation, suggesting a random distribution of indicators [22].

The indicators selected for this analysis were normalized on a scale from 0 to 1 to ensure consistency in variable comparisons. The analysis was conducted on two scales: global, to detect correlations across the entire city, and local, to highlight specific patterns among urban areas. At the local scale, the local bivariate Moran's Index was used to assess whether a given area exhibits similar or dissimilar values compared to its surrounding areas [29]. This approach allowed for identifying high- or low-intensity clusters and outliers, based on a spatial weight matrix that defines the proximity relationships between the analyzed areas.

The analysis began with the calculation of the global bivariate Moran's Index, which revealed low levels of global correlation. Subsequently, a local analysis was conducted to identify significant patterns in specific areas.

The calculation of the local bivariate Moran's Index enabled the identification of five categories of spatial association:

- High-High (HH): areas with high values for both indicators;
- Low-Low (LL): areas with low values for both indicators;
- High-Low (HL): areas with high values of X associated with low values of Y;
- Low-High (LH): areas with low values of X associated with high values of Y;
- Not significant: areas without statistically significant relationships between the indicators.

To define proximity relationships between urban areas, a spatial weight matrix was constructed using the K-nearest neighbors (KNN) method, which considers the k closest areas in terms of distance as neighbors. The KNN method was chosen as it avoids problems related to dimensional heterogeneity among urban areas (which have very different surface areas) and ensures that each area has the same number of neighbors, improving result comparability. The k value in the spatial weight matrix determines how many neighboring elements are considered for each unit of analysis (in this case, the urban zones of Rome).

Since the results of spatial analyses can be sensitive to the choice of the weight matrix, a robustness test was conducted by varying the k value. Specifically, the analysis was repeated for different k values (ranging from 10 to 100), allowing an assessment of how granularity affects cluster stability.

With low k values (e.g., $k = 10$), the analysis emphasized relationships between very close areas, resulting in high variability in clusters.

With high k values (e.g., $k > 80$), spatial relationships were broader, reducing local fluctuations and allowing for the identification of more robust and consistent patterns.

This approach was applied to various pairs of indicators representing the three main components of urban decay: physical-environmental, economic, and social. The analysis was repeated by reversing the roles of variables X and Y to further investigate relationships and potential cause-effect dynamics between indicators.

For the calculation of indices and the geovisualization of results, GeoDa, a software for spatial analysis and geographic modeling, was used [30].

5 Case Study

The case study focuses on the city of Rome, a complex urban environment characterized by a significant variety of social, economic, and environmental dynamics.

The analysis considered the areas within the Grande Raccordo Anulare (GRA), which include the historic center and the city's consolidated residential zones. The areas inside the GRA concentrate the majority of the population, economic activities, and urban infrastructure. These areas are marked by strong contrasts: central districts with high cultural and tourist attractiveness coexist with peripheral zones facing significant challenges in terms of quality of life and urban development [31].

For this research, the chosen territorial unit of analysis was the urban zones, an official administrative subdivision of the municipal territory that allows for the analysis of spatial phenomena at an intermediate scale between neighborhoods and municipal districts. Specifically, the study considered 106 urban zones located within the GRA.

A few urban decay indicators were selected to capture various aspects of the phenomenon, taking into account the three fundamental components that characterize it:

physical-environmental, economic, and social. These indicators were selected on the basis of literature and the socio-economic and environmental context of the city of Rome.

Physical-environmental component:

A. Building vacancy rate (%)
B. Average age of recent housing stock (years)
C. Number of sites containing asbetos per unit area(n/km^2)
D. Pollutante missions (μg/m^3)

Economic component:

E. Functional mix (n)
F. Public expenditure on urban decor interventions 2017–2023 (€)
G. Percentage change in residential property values 2017–2023 (%)
H. Percentage change in commercial property values 2017–2023 (%)
I. Percentage change in tertiary property values 2017–2023 (%)
J. Real estate market intensity trend (IMI) 2017–2023 (%)

Social component:

K. Disposable income (€/year)
L. Unemployment rate (%)
M. Education rate (%)
N. Number of Public Housing units (n)
O. Number of urban decay reports (n)

For the physical-environmental component, building-related data (indicators A and B) were collected using the Urbistat geomarketing software, which references data from the latest update of the ISTAT census. Information on the presence of asbestos (indicator C) was obtained from a regional mapping initiative, while pollutant emission data (indicator D) were sourced from the Regional Environmental Protection Agency of Lazio, considering major outdoor air pollutants.

For the economic component, real estate market indicators (G, H, I, and J) were obtained by constructing historical series based on data collected from the Real Estate Market Observatory (REMO) of the Italian Revenue Agency for the period 2017–2023. The functional mix indicator (E) was calculated using Shannon's entropy index based on economic activity data gathered through Urbistat. The public expenditure indicator for urban decor (F) was developed using information available on the OpenCUP portal, summing public investments allocated to urban decor-related interventions over the same period as the real estate market data (2017–2023).

For the social component, data on disposable income (K), unemployment rates (L), and education rates (M) were acquired through the Urbistat software. The number and location of Public Housing units (N) were obtained by cross-referencing data from Roma Capitale with those from the Territorial Company for the public Residential Construction of the Municipality of Rome. The number of urban decay reports (O) was gathered through resident surveys.

A summary table (Table 1) presents the pairs of indicators considered for the spatial correlation analysis and the results of the global-scale correlation analysis.

Table 1. Urban decay indicators and global spatial correlation analysis results.

Component	Indicators		Bivariate global Moran's index
	X	Y	
Physical-environmental	A	C	−0,030
	A	D	0,004
	B	C	0,217
	B	D	0,013
Economic	E	G	0,099
	E	H	0,038
	E	I	0,158
	E	J	-0,04
	F	G	0,022
Social	N	K	-0,058
	N	L	-0,027
	N	M	-0,004
	N	O	-0,008

6 Results

6.1 General Considerations

Based on the results obtained from the calculation of the local bivariate Moran's I index, a sensitivity analysis of the clusters was conducted by varying the k value. This analysis revealed significant changes in the distribution and stability of the clusters.

For instance, the "High-High" cluster showed a steady increase as k increased, indicating that at a broader scale, it is possible to identify more areas characterized by high values of positive indicators, such as high disposable income and high education levels. Specifically, for the indicator pair E - G, the "High-High" cluster increased from 32 ($k = 10$) to 106 ($k = 100$), stabilizing beyond this value. In general, this pattern was observed for almost all indicator pairs, except for some combinations, such as E - J and A - D.

The "Low-High" cluster was found to be the most unstable, showing significant variations at intermediate k levels, suggesting that transition areas between decay and development consolidate at higher granularities.

Conversely, the "Low-Low" cluster tended to shrink as k increased, reflecting a polarization of decay areas into more defined units. This behavior suggests that policies targeting such areas should be more focused and structural.

Distinct trends emerged for certain indicator pairs. For example, in the case of E - G, the increase in the "High-High" cluster with rising k highlights the positive role of functional space distribution in the real estate market. Simultaneously, the "Low-Low" cluster decreased, suggesting a concentration of decay areas into more specific zones. For the N - M pair, the increase in the "High-High" cluster with higher k values indicates

a correlation between public housing and high education levels, while the reduction of the "Low-Low" cluster suggests that areas with low values for both indicators become less widespread at a broader scale.

In the k ranges where the frequency of certain clusters (e.g., High-High or Low-Low) stabilizes, more explanatory k values can be identified. For the High-High cluster, for example, an increase and stabilization can be observed from $k = 80$ onwards across different analyses. The Low-Low cluster tends to decrease to zero or disappear entirely in many cases for $k \geq 50$, suggesting that significant clusters are mainly concentrated in the High-High and Low-High categories.

6.2 Results of the Physical-Environmental Component

From the analysis conducted, regarding the vacancy rate of residential buildings, the spatial relationships with the presence of asbestos and pollutant emissions appear to be limited. Although some significant correlations were observed, particularly for the number of sites containing asbestos, where some cases of positive spatial correlation were recorded, the geographical distribution suggests that building vacancy and environmental management are weakly interconnected in this case. The average age of the recent housing stock proved to be more relevant, with direct correlations to the presence of asbestos. Areas with older buildings tend to be located near sites containing asbestos, especially in central areas. In terms of pollutant emissions, the spatial relationships are weak, suggesting that the age of buildings has limited influence on the air quality in the surrounding areas.

The results of the analysis allowed for the identification of different distribution clusters of the indicators. For each cluster, it was possible to provide an interpretation, and the related operational implications derived from the results. The number of clusters and their location varies depending on the value of k.

As an example, a summary table (Table 2) is provided, which includes these considerations for the pair of indicators: building vacancy rate (A), considered as X, and the number of sites containing asbestos per unit of area (C), considered as Y.

Table 2. Clusters obtainable from the calculation of the local bivariate Moran's I index between indicators A and C.

Cluster	Description	Interpretation	Implications
High-High	Areas with high vacancy rate and high presence of asbestos	Highly degraded areas due to abandonment and poor maintenance	Urgent intervention required for environmental remediation and building recovery
Low-Low	Areas with low vacancy rates and low presence of asbestos	Well-maintained areas, with potential for new investments	Monitoring to prevent further degradation

(*continued*)

Table 2. (*continued*)

Cluster	Description	Interpretation	Implications
Low-High	Areas with few vacant buildings but high presence of asbestos	Potential environmental problems inherited from historic buildings	Prioritize environmental remediation
High-Low	Areas with many vacant buildings but low presence of asbestos	Decay linked to building abandonment	Rehabilitation programs for repurposing buildings

6.3 Results of the Economic Component

The analysis of spatial correlations between functional mix and changes in property values (residential, commercial, and tertiary) highlights that economic dynamics are primarily concentrated in central areas. Zones characterized by high functional diversity tend to show a significant variation in property values in the surrounding areas (High-High cluster). However, inverse correlations emerge in peripheral areas: in these zones, high levels of functional diversity do not always correlate with positive changes in property values, suggesting divergent economic dynamics compared to the urban center. A particular case concerns public spending on urban decor, which mainly shows inverse correlations. Therefore, it can be said that the variation in residential property values is minimally influenced spatially by proximity to urban zones where urban decor improvement interventions have been made. On the other hand, it appears that for a certain number of urban areas within the historical center, there is a high spatial correlation between the two indicators.

The table (Table 3) below shows the interpretation of the clusters obtainable from the spatial correlation analysis between functional mix (E) as X and the percentage change in residential property values 2017–2023 (G) as Y.

Table 3. Clusters obtainable from the calculation of the local bivariate Moran's I index between indicators E and G.

Cluster	Description	Interpretation	Implications
High-High	Areas with high functional diversification and strong positive changes in residential property values	The functional mix contributes to an increase in residential value, thanks to a balance between residences, commerce, and services	Successful models to replicate in less dynamic areas
Low-Low	Areas with low functional mix and weak or negative residential changes	Areas with low attractiveness, where limited diversification hinders development	Encourage interventions to improve functional diversification and make areas more attractive

(*continued*)

Table 3. (*continued*)

Cluster	Description	Interpretation	Implications
Low-High	Areas with low functional mix but positive residential changes	Areas where the residential market grows independently of functional diversification	Analyze the reasons for residential success to improve functional balance
High-Low	Areas with high functional mix but negative residential changes	Areas where diversification does not generate improvements in the real estate market, possibly due to infrastructure deficiencies	Evaluate infrastructure and available services to maximize the benefits of functional mix

6.4 Results of the Social Component

The analysis of social indicators in relation to public housing reveals a prevalence of inverse correlations. For example, a low number of public housing units is often associated with poorer social conditions, such as low incomes or high unemployment rates, in nearby areas. Similarly, an inverse relationship is observed with the education rate: areas with fewer public housing units tend to be surrounded by areas with higher levels of education rate. On the other hand, areas characterized by a direct correlation, where a high number of public housing units coincides with better social conditions, are mainly concentrated in central areas, although they are fewer in number. Regarding urban decay reports, it is noted that areas with a high number of public housing units are often associated with a higher number of reports in neighboring areas, a phenomenon particularly evident in central zones.

For the social component, the table (Table 4) with the interpretation of the clusters obtainable from the correlation analysis between the number of public housing units (N) as X and disposable income (K) as Y is provided.

Table 4. Clusters obtainable from the calculation of the local bivariate Moran's I index between indicators N and K.

Cluster	Description	Interpretation	Implications
High-High	Areas with a high concentration of public housing associated with relatively high incomes	Indicates efficient management of public housing, with positive effects on average income	Replicate models of socio-economic integration in other areas
Low-Low	Zones with low income and a low number of public housing units	Exclusive residential areas that limit access for the most vulnerable social groups	Expand public housing to reduce spatial inequalities

(*continued*)

Table 4. (*continued*)

Cluster	Description	Interpretation	Implications
Low-High	Zones with high income and a low number of public housing units	Possible exclusion of middle- to low-income groups from the housing market	Promote social inclusion policies to prevent urban segregation phenomena
High-Low	Areas with a high presence of public housing but low incomes	Socially disadvantaged areas, where public housing fails to mitigate economic issues	Integrate housing policies with economic and social support programs

6.5 Cluster Map with k = 50

The spatial correlation analysis with the bivariate local Moran's index was conducted, as mentioned in the methodology section, for several values of k, where changes in k correspond to a different number and distribution of clusters.

Three examples of cluster maps obtained for $k = 50$ are provided, one for each component identified to analyze the phenomenon.

For the physical-environmental component, the map resulting from the spatial correlation analysis between the vacancy rate of buildings (A) considered as X and the number of asbestos-containing sites per unit of surface (C) as Y is shown (Fig. 1).

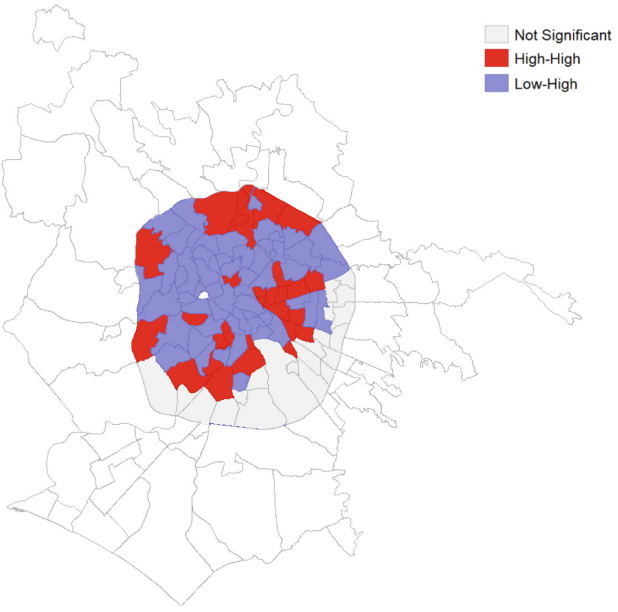

Fig. 1. Map of clusters obtained from the calculation of the local bivariate Moran's index between indicators A and C with $k = 50$.

In the figure, it can be observed that with a parameter $k = 50$, the analysis revealed that, out of 106 urban zones, 80% of the territory exhibits statistical significance, while

for the remaining 20%, the results are not statistically significant. This suggests a random distribution or a high variability of the indicators.

The zones with statistical significance are divided into two clusters: High-High and Low-High. The majority of the zones, accounting for 53%, belong to the Low-High cluster, indicating an inverse spatial correlation: in areas with a low vacancy rate of residential buildings, a high number of asbestos-containing sites are found in the surrounding areas. These zones are relatively evenly distributed across the territory, unlike the High-High cluster, which covers 27% of the considered area and is more irregularly dispersed across different parts of the city.

The Moran's index reaches its lowest values in the central areas of the city, such as *Esquilino* (−0.76), *Flaminio* (−0.74), *Centro Storico* (−0.67), *Prati*, and *Celio* (−0.66). These negative values suggest that in central zones, the relationship between building vacancy and asbestos presence is weak or even absent. Conversely, areas characterized by a strong positive correlation show an uneven distribution within the GRA. The highest value is recorded in the urban zone of *Tor Fiscale* (0.93), located southeast of the urban center, while other high values are observed in *Casal Bruciato* (0.79) and *Testaccio* (0.77). These more peripheral areas may be characterized by poorly maintained buildings, where the presence of asbestos is more likely to be associated with a higher vacancy rate.

For the economic component, the map resulting from the spatial correlation analysis between functional mix (E) as X and the percentage variation in residential property values from 2017 to 2023 (G) as Y is presented (Fig. 2).

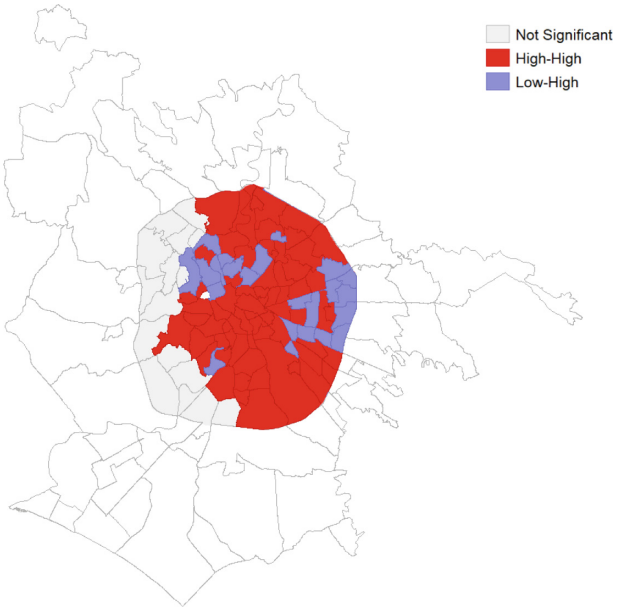

Fig. 2. Map of clusters obtained from the calculation of the local bivariate Moran's index between indicators E and G with $k = 50$.

The analysis conducted with $k = 50$ revealed that, out of 106 urban zones analyzed, only 15% exhibited a spatial correlation that was not statistically significant. Most of the areas belong to the High-High cluster (67 zones), while the remaining 23 fall into the Low-High cluster.

The zones characterized by a direct spatial correlation (High-High), where high levels of functional mix correspond to significant increases in residential property values in the surrounding areas over the past seven years, cover 63% of the analyzed territory and are relatively evenly distributed. However, the positive values of the Moran Index are not particularly high: the maximum value is recorded in the *Università* urban zone (0.59), while other notable values are found in the *Esquilino* and *XX Settembre* zones (0.50). In most cases, the index ranges between 0.10 and 0.15. This may suggest that, although functional diversification is linked to variations in property values, the effect is not strong enough to produce a significant impact.

The zones belonging to the Low-High cluster, where low economic activity diversification corresponds to high increases in residential property values, cover 22% of the analyzed areas and show a more irregular distribution. Two main concentrations can be identified: one in the central area and another in a peripheral area located east of the urban core. Finally, the zones where the correlation is negative present some extreme values, particularly in *Casetta Mistica* (−1.00) and *Tor Fiscale* (−0.88). Other less pronounced negative values are found in the *Omo* zone (−0.53) and the *Centro Direzionale Centocelle* (−0.45), while the most recurrent values range between −0.36 and − 0.21.

In the case of the social component, the map resulting from the spatial correlation analysis between the number of public housing units (N) as X and disposable income (K) as Y is reported (Fig. 3).

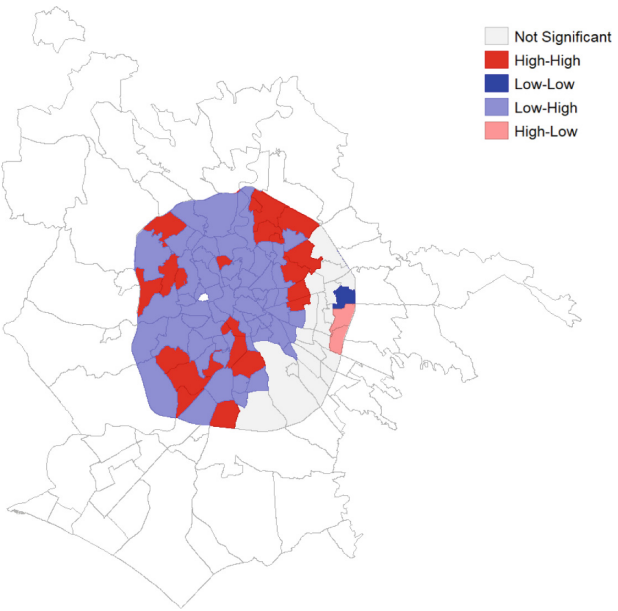

Fig. 3. Map of clusters obtained from the calculation of the local bivariate Moran's index between indicators N and K with $k = 50$.

The analysis conducted with k = 50 on the 106 urban zones showed that only 17% of them do not exhibit a spatially significant correlation. Most of the zones belong to the Low-High cluster (62 zones), while 23 zones fall into the High-High cluster. Additionally, there are two zones in the High-Low cluster and one in the Low-Low cluster, located near the GRA in the eastern part of the city.

The zones are characterized by an inverse spatial correlation (Low-High), where a low number of public housing units corresponds to high disposable income values in the surrounding areas, cover 58% of the analyzed territory and are relatively evenly distributed. However, Moran's index values remain moderate: the highest value is recorded in the *XX Settembre* and *Villa Borghese* areas (−0.25), followed by *Parioli* and Prati (−0.24). Most negative values fall within the range of −0.19 to −0.10.

Conversely, the zones with a direct spatial correlation (High-High), characterized by a high number of public housing units associated with relatively high incomes, show a more heterogeneous distribution across the territory, covering 22% of the area. In these zones, the highest Moran's index value is recorded in the Pineto area (1.00), followed by *Tufello* (0.68), while other areas, such as *Casal Bruciato*, exhibit lower values (0.30). Nonetheless, the most positive index values remain relatively low, ranging between 0.01 and 0.07.

7 Conclusions

Urban decay is a complex phenomenon resulting from the interaction of environmental, economic, and social factors, which manifest through non-random spatial dynamics. Its distribution across the territory is influenced by processes of concentration and diffusion that can exacerbate existing issues. In this context, spatial correlation analysis serves as an essential tool to understand the relationships between the variables contributing to decay and to identify significant patterns that can guide urban regeneration strategies. Urban planners and policymakers can use the results to develop regeneration strategies or targeted interventions, particularly in areas that have significant spillover effects.

This research implements a spatial correlation analysis using the bivariate Moran's index for the city of Rome. This analysis highlights the presence of significant clusters in the distribution of urban decay indicators, demonstrating how certain issues are concentrated in specific areas and can generate spillover effects in adjacent zones.

The stabilization of the High-High cluster beyond $k = 80$ suggests that urban decay in Rome follows large-scale spatial patterns, characterized by:

- Persistent and non-fragmented critical zones requiring coordinated interventions.
- Spillover effects of urban decay, making interventions in single neighborhoods insufficient.
- A minimum intervention scale that must cover entire urban areas rather than isolated points.

This suggests that highly critical urban zones tend to exhibit similar characteristics across a vast area rather than being scattered in a fragmented manner. Urban planning must therefore consider that decay is structured on a broad scale and requires regeneration efforts across extensive areas rather than isolated solutions.

The analysis results show that some areas exhibit decay patterns manifesting simultaneously across all three components (physical-environmental, economic, and social). In particular, the zones of Tormarancia, Testaccio, Serpentara, Casal Boccone, and Casal Bruciato belong to the High-High cluster in all three cases, indicating the presence of environmental issues (such as high building vacancy rates and asbestos presence) alongside a dynamic economic context characterized by a high functional mix and strong variations in residential property values. Conversely, the zones of Prati, Della Vittoria, Medaglie d'Oro, Farnesina, Parioli, Flaminio, Salario, and Trieste belong to the Low-High cluster across all components. These areas are distinguished by significant variations in residential property values but a low level of functional diversification. Additionally, the limited presence of public housing, combined with higher income levels, may exacerbate housing exclusion dynamics, reducing accessibility opportunities for economically vulnerable populations [32].

The findings confirm the need for an urban regeneration approach that considers interactions between indicators [33] and enables more effective intervention strategies by identifying areas where decay is most prevalent [34]. Specifically, urban regeneration policies should: i) promote functional diversification in declining areas to stimulate the real estate market; ii) optimize public housing management, as its concentration in economically disadvantaged areas without accompanying social inclusion policies and urban improvements may fail to enhance social conditions; iii) incentivize environmental remediation in historic areas to reduce environmental degradation [35–39].

The use of the local bivariate Moran's index also demonstrated how the granularity of the analysis influenced the identification of critical areas, with implications for defining the optimal intervention scale.

This research focused on the areas within Rome's GRA, future developments will extend the analysis to the entire city to capture the spatial dynamics characterizing even the most peripheral zones.

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