

Original Article

Received: 2026/05/02
Revised: 2026/10/07
Accepted: 2026/10/07



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HOW TO CITE THIS ARTICLE

Yazdanshenas M.H. Tahmasbi Boeini K. Nazari S. Assessing spatial justice in access to urban services using spatial multi-criteria decision analysis (case study: Khorramabad). *Urban Economics and Planning* 8(2):126-140.

DOI: [10.22034/uep.2026.580146.1877](https://doi.org/10.22034/uep.2026.580146.1877)

Assessing spatial justice in access to urban services using spatial multi-criteria decision analysis (case study: Khorramabad)

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Abstract

In Khorramabad, the spatial distribution of urban services does not align with population distribution or residents' actual opportunities to access them, resulting in inequalities among neighborhoods. Although previous studies in Iran have examined inequalities in the distribution of urban services, the simultaneous integration of network-based accessibility, population-service coverage mismatch, the spatial structure of deprivation, and the prioritization of interventions at the neighborhood scale has received less attention. This study examines these dimensions and translates the results into spatial intervention priorities for the city's 24 neighborhoods. First, network-based service areas were delineated using thresholds of 1,000 m for healthcare services and 500 m for educational and cultural services. The spatial population-service mismatch index (SPMI) was then calculated for each neighborhood, and spatial patterns of advantage and deprivation were identified using local indicators of spatial association (LISA). Next, the relative importance of service types was determined through the analytic hierarchy process (AHP), and the results were integrated into a spatial multi-criteria decision analysis (MCDA) model. The findings revealed a considerable mismatch between population shares and service coverage across Khorramabad's neighborhoods. The integrated model placed neighborhoods 10, 12, 4, 13, 22, and 3 among the highest intervention priorities. The findings suggested that jointly assessing the magnitude and spatial structure of mismatch can provide a more precise basis for place-based urban service policymaking in medium-sized Iranian cities.

Keywords

Khorramabad
network-based accessibility analysis
right to the city
spatial multi-criteria decision analysis
spatial justice
urban services

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1. Introduction

The distribution of urban public services is a key arena where spatial inequality becomes visible, because their location and accessibility determine citizens' opportunities to benefit from the amenities of urban life. The issue is not simply an absolute shortage of services. It becomes particularly consequential when a neighborhood's share of the population does not correspond to its share of opportunities to access services. This issue has been repeatedly reported in studies of Iranian cities. In Mashhad, service distribution is clustered and concentrated in the central and western parts, and does not follow the population density pattern (Rezaee et al., 2025). Another study of the Navid and Ab-o-Bargh districts of Mashhad found a direct relationship between the equitable distribution of urban services and citizens' mobility (Nazarabadian et al., 2024). In Ardabil, an assessment of 44 urban districts found no significant coordination between population distribution and services' distribution (Tavakolinia et al., 2015). In Yasouj, spatial inequality in access to urban services was identified through network analysis and spatial autocorrelation (Pourahmad et al., 2023). In Shiraz, the unequal distribution of services was found to intensify spatial and social inequalities (Abbasi et al., 2025). In Ardabil, a GIS-based assessment of the accessibility and spatial distribution of urban services also revealed a gap between central and peripheral neighborhoods (Ghaffari Chanzanaqah et al., 2024). In Khorramabad, Shamaei et al. (2016) likewise confirmed a mismatch between population distribution and services. Taken together, this evidence indicates that spatial inequality in service provision is a widespread and structural issue in Iran.

From a theoretical perspective, spatial justice cannot be reduced to the numerical, equal distribution of services (Dadashpoor & Dehghan, 2025). Rawls's difference principle draws attention to the circumstances of the least advantaged when allocating resources (Rawls, 1971). Soja regards space as an active dimension in the formation and consolidation of inequality (Soja, 2010). Harvey considers spatial inequality a geographical expression of socioeconomic inequalities and emphasizes democratic control over the processes that produce space (Harvey, 2008). Lefebvre, in turn, understands space as a product of social relations, power, and capital (Lefebvre, 1996). In her theory of the "just city," Fainstein identifies equity, diversity, and democracy as normative criteria for urban policymaking (Fainstein, 2010). Recent studies

also argue that large-scale urban interventions often benefit more advantaged groups and exacerbate spatial injustice (Diaz-Parra & Jover, 2021; Paddison & Hall, 2023; Sjaaf et al., 2025).

Two methodological issues are central to measuring this inequality. The first concerns how accessibility is measured. A neighborhood's geometric proximity to a service facility does not necessarily imply actual access through the street network. Studies have shown that network-based models more accurately capture route constraints and differences between straight-line and actual travel distances (Abd El Karim & Awawdeh, 2020; Apparicio et al., 2008; Bellantuono et al., 2025; Ferrer-Ortiz et al., 2022; Liu et al., 2022; Roumiani et al., 2019; Sun et al., 2026; Zheng & Zhao, 2023). The second issue concerns measuring population-service mismatch and its spatial structure. Composite indicators such as the SPMI enable comparisons of the relative shares of population and service coverage, while local spatial autocorrelation analyses (LISA) can identify spatial clusters and outliers (Anselin, 1995; Chen, 2024; Griffith et al., 2025; Guo & Brakewood, 2024; Roy et al., 2024; Xia et al., 2020). Finally, spatial multi-criteria decision analysis (MCDA) provides an effective instrument for translating this information into intervention priorities (Alam et al., 2025; Dargahi & Shamloo, 2023; Ebrahimipour & Alizadeh, 2026; Elghazouly et al., 2024; Malczewski, 1999; Samani et al., 2024; Zhalehdoost & Taleai, 2025).

The review of Iranian and international research indicates that each of these three analytical dimensions has been examined independently, but their systematic integration into a single analytical sequence remains limited. In particular, the use of clustered patterns of inequality to adjust intervention priorities at the neighborhood scale has received limited attention in studies of medium-sized Iranian cities. This issue is especially relevant to Khorramabad, the capital of Lorestan Province and a medium-sized city whose spatial structure is shaped by topographic constraints. This study therefore aims to assess spatial inequality in access to healthcare, educational, and cultural services across Khorramabad's neighborhoods and to identify spatial intervention priorities according to the magnitude and spatial structure of this inequality. The study addresses the following questions:

1. To what extent is there a mismatch between each neighborhood's share of the population and its share of the spatial coverage of healthcare, educational, and cultural services in Khorramabad, and which neighborhoods experience the most severe under-

provision and over-provision?

2. In which parts of the city are spatial clusters and outliers of service deprivation and advantage concentrated, and what are their spatial patterns?

3. When the magnitude of mismatch, the relative importance of service types, and the spatial structure of deprivation are considered together, which neighborhoods should be prioritized for intervention and resource allocation?

Following the Introduction, the article reviews previous research in three areas corresponding to these questions. The methodology, data, and analytical stages are then presented. The findings for the three research questions are reported and interpreted in light of previous studies. Finally, the study's contribution, policy implications, limitations, and directions for future research are discussed.

2. Theoretical and empirical background

2.1. Spatial mismatch between population and service coverage

From a spatial justice perspective, access to services can be assessed only when considered in relation to population distribution and spatial need. The existence of a service facility, or its proximity to a neighborhood, does not by itself indicate whether the population of that neighborhood has a commensurate opportunity to access it. Accordingly, a key issue in assessing service equity is comparing each spatial unit's share of the population with its share of service coverage (Apparicio et al., 2008).

How service coverage is calculated is also important. Simpler approaches use Euclidean distance or a buffer around a service facility as a proxy for accessibility. However, actual routes travelled through the street network may differ. Apparicio et al. (2008) showed that the type of distance measure and the spatial aggregation of data affect assessments of access to health services. In their study of walking accessibility in Barcelona, Ferrer-Ortiz et al. (2022) found that network-based analysis reveals more realistic differences in accessibility than purely geometric measures. Abd El Karim and Awawdeh (2020) combined network analysis and multi-criteria decision analysis to derive a spatial suitability map for urban living. Bellantuono et al. (2025) analyzed access to healthcare services in Rome using actual travel times. Liu et al. (2022) examined access to medical services through public transport networks. Zheng and Zhao (2023) assessed access to public services for tourists and residents on islands, while Sun et al. (2026)

evaluated access to basic public services for people with disabilities in Beijing.

In Iranian studies, the mismatch between population and services has been reported in various forms. In Ardabil, an assessment of 44 urban districts found no coordinated pattern between population distribution and service provision and no significant relationship between population density and service distribution (Tavakolinia et al., 2015). In Mashhad, services were highly concentrated in some areas, with differences between population density and service provision across the city (Rezaee et al., 2025). In Shiraz, the unequal distribution of urban services was found to intensify spatial inequalities (Abbasi et al., 2025). A GIS-based assessment of urban services' accessibility and spatial distribution in Ardabil revealed a gap between central and peripheral neighborhoods (Ghaffari Chanzanaqeh et al., 2024). In Tehran, an assessment of the spatial system of health and medical land uses identified the spatial pattern of these facilities (Roumiani et al., 2019). Shamaei et al. (2016) also demonstrated a mismatch between population and urban services in Khorramabad through a spatial analysis informed by spatial justice.

In this study, the spatial population–service mismatch index (SPMI) is defined to measure this mismatch. The index measures the ratio between a neighborhood's share of the city's population and that neighborhood's share of a service's standard spatial coverage. A value greater than one indicates relative under-provision; a value below one indicates relative over-provision; and a value close to one indicates a relative balance between the two shares. In other words, SPMI measures the magnitude of the mismatch between population weight and services' spatial coverage.

2.2. Spatial structure of deprivation and advantage

A service mismatch may occur in a single neighborhood or, together with neighboring areas, form a coherent spatial pattern. This distinction is important for planning because deprivation across several adjacent neighborhoods may constitute a problem that extends beyond a single unit and requires intervention at a broader sub-city scale (Griffith et al., 2025).

Local indicators of spatial autocorrelation make it possible to examine the relationship between each unit's condition and that of its neighbors. LISA, formulated by Anselin (1995), identifies High–High, Low–Low, High–Low, and Low–High patterns. In this framework, High–High and Low–Low indicate spatial clusters, whereas High–Low and Low–High indicate

spatial outliers. Chen (2024) proposed reconstructing and normalizing LISA for more precise spatial analyses. Roy et al. (2024) used LISA to analyze housing quality in mountainous towns. Xia et al. (2020) applied spatial autocorrelation to examine the relationship between land-use intensity and urban vitality in five Chinese megacities. Guo and Brakewood (2024) used LISA to identify spatially correlated service deserts in Nashville.

This approach has also been used in Iranian studies of urban services. Pourahmad et al. (2023) used network analysis and spatial autocorrelation to examine the distribution of and access to urban services in Yasouj, identifying spatial differences between parts of the city. Internationally, several studies have used spatial autocorrelation to identify geographical differences in access to services (Li et al., 2024; Lin et al., 2025; Zhang & Pan, 2023).

In the present study, LISA complements the SPMI. The SPMI identifies the magnitude of mismatch within each neighborhood, while LISA determines whether the service-coverage condition of that neighborhood follows a similar pattern in neighboring areas. The two analyses therefore measure different dimensions of spatial inequality.

2.3. Spatial prioritization of interventions

Identifying inequality becomes a planning decision when it can inform the intervention sequencing and resource allocation. Spatial multi-criteria decision analysis allows combining several criteria within a single framework and generating a priority index (Malczewski, 1999). Various studies have demonstrated the application of GIS and multi-criteria decision analysis to assess spatial justice and identify areas requiring intervention (Alam et al., 2025; Elghazouly et al., 2024; Samani et al., 2024; Zhalehdoost & Taleai, 2025). In Iran, multi-criteria decision-making methods have also been used to assess spatial justice in large cities (Dargahi & Shamloo, 2023; Ebrahimipour & Alizadeh, 2026).

However, different types of services are not equally important. When the purpose is to prioritize interventions, mismatch values should therefore be interpreted in relation to the relative importance of services. In this study, healthcare, educational, and cultural services were weighted using the analytic hierarchy process (AHP), and the corresponding SPMI values were used to construct a composite spatial-need index.

The distinctive feature of this stage is incorporating the spatial structure of deprivation into the prioritization process. Accordingly, a neighborhood with a high magnitude of mismatch that is also part of a statistically significant deprivation cluster is not treated in the same way as a neighborhood experiencing a similar condition in isolation.

Recent Iranian studies have also emphasized the need to consider policymaking and decision-making processes in realizing spatial justice. For example, Rashidi et al. (2025) showed that realizing spatial justice in Tehran is not limited to the physical distribution of resources but is also related to the structures and processes of urban management policymaking.

Overall, the Iranian and international literature indicates that each of these analytical dimensions has an independent research history. For instance, the Yasouj study demonstrated the application of network analysis and spatial autocorrelation (Pourahmad et al., 2023), while studies in Ardabil and Mashhad reported a lack of correspondence between population and service distribution (Rezaee et al., 2025; Tavakolinia et al., 2015). The research gap addressed here is therefore not the complete absence of these methods, but the integration of network-based service coverage, a population–coverage mismatch index, the clustered spatial structure of inequality, and multi-criteria prioritization at the neighborhood scale in a medium-sized Iranian city.

3. Methodology

3.1. Research approach

In terms of purpose, this is an applied study; in terms of nature, it is descriptive. It employs a quantitative approach based on spatial analyses. The methodological approach is integrated and hierarchical: the three analytical stages (SPMI, LISA, and MCDA) were designed as a connected sequence in which each stage provides input for the next. Network analysis serves as the instrument for measuring service coverage and provides the basis for calculating the SPMI. The study's spatial population comprises all 24 official neighborhoods of Khorramabad.

3.2. Study area

Khorramabad, the capital of Lorestan Province in western Iran, was selected as the study area. Geographically, the city is situated in a valley basin

surrounded by the Zagros Mountains. This enclosed valley morphology constrains the city's physical expansion and has contributed to linear development patterns and the location of peripheral settlements on

the slopes. All principal analyses were conducted at the level of the city's 24 official neighborhoods, which served as the units of analysis.

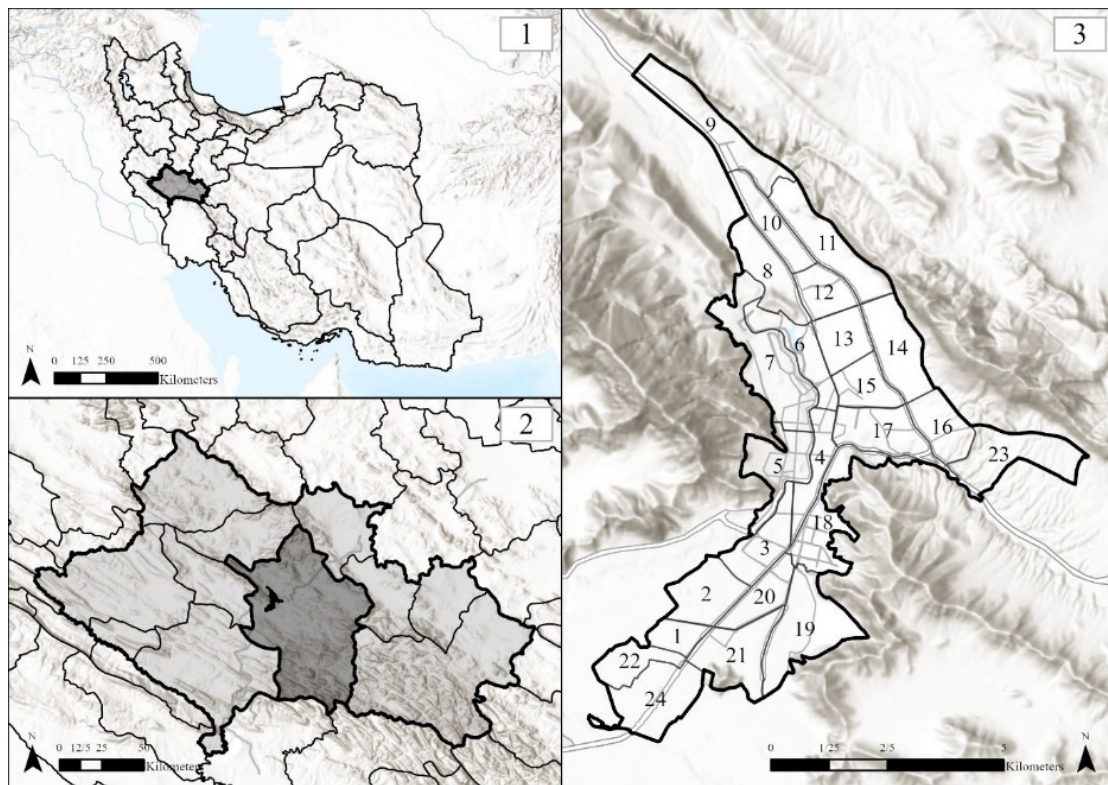


Figure 1. Study area (based on Statistical Centre of Iran, 2016).

3.3. Data and their relationship to the research questions

A comprehensive spatial database was prepared using

three main categories of information. Table 1 identifies the relationship between each data category and the research questions.

Table 1. Relationship between research questions, data, and analytical methods

Question	Data used	Source	Unit of analysis	Method
1	Neighborhood population + network-based service coverage	Statistical Centre of Iran + service data source	Neighborhood	Service Area + SPMI
2	Service coverage + neighborhood boundaries	GIS outputs	Neighborhood	LISA
3	SPMI + service weights + LISA clusters	Outputs of previous stages	Neighborhood	MCDA

Population data: population statistics for Khorramabad's statistical blocks were obtained from the 2016 National Population and Housing Census. After cleaning and aggregation, the data were organized at the level of the city's 24 neighborhoods. Land-use and service data: point and polygon layers representing urban services were compiled for three

main groups: healthcare services (clinics, health centers, and general practitioners' offices); educational services (schools and educational institutes at different levels); and cultural services (libraries and other cultural facilities).

Street network: the linear layer of Khorramabad's road network was extracted from the approved detailed

plan of 2019. It includes primary arteries, secondary streets, and local access roads and was prepared and edited for network analysis.

Data processing, spatial layer preparation, and spatial model implementation were performed using ArcGIS Pro. Additional numerical calculations, matrix preparation, and weight extraction for the multi-criteria decision model were carried out using Excel and Expert Choice.

3.4. Data analysis

The research procedure was designed and implemented in four connected and hierarchical stages.

Stage 1: Network-based service area analysis

To realistically estimate access to urban services, the Service Area tool was used on the urban street network (Network Dataset). The street network was prepared by defining nodes (intersections) and edges (primary and secondary streets) and assigning travel cost by

distance. The service area of each facility was then calculated using actual pedestrian routes. Based on common land-use planning standards and previous studies, the standard accessibility thresholds were defined as a 500-metre walking distance for educational and cultural services and a 1,000-metre walking distance for healthcare services. Because this study assessed equity in residents' everyday access to basic services, only facilities providing basic and routine healthcare (clinics, health centers, and general practitioners' offices) were included within the 1,000-metre healthcare service area. Specialist and subspecialist hospitals were excluded because of their supra-urban functions and regional or provincial catchment populations; including them could distort neighborhood-level access estimates. This stage resulted in a service-area map for each service group at the neighborhood level. These areas were used in the next stage to calculate service coverage area A_{ij} .

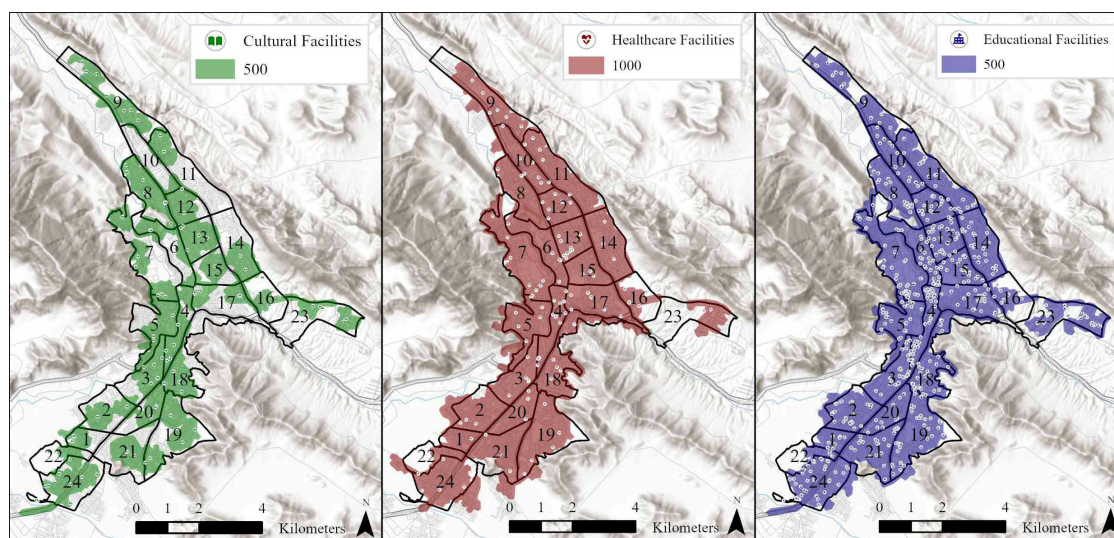


Figure 2. Network-based service areas for the three service groups

Stage 2: Calculation of the spatial population–service mismatch index (SPMI)

To quantify spatial justice and measure the mismatch between “population need” and “service coverage,” we defined and calculated the spatial population–service mismatch index (SPMI) for each neighborhood and service type.

For each service j (healthcare, educational, or cultural) in neighborhood i , the SPMI is defined as follows:

$$SPMI_{ij} = \frac{P_i}{\sum_k A_{kj}} \cdot \frac{A_{ij}}{\sum_k P_k}$$

Where:

P_i = population of neighborhood i ; $\sum_k P_k$ = total population of the city; A_{ij} = area covered by service j in neighborhood i , obtained by overlaying the service area with the neighborhood boundary; and $\sum_k A_{kj}$ = total area covered by access to service j across the city. The numerator is the neighborhood's share of the city's total population, while the denominator is that neighborhood's share of the relevant service's total spatial coverage across the city. Accordingly:

- If $SPMI_{ij} > 1$, the neighborhood's share of the city population is greater than its share of service coverage. The neighborhood is therefore considered relatively

under-provided for that service and subject to relative deprivation.

- If $SPMI_{ij} < 1$, the neighborhood's share of service coverage is greater than its share of the population, and the neighborhood is considered relatively over-provided.
- If $SPMI_{ij} \approx 1$, there is a relative balance between the population share and service-coverage share.

The logic of the proposed SPMI operates on comparing two relative shares: each neighborhood's share of the city's total population and its share of the total coverage area of the same service. It should be emphasized that "service coverage area" is not defined by neighborhood administrative boundaries or by service self-sufficiency within each neighborhood. Rather, it represents the area of each neighborhood that falls within the standard network-based accessibility threshold for the service in question. Consequently, a neighborhood may be covered by the service area of facilities located outside its administrative boundary.

Stage 3: Local indicators of spatial association (LISA)

In the third stage, local spatial autocorrelation analysis was performed in ArcGIS Pro for all three service groups to identify spatial patterns of deprivation and advantage and distinguish clusters from isolated locations. LISA statistics were calculated following Anselin's proposed model (Anselin, 1995). The local Moran's I statistic is expressed as follows:

$$I_i = \frac{(z_i - \bar{z})}{\sigma^2} \sum_{j=1, j \neq i}^n w_{ij} (z_j - \bar{z})$$

Where z_i is the standardized service-access coverage level in neighborhood i (expressed as a deviation from the mean); $\bar{z}$ is the mean of the indicator values; σ^2 is the overall variance; and w_{ij} represents the elements of the spatial weights matrix.

The spatial weights matrix $W = [w_{ij}]$ was defined using polygon contiguity based on both shared edges and shared vertices (Queen Contiguity). Thus, two neighborhoods were considered neighbors if they shared at least one boundary segment or vertex. Weights were defined as binary values (1 for adjacent neighborhoods and 0 for non-adjacent neighborhoods) and were then row-standardized.

Using the local Moran statistic, neighborhoods were classified into four main spatial patterns: High-High (clusters of high service coverage), Low-Low (clusters of deprivation), High-Low (an isolated high-coverage outlier within a low-coverage context), and Low-High (an isolated low-coverage outlier within a high-

coverage context).

Stage 4: Spatial multi-criteria decision analysis (MCDA)

To provide an integrated roadmap for guiding development investment and prioritizing interventions, the results for the three service groups (healthcare, educational, and cultural) were combined into a composite indicator. Expert judgements were structured through weighting based on the analytic hierarchy process (AHP). The weighting procedure defined the three service types as the model's main criteria; constructed a pairwise comparison matrix using the nine-point scale; extracted the priority weight vector through eigenvalue calculation and normalization; and calculated the consistency ratio (CR).

The results indicated that healthcare services had the greatest relative importance for achieving spatial justice. The final weights were 0.648 for healthcare services, 0.230 for educational services, and 0.122 for cultural services. The consistency ratio of the pairwise comparison matrix was 0.003, indicating an acceptable level of consistency in the judgements used in the AHP. The composite spatial-need index for each neighborhood i was then calculated using a weighted linear combination of the SPMI values:

$$MCDA_i = 0.648 \times SPMI_{(health,i)} + 0.230 \times SPMI_{(edu,i)} + 0.122 \times SPMI_{(culture,i)}$$

Because the spatial structure of deprivation identified by LISA may have different policy significance from isolated deprivation, the composite index was adjusted using a cluster-adjustment coefficient:

$$MCDA^*_i = MCDA_i \times (1 + SAS_i), \quad SAS_i = \sum_s w_s \times \delta_{(i,s)}$$

In this model, neighborhoods belonging to a Low-Low deprivation cluster received a positive adjustment for the relevant service. Neighborhoods in a High-High cluster, if any, received a negative adjustment, while no adjustment was applied to High-Low or Low-High outliers. To classify neighborhoods into different intervention-priority levels, the $MCDA^*_i$ values were divided into five priority classes using the Jenks Natural Breaks algorithm.

The δ coefficients were determined based on the authors' expert judgement and were not derived from empirical data. These coefficients affected the final ranking of some neighborhoods, particularly neighborhoods 22 and 24. Therefore, the results of this adjustment should be interpreted as an analytical choice rather than a definitive, immutable finding.

Consistency and robustness checks

The consistency ratio (CR) was used solely to assess the consistency of pairwise judgements in the AHP process. It was not treated as an indicator of the overall research framework' validity. The cluster-adjustment coefficients (δ), which were based on expert judgement, were not subjected to sensitivity analysis. This has been considered a methodological limitation when interpreting the results and drawing conclusions.

4. Findings

4.1. Spatial mismatch between population and service coverage

The spatial coverage of basic healthcare, educational, and cultural services was calculated using Service Area

analysis on the street network, with thresholds of 1,000 and 500 meters. After calculating network-based service coverage, the SPMI was calculated for the three service groups. The results indicate that neighborhood population shares are not fully proportional to their shares of spatial service coverage in any of the three groups. For educational services, 14 neighborhoods had values greater than one and 10 had values below one; the index ranged from 0.07 to 1.62. For healthcare services, 12 neighborhoods had values above one and 12 had values below one; the index ranged from 0.07 to 1.69. For cultural services, 11 neighborhoods had values greater than one, 12 had values below one, and one neighborhood had a value equal to one; the index ranged from 0.18 to 2.27.

Table 2. SPMI values for the five most under-provided and five most over-provided neighborhoods, based on the raw composite index

Status	Neighborhood	Educational SPMI	Healthcare SPMI	Cultural SPMI
Most critical (under-provided)	10	1.62	1.25	2.27
	12	1.52	1.51	0.87
	4	1.62	1.52	0.47
	13	1.07	1.69	0.27
	3	1.01	1.60	0.58
Most advantaged (over-provided)	7	0.07	0.07	1.22
	23	0.50	0.11	1.11
	5	0.48	0.18	0.78
	16	0.84	0.24	0.18
	24	0.76	0.27	0.98

The highest educational SPMI values were recorded in neighborhoods 4 and 10; the highest healthcare SPMI in neighborhood 13; and the highest cultural SPMI in neighborhood 10, with a value of 2.27. Conversely, the lowest index values for both educational and healthcare services (0.07) were observed in neighborhood 7. For cultural services, neighborhood 16 had the lowest value (0.18). These low values

indicate over-provision of spatial service coverage relative to these neighborhoods' population share. Nevertheless, SPMI values represent a relative mismatch between population share and spatial service coverage and should not be interpreted as an absolute measure of advantage or deprivation. Neighborhood-level SPMI values are presented in Figure 3.

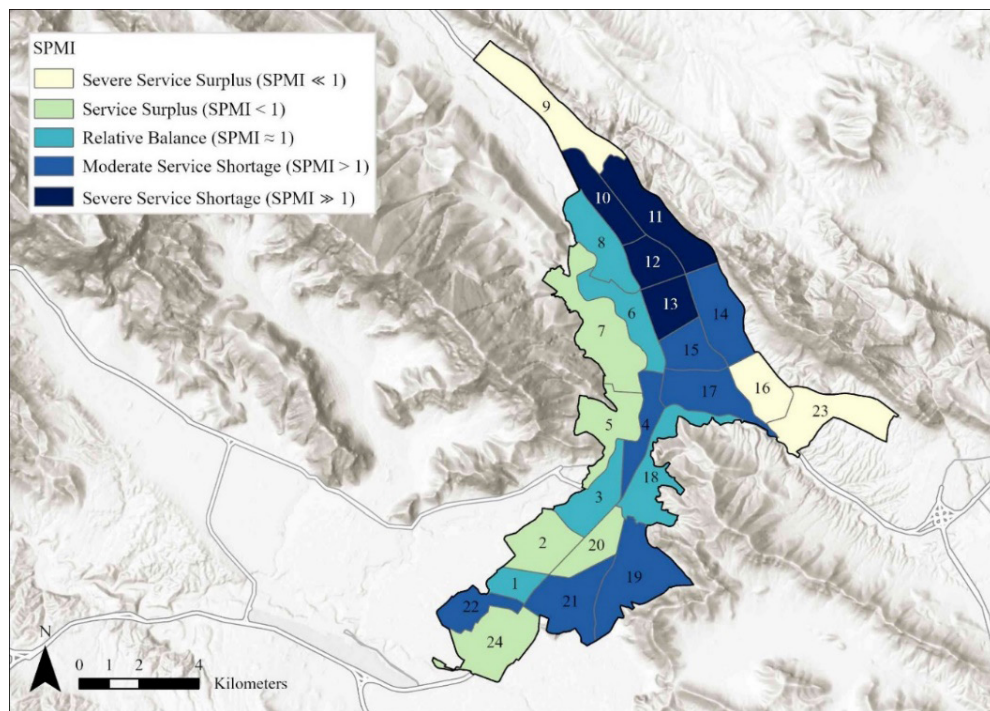


Figure 3. SPMI by neighborhood

4.2. Spatial structure of deprivation and advantage

The LISA results show that inequality in the spatial coverage of services appears in clusters in parts of Khorramabad. For healthcare services, neighborhoods 22 and 24 formed a Low–Low cluster, indicating they are adjacent to areas with low levels of healthcare coverage. For educational services, neighborhoods 2

and 9 also formed a Low–Low cluster. In contrast, neighborhoods 8 and 9 for cultural services and neighborhood 20 for healthcare services were identified as High–Low outliers, meaning that service coverage in these neighborhoods was higher than in their neighboring areas (Figure 4).

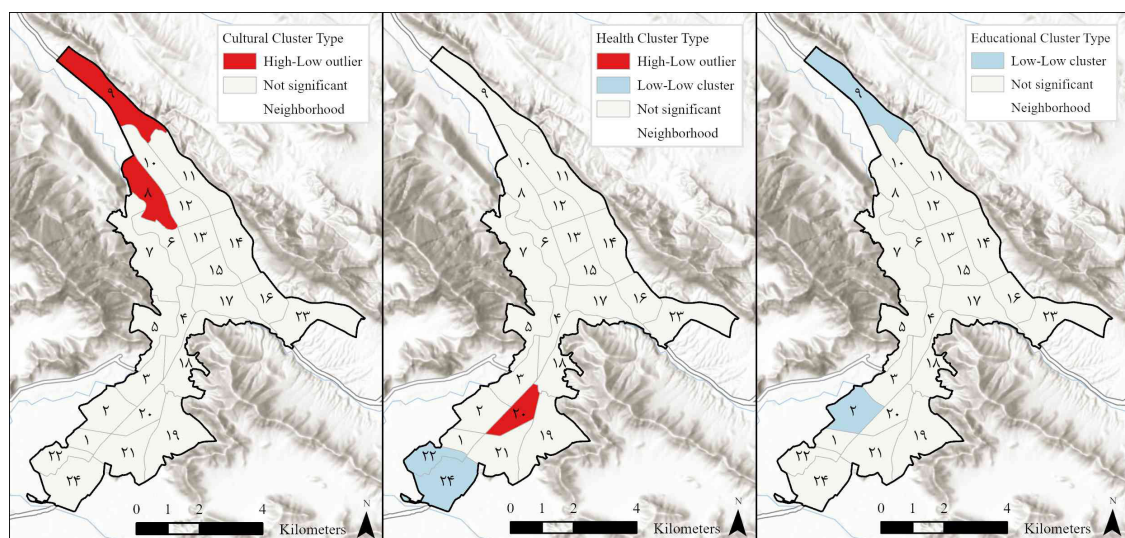


Figure 4. LISA analysis for the three service groups

No statistically significant High–High cluster was identified in the study data. The observed spatial pattern is therefore characterized mainly by localized

concentrations of deprivation in the form of Low–Low clusters and isolated advantage in the form of High–Low outliers.

4.3. Spatial prioritization of interventions

AHP-based weighting was used to determine the relative importance of the three service groups and combine the mismatch results. The final weights for healthcare, educational, and cultural services were

0.648, 0.230, and 0.122, respectively. The weights were based on the authors' expert judgements. The consistency ratio of the pairwise comparison matrix was 0.003, indicating an acceptable level of consistency in the judgements used (Table 3).

Table 3. Pairwise comparison matrix and final weights of the relative importance of urban services

Criteria	Healthcare	Educational	Cultural	Normalized final weight (W)
Healthcare	1	3	5	0.648
Educational	1/3	1	2	0.230
Cultural	1/5	1/2	1	0.122

Based on these weights, the composite spatial-need index was calculated by combining the SPMI values. In the baseline model, neighborhoods 22 and 24 received a 13% adjustment because they belonged to the healthcare deprivation cluster, while neighborhoods 2 and 9 received a 5% adjustment because they belonged to the educational deprivation cluster. In this way, the

effect of the spatial structure of deprivation was weighted according to the relative importance of the relevant service type. The adjustment coefficients were selected based on expert judgement and were not subjected to sensitivity analysis. Their effects on the final ranking should therefore be interpreted as an analytical choice rather than a definitive finding.

Table 4. Ranking of Khorramabad neighborhoods based on the raw and adjusted spatial-need indices

Neighborhood	Educational SPMI	Healthcare SPMI	Cultural SPMI	Raw MCDA	Raw rank	Cluster adjustment	Adjusted MCDA*	Final rank
1	0.89	0.69	1.11	0.79	15	—	0.79	15
2	0.87	0.18	1.50	0.50	19	+5% (educational LL)	0.52	20
3	1.01	1.60	0.58	1.34	5	—	1.34	6
4	1.62	1.52	0.47	1.41	3	—	1.41	3
5	0.48	0.18	0.78	0.32	22	—	0.32	22
6	0.89	0.49	1.80	0.74	16	—	0.74	16
7	0.07	0.07	1.22	0.21	24	—	0.21	24
8	1.11	0.99	0.69	0.98	13	—	0.98	13
9	0.50	0.50	0.67	0.52	18	+5% (educational LL)	0.55	18
10	1.62	1.25	2.27	1.46	1	—	1.46	1
11	1.23	1.19	1.73	1.27	6	—	1.27	7
12	1.52	1.51	0.87	1.43	2	—	1.43	2
13	1.07	1.69	0.27	1.37	4	—	1.37	4
14	1.14	1.14	1.34	1.16	11	—	1.16	11
15	1.32	1.31	0.59	1.22	7	—	1.22	8
16	0.84	0.24	0.18	0.37	21	—	0.37	21
17	1.25	1.13	1.32	1.18	10	—	1.18	10
18	1.03	0.49	1.11	0.69	17	—	0.69	17
19	1.19	1.18	0.68	1.12	12	—	1.12	12
20	0.89	0.88	0.49	0.83	14	—	0.83	14
21	1.19	1.24	1.18	1.22	8	—	1.22	9

Neighborhood	Educational SPMI	Healthcare SPMI	Cultural SPMI	Raw MCDA	Raw rank	Cluster adjustment	Adjusted MCDA*	Final rank
22	1.32	1.21	1.00	1.21	9	+13% (healthcare LL)	1.37	5
23	0.50	0.11	1.11	0.32	23	—	0.32	23
24	0.76	0.27	0.98	0.47	20	+13% (healthcare LL)	0.53	19

After the spatial cluster-adjustment coefficient was applied, the final ranking changed mainly for neighborhood 22. Its raw index score was 1.21, placing it ninth; because it belonged to a statistically significant healthcare deprivation cluster, its adjusted score increased to 1.37, and it rose to fifth place. It therefore joined neighborhoods 10, 12, 4, and 13 among the six neighborhoods with the highest intervention priorities: 10, 12, 4, 13, 22, and 3. Neighborhood 24 also belonged to this cluster and rose from twentieth to nineteenth place. These rank changes resulted from applying the cluster-adjustment coefficients. Although

neighborhoods 2 and 9 belonged to the statistically significant educational deprivation cluster, they received a smaller adjustment (+5%) because educational services had a relatively low weight (0.230, compared with 0.648 for healthcare services); their positions in the overall ranking did not change substantially. Neighborhoods 8 and 20, which were identified only as isolated advantage outliers, received no numerical adjustment. Neighborhood 9 received no adjustment for its cultural-service outlier status, but it was subject to the +5% adjustment because it also belonged to the educational Low–Low cluster.

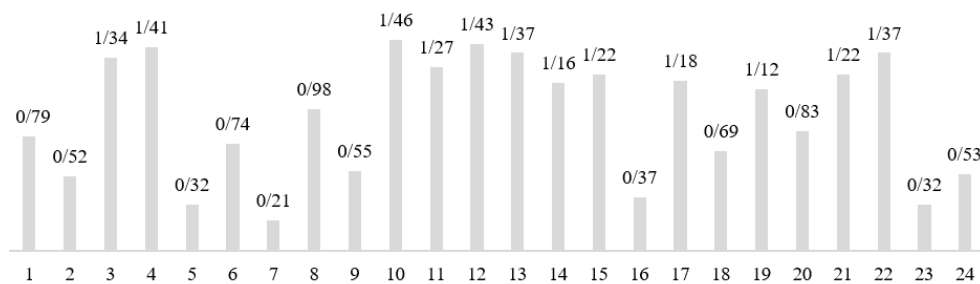


Figure 5. Comparison of Khorramabad neighborhoods by priority for service development (Source: Authors)

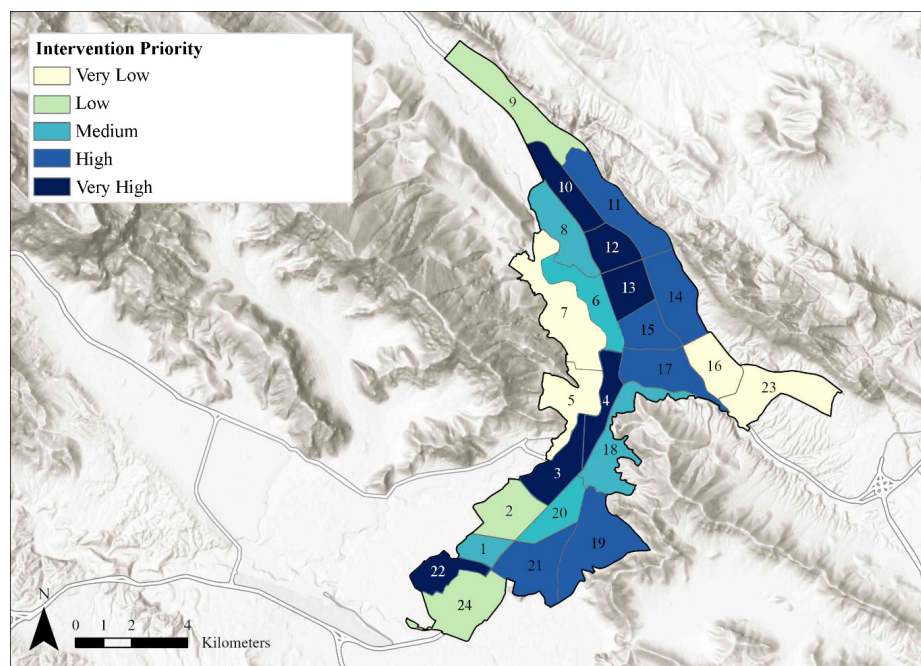


Figure 6. Zoning of urban intervention priorities

5. Discussion and interpretation of findings

5.1. Population–service coverage mismatch

The main finding is that spatial service coverage across Khorramabad's neighborhoods is not fully proportional to their population weights. This result aligns with studies conducted in Ardabil and Mashhad, which likewise found no complete correspondence between population distribution and service provision (Abbasi et al., 2025; Ghaffari Chanzanaqh et al., 2024; Rezaee et al., 2025; Tavakolinia et al., 2015). The difference in the present study is that mismatch was assessed based on spatial coverage derived from network analysis. Population and services were, therefore, not compared solely according to the physical location of facilities or the area of service land use.

The highest educational SPMI values in neighborhoods 4 and 10, the highest healthcare value in neighborhood 13, and the highest cultural value in neighborhood 10 indicate that the magnitude of mismatch differs across service types. Conversely, the very low SPMI values in neighborhoods 7 and 23 indicate that their shares of spatial service coverage exceed their population weights. These two conditions should not be interpreted simply as absolute "deprivation" and "advantage." Rather, the SPMI indicates the relative difference between population weight and standard spatial coverage (Apparicio et al., 2008).

Using network analysis to calculate service coverage also incorporates the distinction between geometric proximity and spatial accessibility into the analysis. This is consistent with previous studies (Abd El Karim & Awawdeh, 2020; Apparicio et al., 2008; Bellantuono et al., 2025; Ferrer-Ortiz et al., 2022; Liu et al., 2022; Zheng & Zhao, 2023), which have shown that the definition of distance and the structure of the network can affect accessibility estimates. Nevertheless, network analysis alone does not measure spatial justice. In this study, its value lies in determining the spatial coverage used to compare population and services based on network routes.

5.2. Spatial structure of deprivation and advantage

The LISA analysis showed that service inequality has a contiguous spatial structure in some parts of Khorramabad. The healthcare deprivation cluster (neighborhoods 22 and 24) and the educational deprivation cluster (neighborhoods 2 and 9) indicate that low coverage in some neighborhoods is accompanied by low coverage in adjacent

neighborhoods. This finding aligns with Iranian research, including the Yasouj study, which emphasized the importance of the spatial structure of services and inequalities between different parts of a city (Pourahmad et al., 2023). It is also consistent with international findings on the spatial concentration of service deprivation (Guo & Brakewood, 2024; Xia et al., 2020).

Nevertheless, a distinction should be made between a "spatial cluster of deprivation" and the "persistence of spatial deprivation." LISA identifies the spatial concentration of similar values at a single point in time, but it is not sufficient to demonstrate the reproduction or temporal persistence of deprivation (Anselin, 1995; Chen, 2024). Therefore, the present findings can be regarded as evidence of the spatial concentration of deprivation; testing the temporal persistence of this pattern would require data from multiple periods.

The presence of High–Low outliers for some services also indicates that advantage may appear as isolated locations without forming an advantage cluster. This condition is important from a policy perspective because, in such cases, improving spatial connectivity and access routes to an existing facility may be more effective for neighboring areas than establishing a new facility. This finding aligns with studies conducted in Shanghai, Xi'an, Chengdu, and Darjeeling concerning the connection between LISA and spatial decision-making (Griffith et al., 2025; Li et al., 2024; Lin et al., 2025; Roy et al., 2024; Zhang & Pan, 2023).

5.3. Spatial prioritization and policy implications

Combining SPMI values with service weights showed that different service types cannot be treated as equal in terms of intervention priority. The weight 0.648 assigned to healthcare services meant that clustered healthcare deprivation in neighborhood 22 had a greater effect on its final position, raising it from ninth to fifth place. This result indicates that mismatch magnitude and service type importance are two distinct components of decision-making (Dargahi & Shamloo, 2023; Malczewski, 1999).

Adding LISA information to the model also allowed us to distinguish isolated deprivation from clustered deprivation. The final model therefore does not simply answer the question "which neighborhood has the greatest need?" but also identifies "which need is embedded in a broader spatial structure?" This feature may be important for resource allocation in cities

facing resource constraints or limited implementation capacity (Alam et al., 2025; Elghazouly et al., 2024; Samani et al., 2024; Zhalehdoost & Taleai, 2025).

The final ranking depends, to some extent, on the cluster-adjustment coefficients (δ) that are determined through expert judgement and were not subjected to sensitivity analysis in this study. Therefore, the final ranking should not be interpreted as a definitive ordering independent of the model assumptions. The proposed model's principal value is that it provides a transparent framework for spatial prioritization based on the magnitude and spatial structure of need, rather than producing an absolute ranking that remains unchanged under all conditions.

From a policy perspective, the findings support a shift from per-capita allocation to place-based allocation. In neighborhoods with severe mismatch, expanding service coverage should be a priority. In deprivation clusters, interventions should be considered at a multi-neighborhood scale. In neighborhoods with relative advantage or High–Low outliers, attention may be given to using existing capacity to serve less advantaged neighboring areas. This approach aligns with recent Iranian literature that emphasizes the need to link spatial justice with urban policymaking and decision-making systems (Diaz-Parra & Jover, 2021; Paddison & Hall, 2023; Rashidi et al., 2025; Sjaaf et al., 2025).

6. Conclusion

This study examined spatial inequality in urban services across Khorramabad's neighborhoods at three levels: mismatch between population and service coverage, the spatial structure of deprivation and advantage, and the spatial prioritization of interventions. The results showed that neighborhood population shares do not correspond evenly to their shares of spatial coverage for healthcare, educational, and cultural services. Neighborhood 13 had the greatest healthcare mismatch; neighborhoods 4 and 10 had the greatest educational mismatch; and neighborhood 10 had the greatest cultural mismatch. The LISA analysis also identified a healthcare deprivation cluster comprising neighborhoods 22 and 24 and an educational deprivation cluster comprising neighborhoods 2 and 9. Finally, integrating mismatch magnitude, the relative importance of services, and

the spatial structure of deprivation placed neighborhoods 10, 12, 4, 13, 22, and 3 among the highest intervention priorities.

The study's contribution lies in distinguishing the "magnitude of inequality" from the "spatial structure of inequality" and then linking these two dimensions to spatial decision-making. The SPMI identifies the relationship between a neighborhood's population share and its share of service coverage, whereas LISA determines whether that neighborhood's condition is also found among its neighbors. Linking these two analytical levels to MCDA allows us to move from identifying neighborhoods in need to prioritizing spatial interventions. The innovation of this study therefore is not in introducing network analysis, LISA, or AHP individually, but in connecting these tools within a single analytical sequence for a medium-sized Iranian city.

The study's main limitation is its use of population data from the city's latest census, conducted in 2016. Although these are the latest available city-level data, they may differ from the city's current population pattern. A second limitation is using spatial coverage as a proxy for access opportunities. Facility capacity, quality, opening hours, and functional differences between service facilities were not incorporated into the model. In addition, using neighborhoods as units of analysis may conceal some within-neighborhood heterogeneity. The third limitation concerns the cluster-adjustment coefficients (δ). These coefficients were determined through expert judgement and were not subjected to sensitivity analysis. Since they affected the final ranking of some neighborhoods, particularly neighborhoods 22 and 24, the final ranking should be interpreted as an analytical choice within the proposed model rather than a definitive finding independent of the model assumptions.

Future studies may pursue three directions: updating population and service data and using dynamic, multi-period datasets; incorporating facility capacity, quality, and socioeconomic characteristics into the assessment of need; and testing the sensitivity of weights, accessibility thresholds, and adjustment coefficients (δ), as well as comparing the results with alternative methods for integrating LISA and MCDA.

Authors' Contributions

The first author contributed 50% to the study's design and writing. The second and third authors each contributed 25% to the study's design and writing.

Acknowledgments

This study received no financial or institutional support. ChatGPT (GPT-6, OpenAI) was used to translate the Persian manuscript into English and assist with English-language editing. The tool was used for translation and language-level refinement; the authors remain responsible for verifying the accuracy of the translation and for the content of the final manuscript.

Conflict of Interest

The authors declare that they have no conflict of interest related to this article.

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