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Research Paper

Spatial Dimensions of Urban Poverty: The Case of Iranian Metropolises

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Abstract
The United Nations Sustainable Development Goals (SDGs) emphasize the urgent need to eradicate poverty by 2030, positioning it as one of the 17 critical objectives for a better world. As a global challenge, poverty demands the unified efforts of international organizations and governments across nations. While comprehensive research has explored diverse dimensions of poverty, its causes, and potential solutions in various contexts, a considerable gap remains: no extensive study has simultaneously examined urban poverty across all metropolises within a single country. This research addresses this critical gap by conducting an in-depth analysis of all metropolises in Iran. We aim to accurately determine the extent of poverty affecting these urban centers' population and land area. We have carefully selected necessary indicators based on the latest national census data and relevant international studies. We ensure robust and reliable results by utilizing a factor analysis model for data evaluation, complemented by kernel density techniques and Moran's spatial autocorrelation for spatial analysis. Our findings reveal that an alarming 44% of the total population in Iran's metropolises and 24% of their land area are living within poverty-stricken cores. These insights are paramount for understanding poverty in Iran and hold profound implications for other countries confronting similar challenges. By identifying the severity of poverty at national and regional levels, we can foster more targeted interventions and create pathways to a brighter, more equitable future for all.

Keywords: *Urban poverty, Spatial analysis, Metropolises, Iran.*

INTRODUCTION

Cities provide better social and economic development, job opportunities, and services than rural areas (Vilar-Compte et al., 2021). They act as hubs for social, cultural, scientific, and technological innovation, attracting large populations (Leal Filho et al., 2019). This population growth has been considerable, with urban populations projected to reach 6.2 billion by 2050, accounting for 68% of the global population (Venerandi et al., 2015). Urbanization is now an irreversible trend (Kuddus et al., 2020), leading to significant changes in economic, social (Guan et al., 2018), and spatial structures. However, as cities expand, local governments often struggle to develop infrastructure and services to meet the demands of the growing population, resulting in unequal access and increasing disparities (Duque et al., 2015). In developing countries, urbanization has surged over the past 50 years, leading to various challenges, such as increased mortality rates, pollution-related diseases (Oduwaye & Lawanson, 2007), social inequalities, poverty, and climate change (Tan et al., 2016). Among all these problems, poverty is a multidimensional issue (Benevenuto & Caulfield, 2020) with significant economic, social, cultural, environmental, and security implications for urban

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sustainability (Silva-Laya et al., 2020) that is closely tied to inequality (Ahluwalia et al., 1979)and restricts people's access to employment, housing, services, and education (Yarahmadi & Nikpour, 2021). However, the most considerable point is that urban poverty has a spatial dimension, which means that poor neighbourhoods often develop in specific areas, leading to the growth of slums, informal accommodations, and dilapidated structures, distinguished by high unemployment, violence, and insecurity. Understanding the spatial distribution of poverty is crucial for local governments and urban planners to create effective policies aimed at poverty reduction (Bemanian et al., 2011). While many existing studies focus on the root causes of poverty in various regions and their effects, few have specifically compared the spatial distribution of urban poverty across different metropolises. In Iran, rapid urbanization has also increased the number of urban poor areas over recent decades. Although poverty has primarily been examined in economic and health contexts, geographical and urban perspectives have received less focus. Rapid population increase and urbanization have worsened urban poverty, social inequalities, and class divides, making poverty reduction a key policy goal for the country's planning system (Nikpour et al., 2021). Effective poverty reduction policies necessitate a clear understanding of the extent and factors contributing to urban poverty. Identifying the spatial distribution of poverty and its underlying reasons is essential for designing targeted interventions. This research uses the latest official census data to investigate urban poverty in Iran's metropolises, specifically in cities with one million populations. The investigation aims to answer the following four research questions:

1. How is the spatial distribution of poverty concentrated in Iranian metropolises?
2. What proportion of the population and area in these cities is located in poverty zones?
3. Which cities have the largest populations and areas affected by poverty?
4. What factors play the most significant role in the formation of urban poverty?

LITERATURE REVIEW

Urban Poverty

Poverty is a complex concept defined through various procedures and ideologies (Aiyedogbon & Ohwofasa, 2012).Traditional definitions often focused on income levels, overlooking the social and institutional contexts, leading to criticism. Critics argued that poverty should be understood as a result of historical, economic, political, and social factors, as it is a dynamic condition (Adams et al., 2020) and is categorized into absolute and relative types (Ghorbani & Dadazade Silabi, 2021). Absolute poverty refers to a shortage of resources to meet fundamental requirements like food and shelter. In contrast, relative poverty indicates households lack what is considered a standard of living compared to others (Chirisa & Matamanda, 2016). A combination of both types is considered when discussing poverty in urban contexts. While parts of a city can be in absolute poverty and identified as slums, economic and social instability resulting from various issues, such as international sanctions, can create relative poverty in different areas (Nikpour et al., 2021). Policymakers and urban managers increasingly focus on identifying poverty in urban contexts, as understanding their growth and distribution is essential to improving human development (Khosravinezhad, 2012) as they are characterized by insufficient infrastructure, poor sanitation, pollution, physical threats like fires and floods, high unemployment, increasing crime, disorganized structures, unsafe housing, and inadequate services (Mahdnejad & Bayat, 2020). Therefore, recognizing and studying these contexts is paramount for improving circumstances and addressing social, economic, and security problems (Ghorbani & Dadazade Silabi, 2021).

Background and Indicators

Many studies have identified and analyzed poverty in urban environments, which can clarify its complexities in different dimensions. For example, a study examined the relationship between housing and poverty in an urban setting in Poland, showing that poor urban contexts affect housing prices in the city as a whole (Kisiała & Rącka, 2021). In another study on urban poverty mapping in an Indian metropolis, spatial patterns of urban poverty resulting from physical, financial, social and human indicators were investigated. This study emphasized that in assessing the spatial aspect of urban poverty, all parts of cities should be considered simultaneously as a comprehensive outlook is significant (Baud et al., 2008). Another investigation studies patterns of spatial inequality and social geography theories, and the results show that urban poverty is often spatially shaped due to geographical factors, social and political processes, relationships, and dynamics. The study argues that spatial inequality is more closely related to physical proximity to services,

infrastructure, and jobs than anything else (Grant, 2010). Concerning poverty indicators, researchers in different fields study poverty from diverse perspectives and measure it based on various indicators. These indicators can differ in each country because poverty is multidimensional (Farhadikhah et al., 2018). However, the most common approach to measuring it is quantitative, using income or consumption to assess whether a household can buy a basket of essential goods at a given time. This basket ideally reflects local tastes and considers price differences in diverse urban areas in each country. Moreover, metric money methods are widely used because they are objective, can be used as a basis for a range of socioeconomic variables, and allow for adjustment for differences between households and within-household inequalities (Chamhuri et al., 2012). Although many indicators are used to measure various dimensions of poverty in developing countries, almost all of them include health, education, and living standards (Vollmer & Alkire, 2022) because, according to the report Multidimensional Global Poverty Index (MGPI) from the United Nations, these indicators, along with many sub-indices, are recognized as the main framework for identifying poverty. Some of these sub-indices include standards in the fields of health, electricity, housing, cooking fuel, drinking water, property, years of education, school attendance, nutrition, and child mortality indicators (Alkire & Kanagaratnam, 2021). However, poverty is not static or a monotonic, one-way procedure. Over time, some people build assets and move out of poverty, while others experience shocks and are pulled into poverty (Hallegatte et al., 2018). In this regard, researchers, in addition to global indicators, use different indicators based on various perspectives and the existing conditions in their study area. For example, Dubey and Mahadevia, who studied the status of poverty in Indian metropolises for over two decades, used transportation factors as an effective indicator—based on their results, urban poverty and the size of the cities had an inverse relationship with new transportation systems. So, the construction of subway lines led to the expansion of poverty in metropolises (Dubey & Mahadevia, 2001). In addition, housing, known as a sub-index to identify urban poverty in global studies, has been examined in some studies in a broader way and with different dimensions. For example, a study titled "Spatial Analysis of Urban Poverty in Tehran Metropolis "is considered a main index along with economic, social, and educational indicators. According to this study's findings, which have been achieved through the factor analysis and application of the fuzzy VIKOR method, housing is the most influential factor in the spatial distribution of urban poverty in the Tehran metropolis. It has a close and complicated relationship with economic conditions (Movahhed et al., 2016). Some researchers also consider cultural factors an effective indicator for identifying poverty; for example, in research entitled "Identification and spatial analysis of urban poverty zones, Case study: Zahedan City," cultural, physical, economic, and social dimensions are considered simultaneously, and the results of this research indicated that cultural factors affect the formation and development of poverty zones than other factors significantly (Zanganeh et al., 2015). In another study conducted in Kumasi, Ghana, researchers analyzed the expansion of poverty areas over five years. They considered factors such as income, cost of living, housing units, the presence of companies, access to social services, and immigration issues for nine city areas that have been investigated. Their findings showed that the level of education and economic and social status are efficient in the distribution of poverty (Poku-Boansi et al., 2020). As mentioned at the beginning of this section, researchers use different indicators to measure poverty based on different conditions and perspectives. In this research, taking into account the international and national indicators and the data available in the country's official census, 20 indicators related to economic, demographic, and housing issues were selected, shown in Table 1.

Table 1. Urban poverty indicators

Dimension	Indicator	References
Economic	**Total unemployment** The ratio of unemployed population to ten years old population and more	1,2,3,4,5,8,26,27,28
	Unemployment of men The ratio of unemployed men to ten years old population and more	6,7,8,11,24,26,27,28
	Unemployment of women The ratio of unemployed women to ten years old population and more	6,7,8,11,24,26,27,28
	Economic burden The ratio of the total population to the working population	27,28,29
	Population burden The ratio of the total population to the employed and unemployed population	27, 28,29
	Dependency rate (net) The total population minus the employed population and then divided by the employed population	20,27,28,29
	Dependency rate (gross) Total population (0-14) and (+65) divided by population (15-64)	20,27,28,29
	Dependency rate (UN) Total population (0-25) and (+65) divided by population (25-64)	20,27,28,29
Population	**Total illiteracy rate** The ratio of illiterate individuals to the total population (6years old and more)	10,12,22,26,27,28,29
	Male illiteracy rate The ratio of illiterate men to the total population (6years old and more)	6,10,11,12,13,22,24
	Female illiteracy rate The ratio of illiterate women to the total population (6years old and more)	6,10,11,12,13,22,24
	Percentage of women never married The ratio of never-married women to the number of women of marriageable age	6,11,17,24,28
	Percentage of men never married The ratio of never-married men to the number of men of marriageable age	6,11,17,24,28
	Divorce rate The ratio of men and women without spouses due to divorce to men and women with spouses	17,18,21,23,26,28,29
	Aging population The ratio of people over 65 years old to the total population	9,19,20,25,26,27,28
Housing	**Dilapidated housing** The ratio of residential units with wood, brick, wood and clay materials to the total number of residential units	14,15,16,28,29
	Housing with 50 square meters and less The ratio of residential units with an infrastructure of less than 50 square meters to the total	28,29
	Rental housing The ratio of rental units to total residential units	14,15,16,28,29
	household size The ratio of population to the number of households	28,29
	Household density in residential unit The ratio of the number of households to the total number of residential units	14,15,16,28,29

1. (John & Morufu, 2013), 2. (Xue & Zhong, 2003), 3. (Aiyedogbon & Ohwofasa, 2012), 4. (Egunjobi, 2014), 5. (Adelowokan et al., 2019), 6. (Kimani & Kombo, 2010), 7. (Okojie, 2003), 8. (Chen et al., 2006), 9. (Walker, 1980), 10. (Tarabini, 2010), 11. (Shrider et al., 2021), 12. (Awan et al., 2011), 13. (Antony & Rao, 2007), 14. (Chirisa & Matamanda, 2016), 15. (Medina et al., 2020), 16. (Zhao et al., 2021), 17. (Leopold, 2018), 18. (Arditti, 1997), 19. (Barrientos et al., 2003), 20. (Barrientos, 2002), 21. (Espenshade, 1979), 22. (Hofmarcher, 2021), 23. (Hogendoorn et al., 2020), 24. (Jackson, 1996), 25. (Lloyd-Sherlock, 2000), 26. (Ghorbani & Dadazade Silabi, 2021), 27. (Nazmfar et al., 2020), 28. (Nikpour et al., 2021), 29. (Yarahmadi & Nikpour, 2021)

STUDY AREA

In the northern hemisphere of southwest Asia, Iran is the 17th largest country globally, encompassing approximately 1,874,000 square kilometres (Nami & Heidaripour, 2012). According to the most recent official census, the nation boasts a population nearing 80 million, with a substantial 74% living in urban areas. This transformation is outstanding, especially considering that only 31% of the population were urban residents during the first census. The data reveals a substantial change in Iran's urban landscape over the decades. The number of cities has surged from just 200 in 1956 to an impressive 1,245 by 2016, highlighting the rapid urbanization and development taking place in the country. Even more notable is the growth in the number of metropolises; Tehran was the only metropolis with a population exceeding one million in the first census, while by 2016, Iran was home to 18 bustling metropolises. This extraordinary urban growth underscores the dynamic changes shaping Iran today.

UN-Habitat defines a *metropolis* as a city with at least 300,000 inhabitants, functioning as a vital economic, political, and cultural center within a region. However, definitions differ across countries based on unique administrative and cultural criteria (da Cruz & Choumar, 2020). In Iran, the Supreme Council of Urban Planning and Architecture established that a metropolis is a city with a minimum population of 500,000. However, only cities with populations exceeding one million qualify for tax benefits, meaning cities above 500,000 are considered unofficial metropolises. At the same time, those above one million are officially recognized (Statistics Center, 2016). According to the 2016 census, Iran has 18 cities with populations over 500,000, of which nine exceed one million. Tehran has the highest population, while Arak has the lowest. Notably, Karaj showed the highest growth rate at 8%, compared to Tabriz's 2.84%. This study concentrates on the nine Iranian metropolises exceeding one million inhabitants, all eligible for tax law benefits (see Table 3 and Figure 1). Highlighting these cities is crucial for understanding Iran's urban development and economic importance.

Table 2. The Number and Population of Metropolises in Iran

Census Year	The number of cities	The number of metropolises	Total population of the country	Urban population of the country	Urban population / total population of the country (%)	Metropolises' population / total population of the country (%)	Metropolises' population / urban population of the country (%)
1956	200	1	18954704	5953563	31	8	25
1966	271	1	25788722	9794246	38	10	28
1976	452	4	33708744	15854680	47	19	41
1986	496	9	49445010	26844561	54	25	47
1996	614	9	60055488	36817789	61	26	42
2006	1014	13	70495782	48259964	68	28	42
2011	1139	14	75149669	53646661	71	31	43
2016	1245	18	79926270	59146847	74	34	45

Source: (Statistics Center, 2016)

Table 3. The Population of Iran's Metropolises in 2016

Row	Metropolis	Population	Growth rate	Row	Metropolis	Population	Growth rate
1	Tehran	8,693,706	2/95	10	Urmia	736224	4/06
2	Mashhad	3,001,184	4/28	11	Rasht	679995	3/09
3	Isfahan	1,961,260	3/52	12	Zahedan	587730	6/03
4	Karaj	1,592,492	8/14	13	Hamedan	554406	2/89
5	Shiraz	1,565,572	3/76	14	Kerman	537718	3/66
6	Tabriz	1,558,693	2/84	15	Yazd	529673	3/59
7	Qom	1,201,158	4/23	16	Ardebil	529374	3/53
8	Ahvaz	1,200,000	3/91	17	Bandar-Abbas	526648	5/81
9	Kermanshah	1,146,651	3/75	18	Arak	520944	3/69

(Source: Statistics Center, 2016)

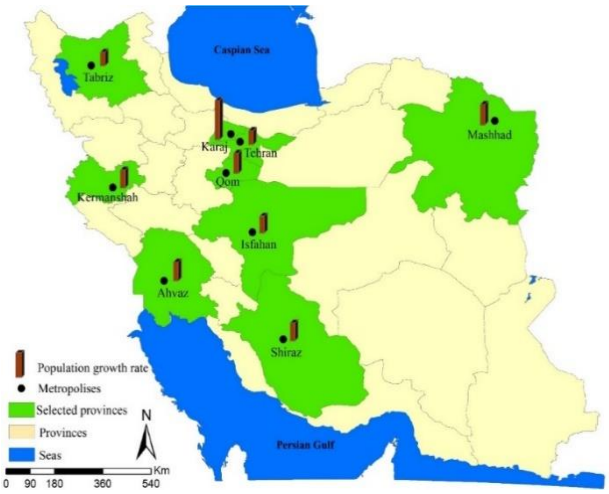

Fig 1. The Location and Population Growth Rate of Iranian Metropolises. (Source: Statistics Center, 2016)

METHODOLOGY

The current study employs a descriptive-analytical approach and consists of several interconnected steps. In the first stage, we selected the required indices for measuring urban poverty based on past research and the country's most recent official census data. In the next step, we utilized SPSS software and the Factor Analysis (FA) method to evaluate urban poverty in the selected metropolitan areas. This analysis helped us determine the number of poverty factors in each city, and we calculated the overall poverty level from the total number of identified factors. In the third step, we transferred the data to the ArcGIS software environment to analyze and create a poverty map. The kernel density method was employed to highlight the centers of urban poverty, categorizing city blocks into three main levels: primary, secondary, and tertiary. Finally, we used the local Moran statistic available in GeoDa software to identify the spatial patterns of poverty.

RESULTS AND DISCUSSION

Analytical Model

FA is a multivariate statistical technique (Shrestha, 2021) that encompasses two types: exploratory (EFA) and confirmatory (CFA) (DeCoster, 1998). EFA identifies the underlying structure among significant variables without an initial theory. It uncovers relationships and extracts factors based on variable correlations, which are then interpreted. In contrast, CFA involves pre-defined factor structures researchers seek to confirm or reject (Afshani et al., 2019). This research employs EFA due to the large data set and the complex dimensions of urban poverty indicators.

Evaluation of Data Suitability for EFA

Before conducting Exploratory Factor Analysis (EFA), evaluating the data using the Kaiser-Meyer-Olkin (KMO) and Bartlett's tests is essential. These tests help determine if a dataset can be condensed into key latent factors. The KMO test assesses whether a few underlying factors explain the variance among variables, while Bartlett's test identifies correlations and reveals the data's structure. For practical factor analysis, the KMO value should exceed 0.6, and Bartlett's test must reach a 95% confidence level (Sadeghpour & Moradi, 2018). Table 4 shows that the KMO value for all metropolitan areas exceeds 0.6, and Bartlett's statistic indicates a favourable outcome, confirming the robustness of the data correlation.

The main point is that initial SPSS tests revealed that some variables had commonality values below 0.4, indicating they did not significantly contribute to the analysis. Following the guideline from (Zebardast, 2017), these variables were removed, and the tests were re-run. The final results are shown in Table 4, while Table 5 lists the omitted indicators, notably "dilapidated housing" and "divorce rate," which do not significantly explain urban poverty in Iran's metropolises.

Factor Extraction

After completing the initial steps, we extracted poverty factors for each metropolis. While several criteria exist, Kaiser's rule is the most commonly used, stating that factors with an eigenvalue of one or greater should be extracted (Kaiser, 1960). Additionally, factors should explain at least 60% of the cumulative variance (Howard, 2016). In this study, Isfahan identified four factors, explaining 82% of the variance, making it the most effective city in capturing the essence of poverty.

In contrast, Tehran identified five factors but only accounted for 70% of the variance (see Table 6).

Effective Indicators of Poverty Rate

This section uses the factor loadings from the previous phase to identify effective indicators of urban poverty in each metropolis. For this analysis, we selected each city's three most significant indicators, as shown in Table 7. The results indicate that, among all the indicators examined in the research, three indicators—population burden, economic burden, and dependency rate (net)—were the most frequently identified and received the highest values as effective indicators.

Table 4. KMO and Bartlett's Test

City	KMO	Bartlett's Test	Sig
Tehran	0/711	737451/987	000/0
Mashhad	0/622	338055/023	000/0
Isfahan	0/763	585279/384	000/0
Karaj	0/724	232282/762	000/0
Shiraz	0/711	355839/460	000/0
Tabriz	0/841	534346/174	000/0
Qom	0/636	253692/963	000/0
Ahvaz	0/783	304249/936	000/0
Kermanshah	0/633	175945/497	000/0

Table 5. Indicators Excluded from Factor Analysis Calculations

City	Removed Index
Tehran	Dilapidated housing
Mashhad	Total illiteracy rate, Divorce rate, Dilapidated housing
Isfahan	Divorce rate, Dilapidated housing, Housing with 50 square meters and less
Karaj	Total illiteracy rate, Divorce rate, Dilapidated housing
Shiraz	Housing with 50 square meters and less
Tabriz	Divorce rate
Qom	Dilapidated housing, Divorce rate, Percentage of women never married, Total illiteracy rate
Ahvaz	Divorce rate
Kermanshah	-

Table 6. Factors Extracted in each metropolis

City	Number of components	Total Eigenvalue	% of Variance	Cumulative Variance
Tehran	1	3/123	17/384	17/384
	2	2/597	14/429	31/778
	3	2/465	13/692	45/469
	4	2/304	12/801	58/271
	5	2/179	12/106	70/377
Mashhad	1	3/668	21/575	21/575
	2	2/265	13/322	34/897
	3	2/198	12/929	47/825
	4	1/881	11/067	58/893
	5	1321	7/773	66/665
	6	1/168	6/870	73/535
	7	1/092	6/424	79/959
Isfahan	1	5/170	30/411	30/411
	2	3/170	18/646	49/057
	3	2/982	17/538	66/595
	4	2/605	15/323	81/918
Karaj	1	5/141	30/243	30/243
	2	3/454	20/315	50/558
	3	2/604	15/318	65/876
	4	2/384	14/024	79/900

City	Number of components	Total Eigenvalue	% of Variance	Cumulative Variance
Shiraz	1	3/879	20/417	20/417
	2	3/462	18/223	38/640
	3	2/831	14/898	53/537
	4	2/494	13/125	66/662
	5	1/382	7/274	73/935
	6	1/187	6/249	80/185
Tabriz	1	8/243	43/382	43/382
	2	4/139	21/784	65/166
	3	2/639	13/887	79/053
Qom	1	3/125	19/531	19/531
	2	3/066	19/161	38/692
	3	2/711	16945	55/637
	4	2/132	13/323	68/960
	5	1/551	9/691	78/651
Ahvaz	1	5/692	29/956	29/956
	2	2/601	13/687	43/643
	3	2/176	11/453	55/096
	4	1/687	8/879	63/976
	5	1/682	8/854	72/830
	6	1/149	6/048	78/878
Kermanshah	1	2/995	14/977	14/977
	2	2/840	14/199	29/176
	3	2/783	13/917	43/093
	4	2/197	10/984	54/077
	5	1/257	6/283	60/360
	6	1/071	5/357	65/717
	7	1/054	5/271	70/988

Table 7. Top Three Effective Indicators in each Metropolis

City	Effective indicators	Factor loading
Tehran	Dependency rate (net)	0.95
	Economic burden	0.919
	Population burden	0.876
Mashhad	Economic burden	0.97
	Dependency rate (net)	0.981
	Population burden	0.974
Isfahan	Household density in residential unit	0.826
	Dependency rate (gross)	0.769
	Population burden	0.700
Karaj	Percentage of women never married	0.988
	Population burden	0.982
	Dependency rate (net)	0.981
Shiraz	Household density in residential unit	0.849
	Dependency rate (UN)	0.824
	Household size	0.772
Tabriz	Population burden	0.944
	Household size	0.891
	Household density in residential unit	0.887
Qom	Dependency rate (gross)	0.982
	Household density in residential unit	0.804
	Rental housing	0.793
Ahvaz	Aging population	0.952
	Percentage of women never married	0.949
	Dependency rate (gross)	0.939
Kermanshah	Dependency rate (net)	0.875
	Economic burden	0.863
	Population burden	0.849

Spatial Analysis:

Urban Poverty Cores

After using factor analysis (FA) to reduce data volume, the resulting information was transferred to a geographic information system (GIS) environment. The Kernel Density Estimation (KDE) method illustrated urban poverty cores as a continuous surface. KDE is a widely utilized method for estimating a dataset's probability density function, offering flexibility in managing complicated distributions (Chen, 2017). This method is essential in spatial analysis and urban planning, effectively visualizing geographical densities. It is particularly effective for displaying linear and point data (Fazelniya et al., 2012). Due to its visual transparency and accuracy, KDE is widely used in various studies (Sargazi et al., 2021). In Iran's metropolises, three types of poverty cores have been identified: 1. Central Core of Poverty: Highest concentration, shown in red. 2. Secondary Core of Poverty: Lower concentration, depicted in orange. 3. Tertiary Core of Poverty: Lowest concentration, illustrated in green. Figure 2 presents these poverty cores in major cities across Iran.

The map indicates that cities like Tehran, Isfahan, Karaj, Ahvaz, and Kermanshah have multiple robust poverty cores, while Mashhad, Shiraz, and Tabriz have only one significant core. Qom is in the early stages of developing its central core. Poverty cores in Tehran, Isfahan, and Shiraz are mainly located in central areas, whereas Mashhad, Karaj, Tabriz, Qom, Ahvaz, and Kermanshah exhibit marginal contexts. The development process of these cores progresses through three stages:1. Formation of third-degree cores. 2. Increase in poverty intensity to second-degree cores. 3. Emergence of first-degree cores with severe poverty concentrations.

These cores are interconnected, with new cores forming around existing ones. Data in Table 8 shows that Isfahan has the most extensive area in the first and second cores, while Mashhad ranks highest in the third. Conversely, Qom, Tabriz, and Mashhad have the most minor areas. Regarding population, Isfahan leads in the first and second cores, while Qom has the highest in the third. The lowest populations of poverty cores are found in Qom, Mashhad, and Shiraz.

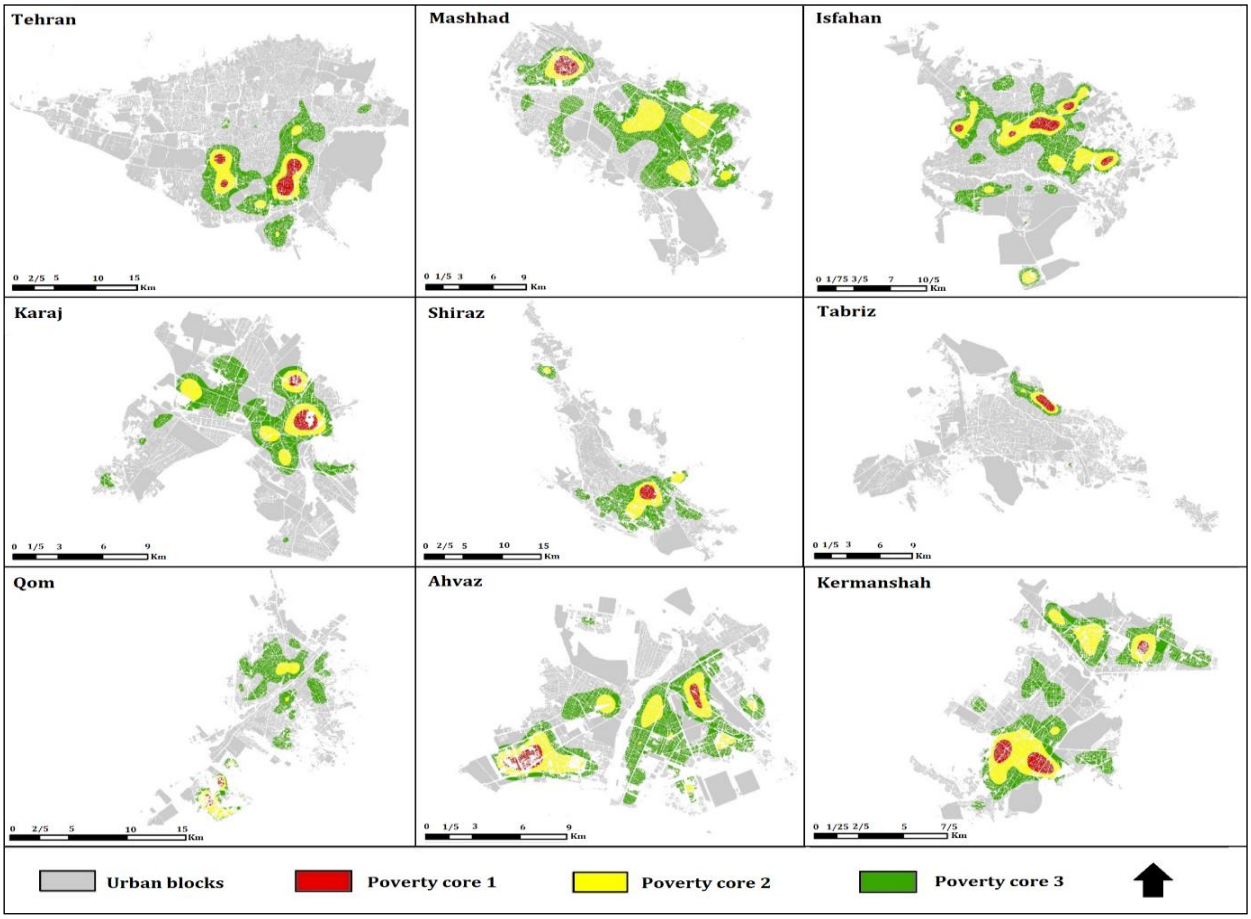

Fig 2. Urban Poverty Cores in Iran's Metropolises

The analysis of urban poverty in Iran shows significant disparities among cities. Mashhad and Kermanshah have the largest poverty areas, while Tabriz and Tehran have the smallest. For example, Mashhad has 39% of its area in poverty, followed by Kermanshah at 38%, Isfahan at 34%, Ahvaz at 33%, and Qom at 27%. In terms of population living in poverty, Isfahan and Ahvaz have the highest rates, with 61% and 60%, respectively. Tabriz and Tehran have lower figures, with Tabriz at only 13%. Among the cities, Mashhad has the highest proportion of urban poverty area, while Tabriz has the lowest. (Table 9) (Fig. 3)

Table 8. The Area and Population in each Poverty Core

City	Poverty Core 1				Poverty Core 2				Poverty Core 3			
	Population	%	Area	%	Population	%	Area	%	Population	%	Area	%
Tehran	334612	4	682	1	725426	8	1611	3	1799238	21	5043	11
Mashhad	41306	1	155	1	468496	16	1358	9	1223759	41	4719	30
Isfahan	120876	6	673	3	439278	23	2434	11	623728	32	4451	20
Karaj	43342	3	123	1	168714	11	539	5	468075	30	1887	18
Shiraz	30669	2	241	2	136144	9	817	5	472235	31	2685	17
Tabriz	45803	3	101	1	45259	3	105	1	115131	7	292	2
Qom	13801	1	24	0	93981	8	277	4	561267	47	1584	23
Ahvaz	44292	4	138	1	184504	16	765	8	467908	40	2180	24
Kermanshah	53351	6	178	3	145618	15	664	11	331299	35	1516	25

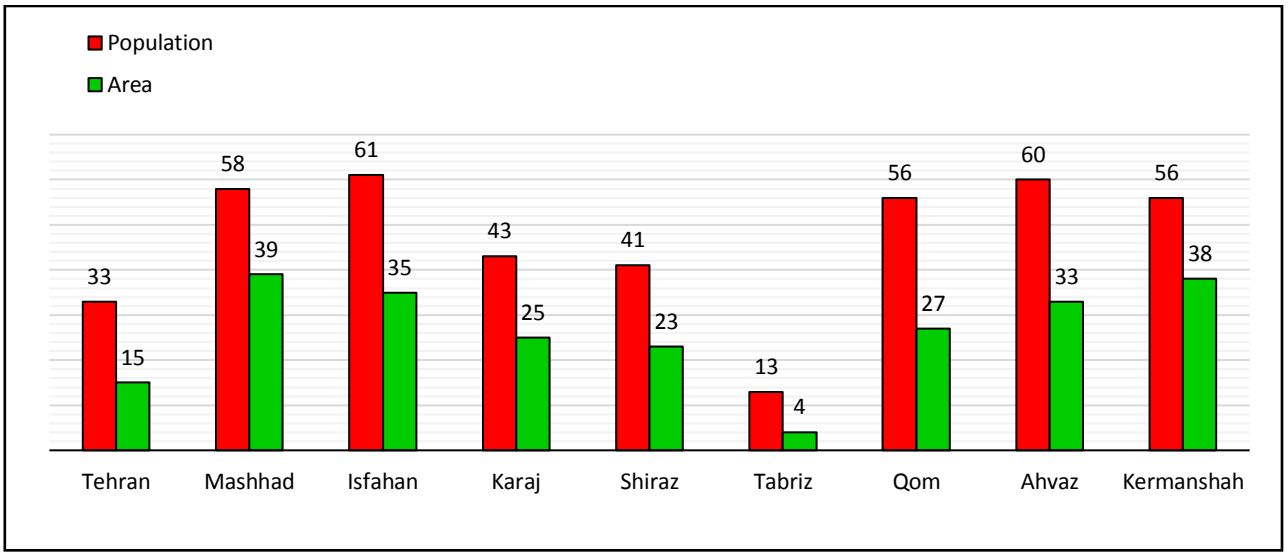

Fig 3. The Total Percentage of Poor Area and Population in Iranian Metropolises.

Table 9. The Total Population and Area of Iran's Metropolises

City	population	Area (Hectares)	Population of Poverty	%	Area of Poverty	%
Tehran	8,693,706	47572	2859276	33	7336	15
Mashhad	3,001,184	15919	1733561	58	6232	39
Isfahan	1,961,260	21898	1183882	61	7558	34
Karaj	1,592,492	10292	680131	43	2549	25
Shiraz	1,565,572	15930	639048	41	3743	23
Tabriz	1,558,693	12810	206193	13	498	3
Qom	1,201,158	6931	669049	56	1885	27
Ahvaz	1,200,000	9251	696704	60	3083	33
Kermanshah	1,146,651	6110	530268	56	2358	38

(Source: Statistics Center, 2016; and findings of the authors)

Spatial Pattern of urban poverty

This section investigated the distribution pattern of poverty in Iran's metropolises using spatial autocorrelation. In definition terms, "Spatial autocorrelation analysis examines whether the observed value of a variable at a particular point is significantly dependent on the values of the variable at neighbouring points or not." In this vein, Moran's I is a measure of spatial correlation statistics designed to test this dependence (Darand et al., 2017). This method generally discovers "the patterns and the levels of spatial clustering among neighbouring districts" (Tsai et al., 2009). This tool compares the resemblance of every object to its neighbours and presents a general view of the variable spatial pattern through an average of all comparisons. However, Local Moran's I explore which objects are similar or different to the objects in their neighbourhood and considers more details. In the local Moran statistic, the map and the distribution diagram of complications are divided into four clusters, showing the local correlation pattern between the regions and their neighbours. The High-High cluster represents areas where poverty is spatially self-correlated, and other poor blocks surround an inferior block. The High-Low cluster represents areas where a poor block is surrounded by other blocks that do not have poverty. The Low-Low cluster displays the absence of poverty in a region and its neighbouring regions. Finally, the Low-High cluster illustrates the areas where other poor blocks surround a non-poverty block (Nikpour et al., 2022). In this study, Local Moran's I tool was utilized to determine the pattern of poverty distribution, and based on the results (Fig. 4, Fig. 5), the poverty clusters in the cities of Isfahan, Tabriz, Tehran, Shiraz, and Qom consist of one or two extensive clusters. However, these clusters do not follow a regular spatial pattern despite their formation in cities such as Mashhad, Karaj, Ahvaz, and Kermanshah. They are seen in a scattered form throughout the city. Moran's scatter diagram of Iran's metropolises shows many urban blocks within the high-high cluster. This situation indicates that many cities block in the vicinity of each other have caused the formation of poverty clusters. This graph shows that many urban blocks in Isfahan and Tabriz are located in the High-Low area. The location of the blocks in this range indicates that some poor urban blocks are in the neighbourhood of non-poverty blocks; Therefore, they could not form a cluster and became single-celled (non-clustered). Based on this diagram, it was found that several urban blocks, especially in Tabriz and Isfahan, are in the Low-High range; this shows that the number of non-clusters of poverty in these two cities is higher than in other cities. Finally, there is the low-low cluster; except for Isfahan and Tabriz, other cities are in almost the same situation. The location of the blocks in this cluster shows that several blocks without poverty have formed a cluster in the vicinity of other blocks without poverty.

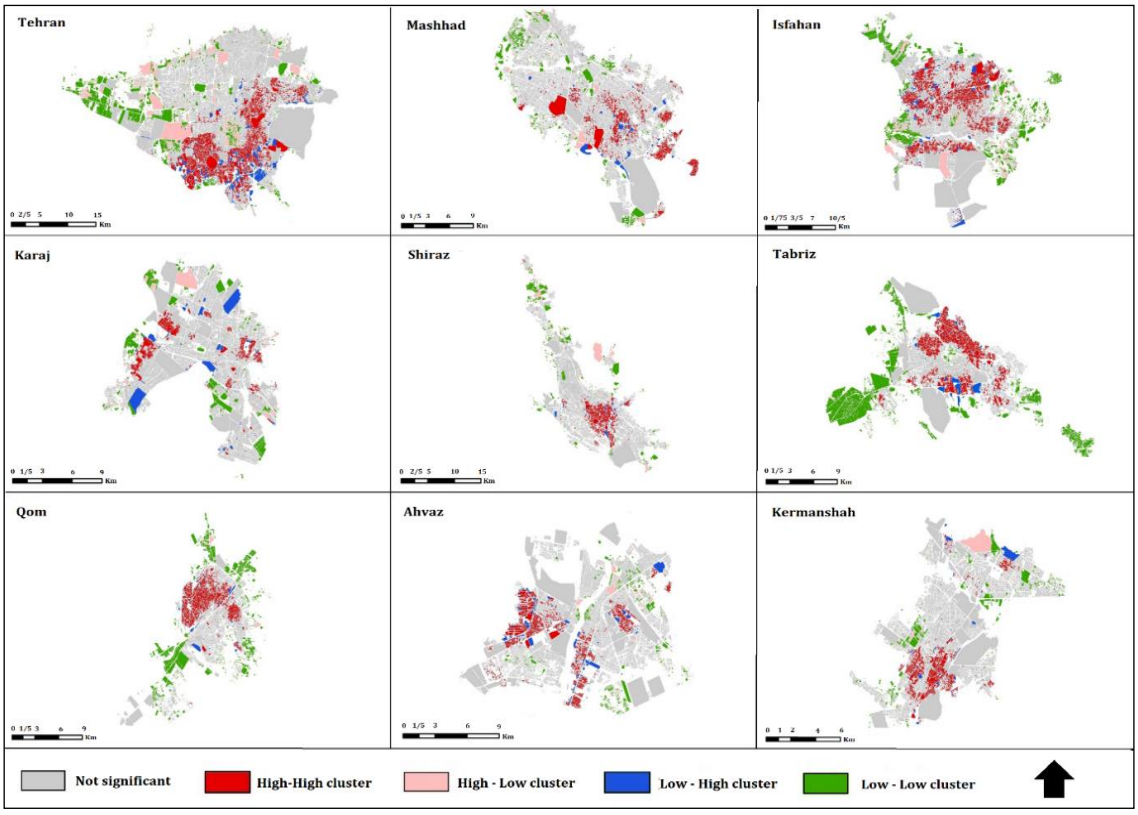

Fig 4. Urban Poverty Clusters Based on Moran's autocorrelation test

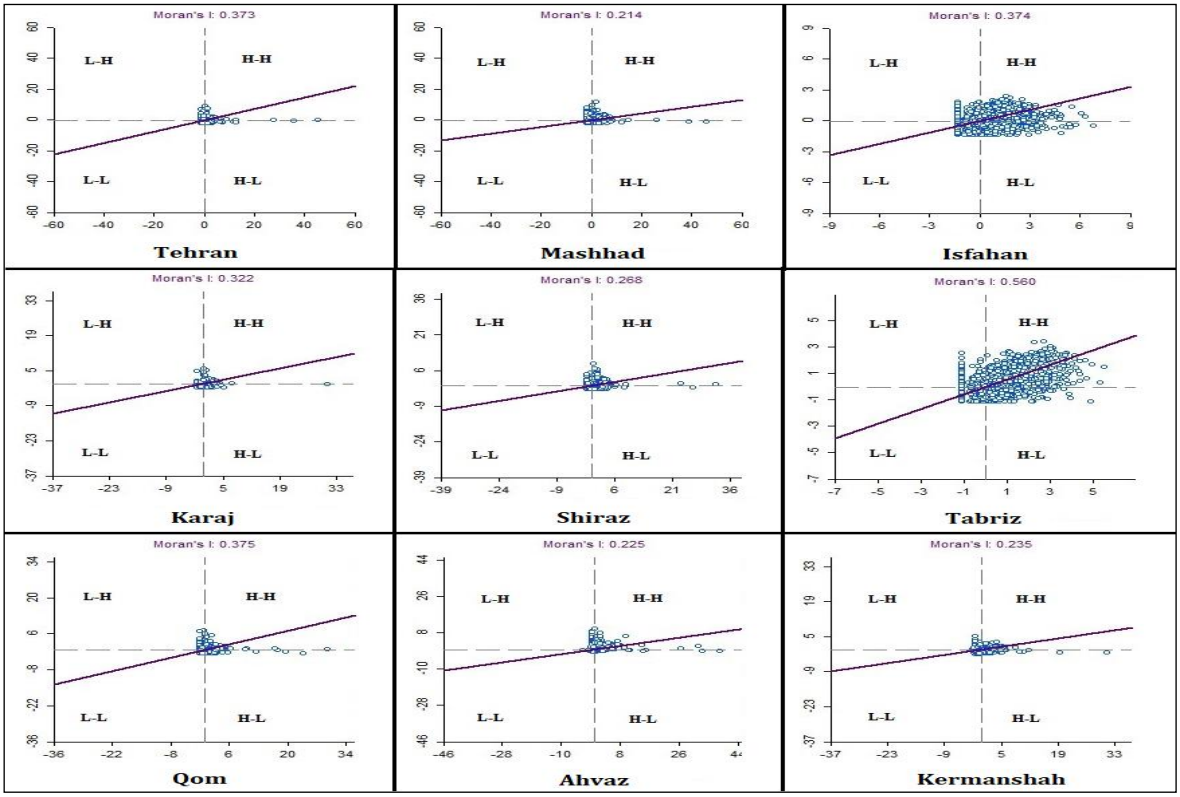

Fig 5. Spatial Distribution Diagram of Urban Poverty

CONCLUSION

In recent decades, poverty and its measurement have received considerable attention in development policies worldwide, particularly in developing countries. Poverty is a complex and multidimensional phenomenon that manifests through various perspectives, such as lack of opportunities, inability to meet basic needs, inadequate social services, low income, inequalities, and marginalization. This study has focused on urban poverty across nine metropolises in Iran, analyzing three dimensions—physical, social, and economic—through 20 carefully selected indicators.

The findings demonstrate significant social-spatial heterogeneity among urban blocks in these metropolises. The clustering of slum areas has resulted in concentrated poverty cores, predominantly in marginalized areas with outdated and deteriorating infrastructure. The study reveals that approximately 44% of the total population and 24% of the land area in these metropolises fall within poverty cores. Key factors such as population burden, economic burden, dependency rate, household density, and unemployment significantly contribute to the spread of urban poverty.

Economic challenges, such as the declining economic growth caused by extensive international sanctions, have exacerbated unemployment, income inequality, and inadequate public services. Additionally, rapid rural-to-urban migration has added pressure on urban infrastructure and services, resulting in the expansion of informal settlements and slum areas. Ineffective governmental policies, including poor urban planning, inequitable resource distribution, and reductions in social housing budgets, have further concentrated poverty in specific regions. Social dynamics, such as low education levels, divorce rates, and high celibacy rates, have also contributed to the prevalence of poverty, particularly in central urban areas.

Despite the study's robust methodology, it is essential to acknowledge its limitations. The selected indicators may not fully capture the multidimensional nature of poverty, overlooking cultural and social dimensions. Additionally, census data, while valuable, may not reflect rapid changes in poverty patterns due to its periodic nature. Furthermore, spatial models such as Kernel Density Estimation (KDE) are highly dependent on data quality and may underrepresent low-density regions.

To address these limitations, future research could employ longitudinal studies to track poverty dynamics over time and incorporate qualitative methods, such as interviews or focus groups, to understand the lived experiences of individuals in poverty cores. Evaluating the impact of specific government policies on poverty reduction or exacerbation and conducting

comparative analyses with other countries could also provide valuable insights and innovative solutions.

Understanding the socio-political context, such as the impact of international sanctions, migration patterns, and government policies, is essential for developing effective poverty reduction strategies. Policymakers must prioritize equitable resource distribution, infrastructure improvements, and targeted social programs to address the root causes of poverty.

By situating the findings within the broader socio-political and economic context, this research provides a comprehensive framework for addressing urban poverty in Iran's metropolises and offers insights applicable to similar challenges in other developing nations. Future efforts must focus on multi-dimensional and inclusive approaches to alleviate poverty and foster sustainable urban development.

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