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Spatial Analysis of Local Scale Socioeconomic Disparities: The Case of Izmir, Turkey

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The spatial disparities present in modern cities pose many challenges, such as social, demographic, and economic dimensions, and create obstacles to achieving equitable opportunities and the sustainability of cities. A wide range of variables is utilized to demonstrate the socioeconomic structure of a city; however, much of this data is often limited at local levels, such as neighborhoods, particularly in developing countries. This study aims to analyze socio economic structure of urban areas through a number of indicators. At a local scale that take neighborhood units as basis, a set of key indicators; basic demographics and education levels, were utilized to assess the socioeconomic structure and disparities across the space to identify areas that may be experiencing inequalities or social disadvantage. The study area encompasses the urban core of İzmir, Turkey, which includes the urbanized residential areas of 340 neighborhoods. Multivariate statistics and spatial statistics were performed to gain a deeper insight into socioeconomic nexuses, and their spatial patterns. Empirical results reveal that there are clusters of low and high socioeconomic status neighborhoods which can help making informed decisions regarding local disparities and social disadvantage. This type of analysis can promote more equitable and sustainable development across a city by supporting formulation of targeted interventions, and can also help inform efficient resource allocation decisions.

Keywords: *disparities, cluster, neighborhoods, socioeconomic, limited data*

Introduction

As urbanization continues to accelerate worldwide, the complexities and threats in modern cities become more increasingly pronounced (Van Ham et al. 2021). Among these complexities and threats are the spatial disparities that manifest across various social, demographic, and economic dimensions. Communities facing socio-demographic and economic disparities often experience unequal access to essential resources such as quality education, healthcare, transportation, recreation, and housing (Fan et al. 2017, Owens and Candipan 2019, Wen et al. 2018). In this regard, understanding the socioeconomic structure of a city is crucial to addressing these challenges. Socioeconomic structure of a community or a city is a multidimensional construct and there are many variables that are used to represent the different aspects of it, such as, demographic profile, household structure, employment, income, education level, social aid, to name a few. However, accessing detailed data at the local level—particularly in developing countries—remains a persistent issue. In many cases, existing data of socioeconomic indicators

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are at the provincial or regional scales. The local scale data is either unavailable or of restricted use, thereby obscuring the specific conditions at the intra city scale, i.e., of neighborhoods. This lack of localized data not only makes it challenging to depict the actual situation, it impairs the development of targeted policies aimed at alleviating social disadvantages and inequalities faced by certain communities or localities across the city. Therefore, there is a need for analyses which are less data demanding that utilize basic indicators to depict socioeconomic landscape at finer spatial resolutions. This study seeks to bridge this gap by analyzing the socioeconomic structure of urban areas, providing insights into the variability of conditions across the urban environment and examines the following research questions, i) How do basic socioeconomic indicators, such as elementary demographics and educational attainment, vary across the neighborhoods of urban İzmir, and what spatial patterns can be identified that correlate with social disadvantage and inequality?, (ii) What multivariate and spatial statistical methods can be effectively utilized to analyze the relationships among socioeconomic components at a neighborhood scale, and how might these methods help in developing targeted policies for alleviating social disparities in urban areas?

By concentrating on the urbanized residential areas of İzmir, Turkey, which comprises 340 neighborhoods, the research aims to unveil the spatial pattern of these indicators and identify areas most affected by inequality and social disadvantage. Utilizing multivariate and spatial statistical methods, the study aims to uncover the intricate relationships among socioeconomic components and their spatial patterns.

Background

Communities facing socio-demographic and economic disparities often experience unequal access to essential resources. Socioeconomic disparities in a city can lead to social fragmentation, social tension, and conflict (de Jeude et al. 2016). Areas with significant economic disparities may face challenges such as, unemployment, a lack of investment, and housing (Andersson and Hedman 2016, Custers and Engbersen 2022). Socioeconomic inequalities often correlate with health disparities, where marginalized communities may suffer from poor health outcomes, low quality of life, and safe living environments (Woolf and Braveman 2011, Braveman and Gottlieb 2014). These disparities of social, demographic, and economic dimensions create obstacles to achieving equitable opportunities and outcomes for individuals and negatively impact the sustainability of cities as social and economic systems (Buck et al. 2021). The process is usually accompanied by decline in both the quality and availability of services that negatively impact quality of life, exacerbating spatial clustering and segregation and diverting communities from their sustainability objectives (Brorström 2015). Amongst 17 Sustainable Development Goals (SDGs) (UN 2015), Goal 11 aims to create inclusive, safe, resilient, and sustainable cities and human settlements, acknowledging the persistent challenges faced by urban areas. Rapid urbanization contributes to the emergence of slums and underprivileged neighborhoods struggling with inadequate infrastructure and services.

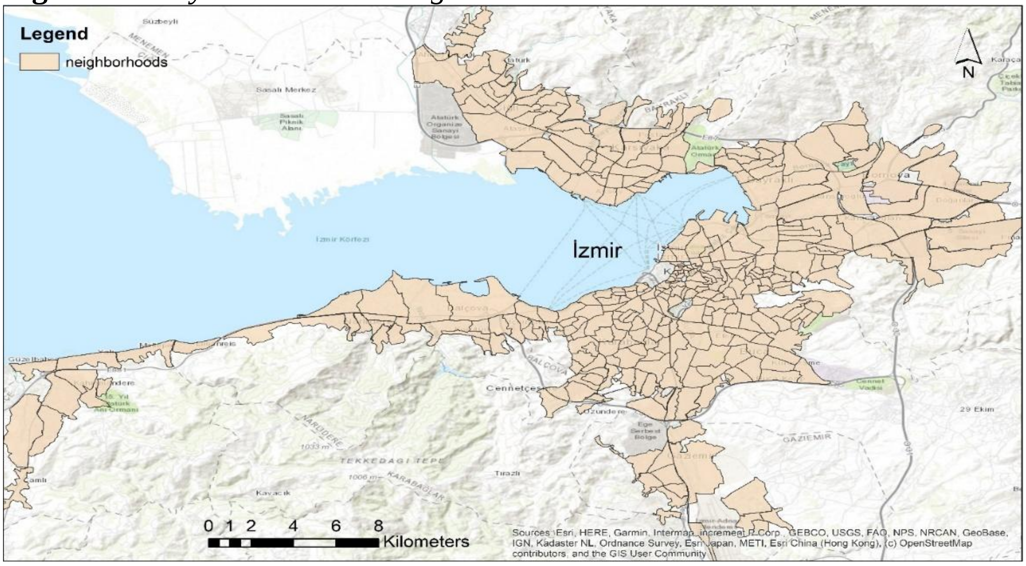
Urban population characteristics distributed across space homogeneously is quite uncommon. In cities with a background of industrial development, such as İzmir, spatial segregation is usually inevitable (Alver 2010). Segregation is a condition that manifests as exclusion and isolation among social groups across urban space (Boal 1987). All developed societies demonstrate an extent of social inequity, which manifests as residential segregation in spatial context (Jürgen 1998). Yet, the main concern is the degree and severity of that segregation rather than its mere existence. These disparities create challenges for policymakers and city planners, as they hinder the ability to provide equitable opportunities for all residents and maintain the sustainability of urban environments.

Study Area

The concentrated residential area of the city, İzmir, was selected as the study area (Figure 1). Izmir has been an important port city for more than 8000 years. It is the third largest city in Turkey with population 4,479,525 as of 2023 (TUIK 2023)[1]. With the heavy industrialization, Izmir has been a key destination for uncontrolled migration and rapid urbanization since 1950s (Yetişkul and Kul 2023). It's warm climate, geographical advantages, attractions and lifestyle have consistently made the city appealing, contributing to the ongoing trend of urbanization to this day. Conversely, the city suffered from a lack of organized and comprehensive planning, resulting in poorly coordinated development, which could only be eased with rapid solutions and haphazard planning. As a consequence, there are substantial disparities among the different parts of the city, such as between old neighborhoods, rapidly grown informal residential areas (squatters), or other new residential areas that are formal.

[1]https://data.tuik.gov.tr/Bulten/Index?p=Adrese-Dayali-Nufus-Kayit-Sistemi-Sonuclari-2023-49684.

Figure 1. *Study Area and the Neighborhoods*



Data and Materials

The study scale was set as the neighborhoods level that is the smallest administrative unit in the country. Neighborhoods in this context are the building blocks of a city and they represent a relatively homogeneous area in terms of demography, socioeconomic status and housing characteristics. The urbanized area of the city encompasses a total of 367 neighborhoods. However, 27 of these were excluded, as some represented low-density peripheral semi-rural residential, while others coincided with the commercial central district, where residential use was minimal. Consequently 340 neighborhoods remained for the analyses.

In Turkey, as in many developing countries, fine-scale data is often either unavailable, inaccessible, or subject to restrictions on its use. As a result, much of the statistical data needed to fully understand the socioeconomic structure at the neighborhood level, including income, employment/unemployment, and household composition, remains out of reach. In an effort to reveal underlying information on the socioeconomic structure of the city, a limited set of sociodemographic data available at the neighborhood scale was employed (Table 1). The data was obtained from the Census Office of the Turkish Statistical Institute (TUIK) belonging to date 2021. The data is accessed in its raw format upon request and is then restructured into rows and columns, with rows representing neighborhoods and columns representing variables. The up to date neighbourhood borders vector data was obtained from İzmir Metopolitan municipality, GIS department.

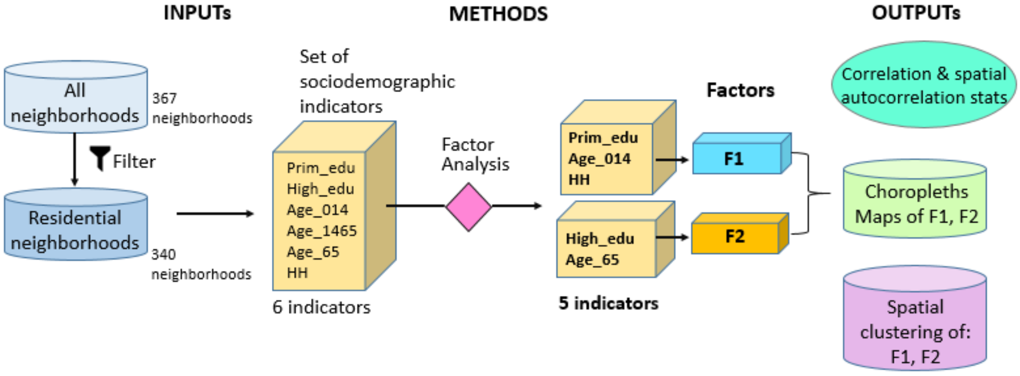
Table 1. *Sociodemographic Indicators at Neighborhood Scale*

Indicator (abbreviation)	Explanation
Age_014	% of Child population at age 0 to 14
Age_1465	% of Active population at age 15 to 65
Age_65	% of Elderly population at age 65 +
Prim_edu	% of Primary education graduates
High_edu	% of High education graduates (Bachelor's degree)
HH	Average Household size (number of persons per house)

Methods

The methods for the study area include a correlation analysis to explore the bivariate relationships among all the variables utilized in the study. A Factor Analysis (FA) was conducted to reduce the dataset's variability to a few underlying dimensions. Multivariate statistics including Pearson Correlation and Factor Analysis were conducted using SPSS 25. Additionally, a spatial autocorrelation test was performed using the "Spatial Statistics" toolbox of ArcGIS Pro to determine whether there is spatial clustering of the variables and Factors (components), as well as the strength of this clustering. This measure helps to reveal whether districts exhibiting similar characteristics are grouped together within the study area, indicating potential socio-spatial segregation. Furthermore, the Factors representing socioeconomic status were mapped to visualize any spatial patterns of clustering. The workflow of the methods is illustrated in Figure 2.

Figure 2. *Method Workflow*

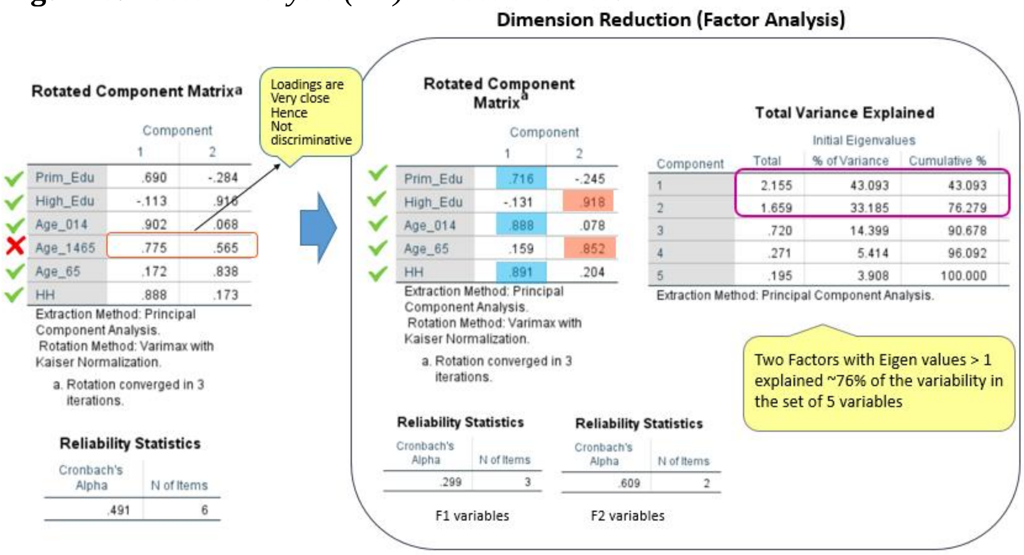


Results

Factor Analysis

The socioeconomic and demographic data are usually correlated, and there is usually redundancy in the datasets. Factor analysis (FA) was performed to reduce the dimensionality of the data and identify the principal directions in which the data vary, by transforming a set of correlated indicators into a small set of uncorrelated ‘components’ that represent the underlying dimensionality of the data. The factor loadings represent the correlation of the variables with the derived factors. The highest factor loadings help in understanding the semantics of those components/ factors. Conversely, if a Factor loading does not indicate a strong correlation with any of the factors or its correlation with two or more Factors are close in value, it is considered a non-discriminative variable in the dataset, as was the case with Age_1465, representing active population. These variables are better removed, if their removal does not make much difference in the total variance explained. Therefore, Age_1465, was removed from the dataset. From the remaining five variables, three of them was linked with Factor 1 (F1), and two of them was linked with Factor 2 (F2). These two Factors with Eigen values greater than 1, explained about 76% of the variability in the whole dataset. The phases and results of FA procedures is demonstrated in Figure 3.

Figure 3. *Factor Analysis (FA) Phases and Results*



Accordingly, Factor 1 (F1) is related to low education, large households, and high children rate, that is an indication of a low socioeconomic status. Factor 2 (F2) is related to high education, and high elderly rate, with more educated and wealthy people and relatively old/quaint neighborhoods with older residents that is an indication of higher socioeconomic status.

Correlation Analysis

Correlation serves as an inferential statistical tool to analyze the data and assess how the variables in the dataset are interrelated. The relationship between the variables, their degree and direction were quantified using Pearson’s r Correlation coefficient. Accordingly, it was observed that there is high correlation between F1, and relevant variables of F1, namely, Prim_edu, Age_014, and HH. Similarly, there is high correlation between F2 and relevant variables of F2, namely, High_edu, Age_65 (Table 2). For F1, rate of children, rate of graduates of primary education (lowest education level) and household size is correlated, which means large families with lower level of education and many children characterize lower socioeconomic status and visa versa. On the other hand, high education rates (university graduates) negatively correlate with low education in the neighborhood and high education is not correlated with household size or children rate. High education is rather correlated with age_65, where more educated people tend to exist in neighborhoods with older people or the older people living in these neighborhoods are more educated. However, the underlying phenomenon about this condition should be further checked in the spatial context.

Table 2. *Pearson Correlation Results for the Indicators and Factors*

Correlations								
		Prim_Edu	Age_014	HH	High_Edu	Age_65	**F1**	**F2**
Prim_Edu		1	.408**	.423**	-.313**	0.079	.716**	-.245**
Age_014		.408**	1	.794**	-0.011	0.095	.888**	0.078
HH		.423**	.794**	1	0.079	.219**	.891**	.204**
High_Edu		-.313**	-0.011	0.079	1	.607**	-.131*	.918**
Age_65		0.079	0.095	.219**	.607**	1	.159**	.852**
F1		.716**	.888**	.891**	-.131*	.159**	1	0.000
F2		-.245**	0.078	.204**	.918**	.852**	0.000	1
**. Correlation is significant at the 0.01 level (2-tailed).								
*. Correlation is significant at the 0.05 level (2-tailed).								

Spatial Autocorrelation (Hotspot Analysis)

Global Moran's I is a measure that quantifies spatial dependence between values of the same variable across space, that is spatial autocorrelation. Global Moran's I index statistics were calculated for each variable and the two factors (F1, and F2). The index values may range between -1 +1, where values close to +1 indicate a high spatial dependence of variables. P value < 0.05 indicates the significance of the clustering at 95% confidence interval (Table 3).

Table 3. *Global Moran's I Statistics of the Indicators and Factors*

	Prim_edu	Age_014	HH	High_edu	age_65	**F1**	**F2**
Moran's I	0.159	0.231	0.276	0.395	0.371	0.289	0.356
Z-score	3.79	7.26	7.33	10.59	9.56	8.057	10.58
p value	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Accordingly, all of the variables and components show some sort of spatial clustering that is statistically significant. Neighborhoods with similar socioeconomic characteristics tend to be closer to each other. The highest amount of spatial dependence (clustering) is for F2 and its relevant variables, whereas F1 and its relevant variables show less thereof. This indicates that more established, old, and quaint neighborhoods that are considered wealthy are at certain parts of the city. Low socioeconomic status neighborhoods also show clustering that are observed to coincide with the rapidly urbanized informal settings of the city.

Besides mapping of F1 and F2, a local spatial autocorrelation analysis (Getis Ord Gi*) was performed to depict the hotspots of low socioeconomic status and high socioeconomic status across the city. Figure 4, and 5 represents F1's choropleth map and hotspots map, respectively. Low socioeconomic status neighborhoods have standard deviation of 0.5 and above, and are shown in shades of red-orange (Figure 4). Low socioeconomic status neighborhoods that shows significant clustering at confidence interval > 95% and above were identified as hotspots and shown in red color (Figure 5).

Figure 4. *Choropleth Map of Low Status Neighborhoods (std. dev > 0.5)*

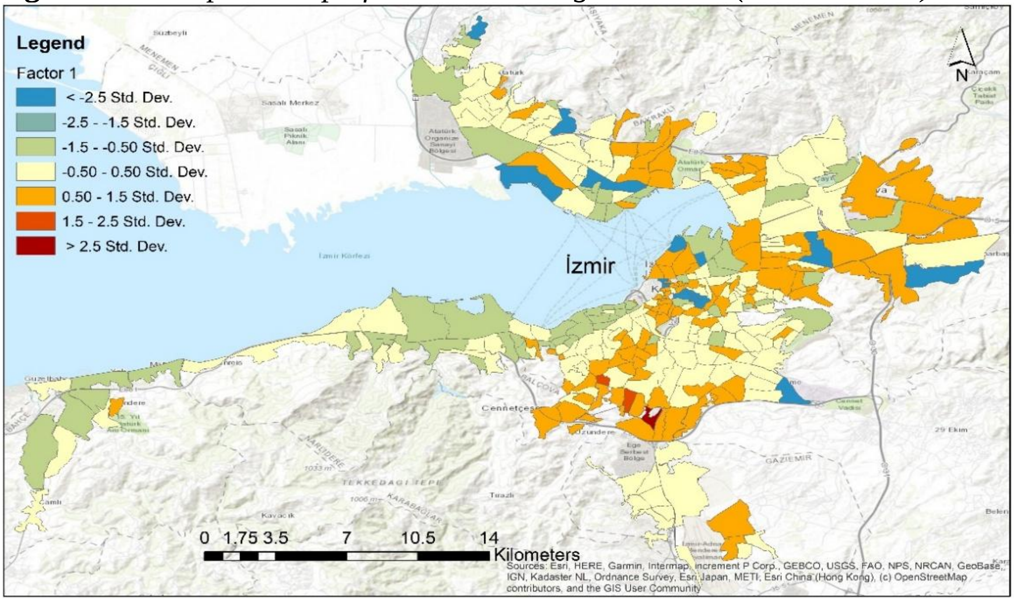
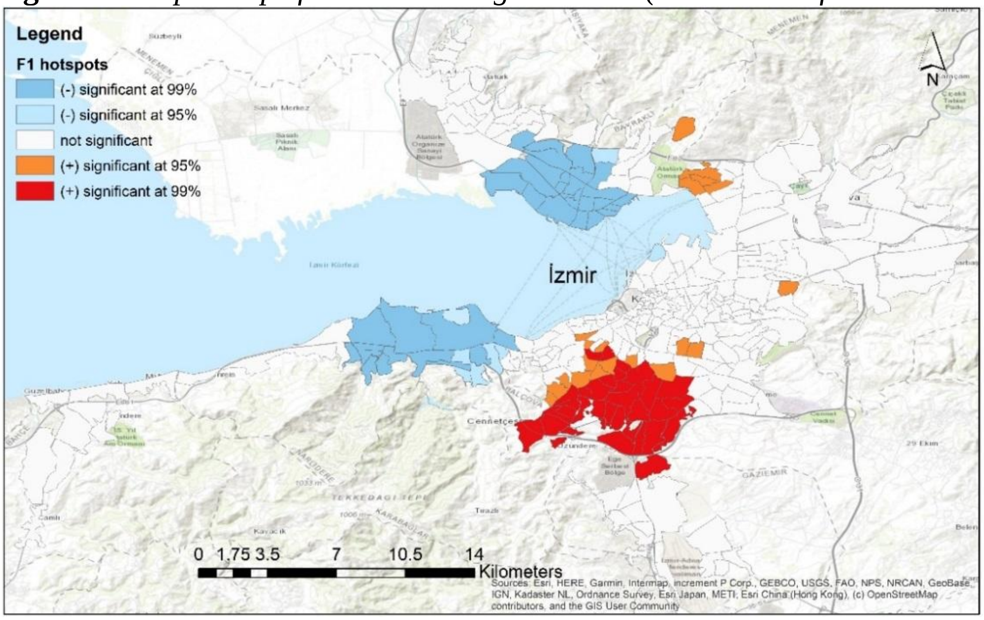


Figure 5. *Hotspot Map of Low Status Neighborhoods (at >95% Confidence Interval)*



Figures 6 and 7 represent F2's choropleth map and hotspots map, respectively. Old wealthy neighborhoods showcasing high socioeconomic status have standard deviation of 0.5 and above, and are shown in shades of blue (Figure 6). Those neighborhoods that shows significant clustering at confidence interval > 95% and above were identified as hotspots and shown in red color (Figure 7).

Figure 6. *Choropleth Map of Old Quaint and Wealthy Neighborhoods Showcasing a High Socioeconomic Status (std. dev > 0.5)*

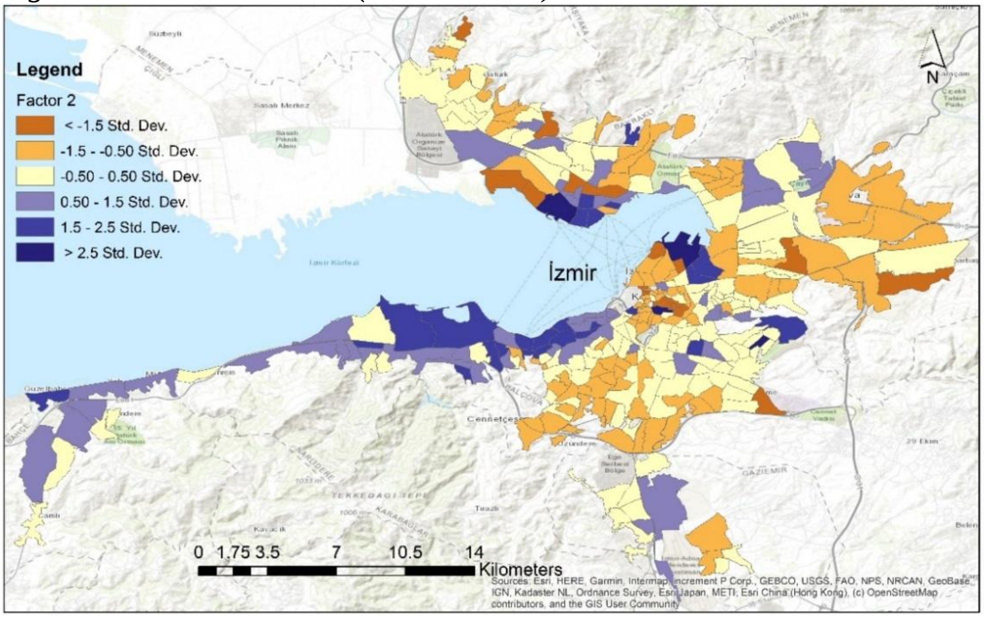
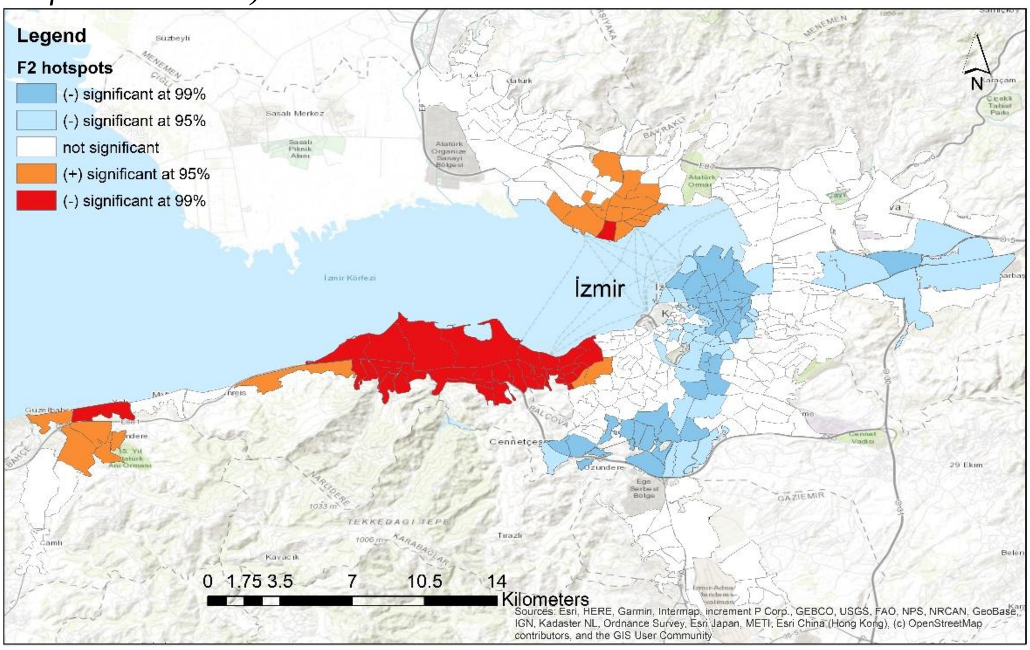


Figure 7. *Hotspot Map of High Socioeconomic Status Neighborhoods (at >95% Confidence Interval)*



Discussion and Conclusion

In an effort to reveal underlying information on the socioeconomic structure of a city at the neighborhood scale, a limited number of sociodemographic data available at the neighborhood level was used. Multivariate statistics and spatial statistics were employed to gain a deeper insight into components of socioeconomic nexuses, and their spatial patterns. The empirical findings reveal that there is significant clustering in socioeconomic status across the city. This means that high socioeconomic status neighborhoods tend to be close to each other in particular areas of the city, known as established, quaint neighborhoods, deemed wealthy. The situation is similar for low socioeconomic status neighborhoods as well, which are the areas were subject to rapid urbanization and informal housing. As the main concern is the degree and severity of the segregation rather than its mere existence, results reveal large clustering of the sociodemographic characteristics of the neighborhoods, primarily, higher education rate and elderly rate, indicating disparities across the urban space.

From a methodological perspective, a very limited set of demographic and education variables were effectively used in understanding spatial patterns of deprived and wealthy neighborhoods. Multivariate statistics, such as Factor analysis was adequate in removing redundancy and reducing the dimensionality of the data to meaningful Factors. Using spatial statistics, such as spatial autocorrelation and Hotspot Analysis was very beneficial in understanding the spatial patterns of clustering that may be an indication of spatial segregation. From policy perspective; this approach that utilize limited data, can help strategic prioritization of improvement of deprived neighborhoods in the city. It promotes spatially nuanced interventions to effectively enhance quality of life, particularly in less developed cities with limited resources to allocate to such improvements. This data-efficient approach also allows for the rapid collection of preliminary information about both deprived or wealthy neighborhoods in a city, even with no or limited prior knowledge of the area.

However, relying on limited set of sociodemographic variables, may not capture the full complexity of socioeconomic dynamics across neighborhoods which could lead to an incomplete understanding of the factors influencing inequities, such as the qualitative aspects of life in these neighborhoods, including access to services and community cohesion. For example, the empirical findings highlight a spatial association where neighborhoods with higher education rates tend to be located in areas perceived as wealthy. However, this correlation does not prove causation and that socioeconomic status encompasses other factors beyond education alone. Due to limitations in the available data, the higher education rate was set as a key indicator of wealth.

To enhance the impact of the findings of this study, it is recommended that future research focus on the collection of more detailed demographic and socioeconomic data in neighborhoods identified as having substantial disparities. Such efforts could facilitate the development of targeted policies and interventions by the municipality of Izmir, ultimately leading to improved quality of life in deprived areas. Building on this foundation will lead to a more nuanced understanding of the city's socioeconomic dynamics and enable the implementation of proactive approaches to urban development. While the present study utilized a limited dataset, the analysis aims to draw attention to significant trends and potential areas for further inquiry and intervention and serves as a starting point for more extensive research.

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