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The Clustering of the Population at Building Scale in Bursa City (Türkiye)

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Abstract: Research on spatial statistical methods related to population estimation at the building scale and its implications for urban land use has attained little attention. The main target of this study is to propose a new method for population estimation at the building level with minimal data and methodology and a high accuracy rate. In addition to this, it discusses urban population from various perspectives by using spatial statistical methods (Local Moran's I and Hot–Cold Spot) to examine the population calculated based on the number of residential units in buildings and the household size of the neighborhood along with urban land use types in the case of Bursa. The results showed the following: (1) The suggested method achieves a 76% accuracy rate in population estimation at the building level; (2) 64.6% of the city's population (2,101,581 individuals) is located in areas classified as Discontinuous High-Density Urban Fabric (50–80%) and Continuous Urban Fabric (>80); (3) 13.2% of the population is located in hot spot areas of these two types, while 14.5% is in cold spot areas. This research provides decision-makers with a framework for addressing urban problems related to housing, transportation, health, and energy in addition to the methods it proposes.

Keywords: population estimation; building; spatial statistics; urban fabric; Bursa

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1. Introduction

Detailed population information is crucial for the micro-scale modeling and analysis of human factors and processes in urban areas. Ideally, this information should be individually based, but such data are often unavailable due to privacy reasons. Therefore, it has become necessary to generate estimated data and conduct analyses from aggregated datasets such as census data [1]. Actual population data on a building basis are held by governments or local authorities. However, due to various reasons (e.g., security concerns), these data cannot be used in academic research. Therefore, it is important to estimate the population at a building scale. In this study, the population is estimated at the micro-scale by using the average household size in the neighborhood and the number of housing units in buildings. The research suggests analyzing the distribution/clustering of the population at a micro-scale or building scale and considering the results according to urban land types. There are various benefits to conducting population estimations and analyses at the micro-scale. Analyzing the distribution/clustering of the population at a micro- or building scale can provide significant benefits in urban planning, resource management, social services, and various other fields. The analyses that reveal the clustering of the population at the building scale are important for determining housing needs, optimizing urban social infrastructure, identifying service demands such as water, energy, and transportation, and understanding demographic trends and population settlement patterns at building and neighborhood scales. In the literature, analyses at the building scale often depend heavily on population estimations. One common characteristic of these studies is that they use previously existing/tested methods by developing and improving them. Undoubtedly, research carrying out population estimates at the building level is crucial for

delineating current situations and projecting future scenarios. However, lack of general observation, inadequacy in assessing local spatial relationships, and limitations in revealing heterogeneity or homogeneity in spatial relationships in these studies can be regarded as certain drawbacks.

Another prominent aspect of this study is that it presents the distribution of the population according to the types of urban land use. One of the results drawn from the past population estimation studies and analyses is that small-area population estimates generally have higher errors compared to larger areas [2–4]. Analyzing the distribution of findings obtained through spatial statistical methods according to urban land types may contribute to carrying out more accurate analyses at the micro-scale, thereby reducing error rates. This situation can be utilized to make strategic decisions in areas such as urban planning, infrastructure and superstructure management, and social services. This type of analysis can offer city managers, planners, and decision-makers the opportunity to manage cities more effectively and sustainably.

In the literature, there are studies that conduct population estimates and analyses at both macro- and micro-scales. While the dynamics, demographic characteristics, economic, and social aspects of the population at the scale of countries, regions, etc., can be analyzed at the macro-scale [5,6], the analyses at the micro level are carried out at the scale of cities, neighborhoods, and even buildings [1,7,8]. Various methods are used while conducting population estimations at the building scale. Lo [2] classified these methods into four categories: (a) The number of housing units, (b) measuring urbanization areas, (c) measuring different land uses, and (d) automatic digital image analysis. Many studies in the literature that engage in population estimations at both macro- and micro-scales draw upon the methodological classification established by Lo [1,2,7–12]. One of the most used methods among Lo's [2] approaches is automatic digital image analysis. Within the scope of these analyses, with the use of remote sensing methods, the studies that estimate building populations have become more widespread, and thus, significant decreases in error rates have been observed. The starting point of these studies is to estimate building populations using morphological operations on high-resolution images [4,8]. As seen at most micro-scales, the distribution of the population at the building scale has been studied using various approaches such as area-metric methods or volumetric methods, interpolation methods, and grid-based models. The main common feature of these studies is to depict the population at both micro- and macro-scales [1,7–13]. Some studies in the literature have used Urban Functional Zones (UFZ), Point of Interest (POI), Night Light (NTL), and Light Detection and Ranging (LiDAR) data to estimate the population with complex and specialized methods [8,12,14,15]. This study, instead of the complex and more time-consuming population estimation methods in the literature, tried to reveal the accuracy analysis showing the relationship between the reference population and the approximate population with a simpler method using the average number of households in the neighborhood and the number of residences in the buildings.

In international (such as Google Scholar, Web of Science, Scopus, Proquest, British Library, etc.) and national (such as TÜBİTAK, Dergipark, YÖK-Tez, etc.) databases, scans were carried out using the key concepts of building, population, Anselin Local Moran's I Statistics (LISA), and hot spot. However, no studies were found that analyzed the population at the building scale using spatial statistical methods. In this context, the researchers reached a conclusion that the analysis of the population at the building scale was carried out through spatial statistical methods, and the studies that examined the results obtained according to the types of urban land use were not widespread. This study can provide guidance to research that applies spatial statistics to urban and settlement analyses and contribute to the literature. This contribution may be beneficial in planning social services, infrastructure, and superstructure services in urban areas, identifying spatial inequalities, risk analyses, and enhancing disaster management. Considering the increasing needs and decreasing resources, the importance of planning and managing land assets becomes self-evident [16].

Today, scientific research extensively utilizes spatial statistical analysis through Geographic Information Systems (GISs). Spatial statistical methods, which arise from the integration of technology with the principle of association, one of the fundamental approaches of geography, express the correlation of one or more variables with different spatial locations [17]. Since the 1990s, with the proliferation of GIS applications in social sciences internationally, disciplines such as sociology, anthropology, epidemiology, geography, economics, statistics, and especially criminology have frequently started using spatial statistical methods for the analysis of the distribution, clustering, and hot and cold spot analyses of spatial elements [18–22]. Considering the literature, there are research studies that theoretically address spatial statistical methods as well as works that emphasize the practical application dimension, especially through GISs. In terms of theoretical aspects of spatial statistical methods in a conceptual context, notable works include Griffith [23], Anselin [24], Getis and Ord [25], Cressie [26], and Bailey and Gatrell [27]. Parker and Asencio [28], Mitchell [29], Okabe and Sugihara [30], and Chang [31] can be given as examples for their works that give ample space to the relationship between spatial statistics and GISs. Spatial statistical methods, widely used in multidisciplinary fields such as tourism, health, economics, agriculture, crime, urban planning, and settlement analysis, cover a broad range of topics and provide researchers in different disciplines with an important tool. When examining the works at a thematic scale in urban planning and settlement analyses, it is evident that there are studies including topics such as traffic accidents, transportation planning, environmental quality and planning, risk and disaster management, urban growth, and density determination and these studies provide recommendations to decision-makers [32–37]. These studies generally examine the spatial patterns, structures, and dynamics of cities using GISs, spatial analysis methods, and statistical models. When the national literature in Türkiye is examined, it is found that studies conducted using spatial statistical analysis have a more recent history than international literature. Regarding thematic context, publications arising from the collaboration between spatial statistics and GISs can frequently be found in national literature, just as in international literature. When examining the works focusing on the thematic scale in urban planning and settlement analysis in the national literature, topics such as traffic accidents, urban growth and housing determination, income distribution inequality, the relationship between population growth and migration, and spatial distribution of population are addressed [38–43].

This study aims to analyze the population at a building scale using spatial statistical methods and examine the relationship between these results and the types of urban land use. The approach used for estimating the building-scale population in the research aims to go beyond merely portraying the population at the micro-scale. This method was also used in some studies related to green space accessibility in smart cities and urban areas [44,45]. In this context, the purposes of this study are as follows: (a) To propose a new method for population estimation at the building level with high accuracy using minimal data and methods, (b) to determine the clustering/distribution of population at a building scale, and (c) to determine the distribution of population at a building scale according to the types of urban land use. Based on the objectives of the research, the following research problems are investigated:

(1) How can a new and useful building population estimation method be developed using minimal data and methods? In what ways does this method differ from existing approaches?
(2) Is there clustering in the spatial distribution of the population in Bursa City? If clustering exists, how can this clustering be classified according to land use types?
(3) Where does this clustering create hot and cold spots? What factors may contribute to the formation of these hot and cold spots?

This research addresses the population estimation method used at the building scale in the context of sustainable development of cities. Sustainable urbanization is a comprehensive approach that aims to keep the social, economic, and environmental components of cities in balance [46]. Effective management of the economic resources of cities is possible with an accurate estimation of the population. The building-scale population estimation method enables the more efficient planning of city resources [47]. In the context of sustainable urbanization, accurate population estimation at the building scale helps in many issues, ranging from the fair distribution of social services to the improvement of infrastructure applications, from reducing environmental pressure to the protection of green areas [48]. In addition, in this study, social inequalities in population distribution are emphasized through spatial analyses, and decision-makers are expected to develop sustainable social policies based on these data. It is predicted that the population estimation method used in the study will support the important components of "sustainable urbanization" by enabling accurate and sustainable planning decisions with the minimum data. The objectives and questions related to the objectives of our study have been shaped with this perspective. In order to answer the problems and achieve the objectives of the research, a new population estimation method at the building scale has been created by developing a simple algorithm based on minimum data and methods. Clustering analyses were performed at the building scale by using Moran's I Analysis, Anselin Local Moran's I Statistics (LISA), and Optimized Hot Spot Analyses (OHSA); the results were distributed and interpreted to urban land use types. These steps, which reveal the general course of the research, were prepared as a workflow chart and reflected in the study (Figure 1). The micro-scale population analysis conducted with spatial statistics can provide a more comprehensive understanding geographically and can effectively guide planning and decision-making processes at the local level. The unique aspects of this research are that it creates a new population estimation method that is simpler and more useful than the population estimation methods in the literature by using complex data and methods; it deals with the spatial distribution of the population in Bursa City, which is the research area, by spatial statistical analyses based on building-based population, and explains the results according to land use types. Thus, it has been intended that the population analysis at the building scale stands out as a valuable tool for decision-makers in various fields, including investment decisions, planning, education, health, disaster management, landscaping, and sustainable development.

The city of Bursa is an ideal example for this study due to its demographic diversity, rapid spatial development, and rich structure in terms of urban land use. The rapid population growth and urbanization processes experienced by the city, especially in the 21st century, provide an important opportunity to test the building-scale population estimation method developed in this study. In our opinion, this process is a miniature of the problems encountered in many large cities and prepares the ground for the applicability of the method in other places. In this context, the choice of Bursa as the research site is important not only in the context of Türkiye but also in understanding the common problems encountered in many cities. Many cities face similar demographic changes, rapidly developing urban areas, and increasing population pressure. Therefore, the building-scale population estimation method applied in Bursa, its spatial analysis, and integration with urban land use types have the potential to produce generalizable results for other cities. This is thought to make this study valuable both academically and practically at the international level.

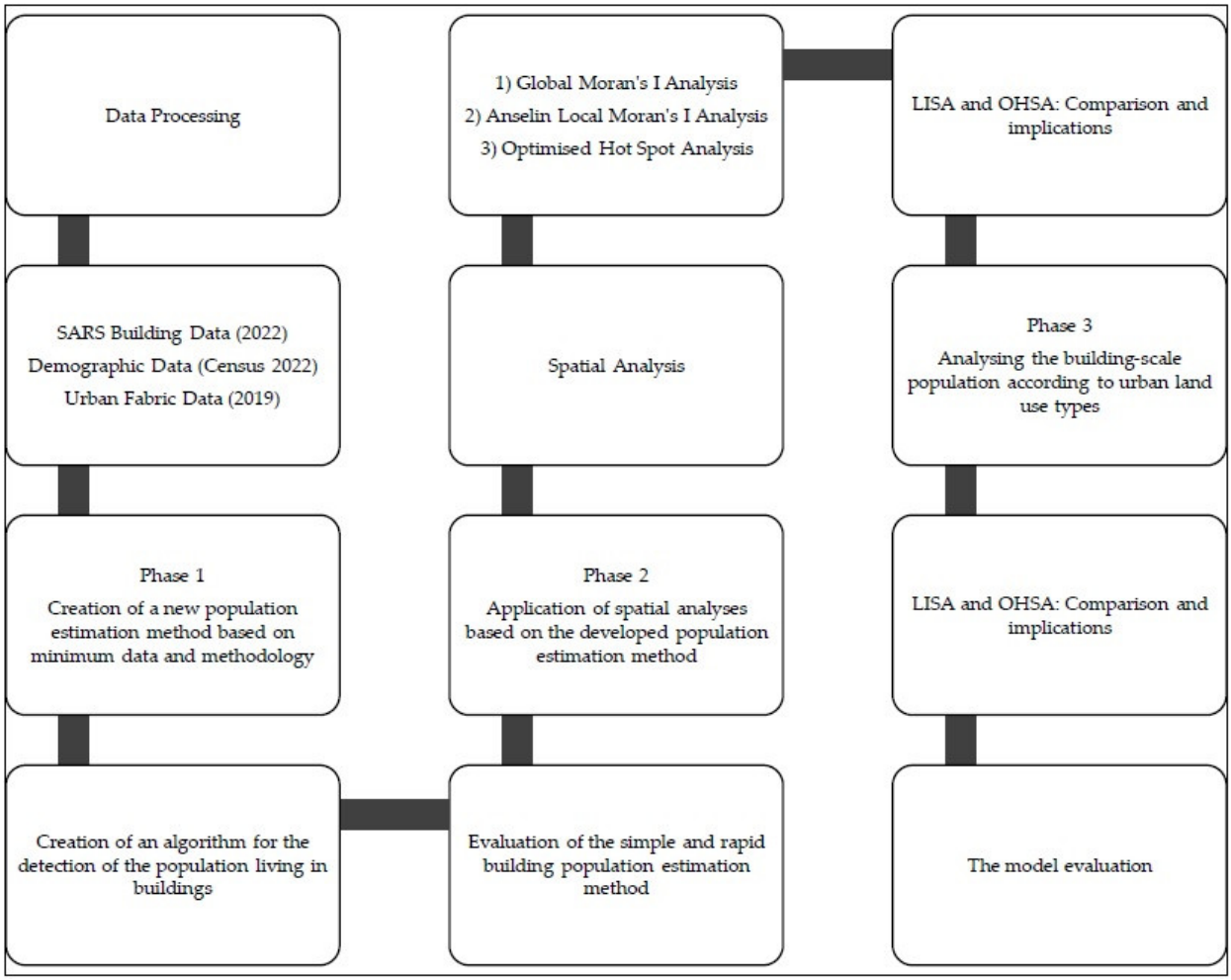


Figure 1. Workflow chart of the research.

2. Materials and Methods

2.1. Study Area

It is important to address the population in Bursa, a large Turkish city where industry occupies an important place, from different aspects [49]. Bursa is a city that has received intensive migration due to industrialization since the 1960s and has gained population dynamism. This situation has also affected the spatial development of the city. The city's development rate is above the average in Türkiye. The city has experienced a rapid development process since the 1970s and has grown spatially [50–52]. In this context, Bursa has a rich structure in terms of demographic diversity and urban fabrics. This situation provides a suitable environment for population estimation at the building scale and analyses at the scale of urban fabrics.

Bursa is a city located in the western part of Türkiye, in the Southern Marmara Region. The province covers an area of 10,813 square kilometers. With this area, it is the 27th largest province among the provinces of Türkiye. According to the end-of-year 2022 data from the Turkish Statistical Institute (TÜİK), Bursa, with a total population of 3,194,720, is the fourth-largest province in Türkiye in terms of population. It borders the Sea of Mar-mara and Yalova to the north, Kocaeli and Sakarya to the northeast, Kütahya to the south, Bilecik to the east, and Balıkesir to the west. The longest border is with Balıkesir, while the shortest border is with Sakarya [53]. The study area is the city of Bursa, located within the boundaries of Bursa province (Figure 2). The study area consists of areas within the provincial boundaries where the city exhibits continuous settlement. This continuous site within the boundaries of Bursa's metropolitan area comprises the urban zones of the Os-

mangazi, Nilüfer, Yıldırım, Gürsu, and Kestel districts [54]. The urban area was determined using the 2022 Google Earth satellite images (Figure 2). The TÜİK, in its new urban scale published on 31 December 2022, has adopted the "Degree of Urbanisation (DEGUR-BA)" developed by the Statistical Office of the European Union (Eurostat) [55]. According to this scale, the study area consists of densely populated and moderately populated urban neighborhoods. Considering this scale and the boundaries of the study area, the total population is 2,101,581.

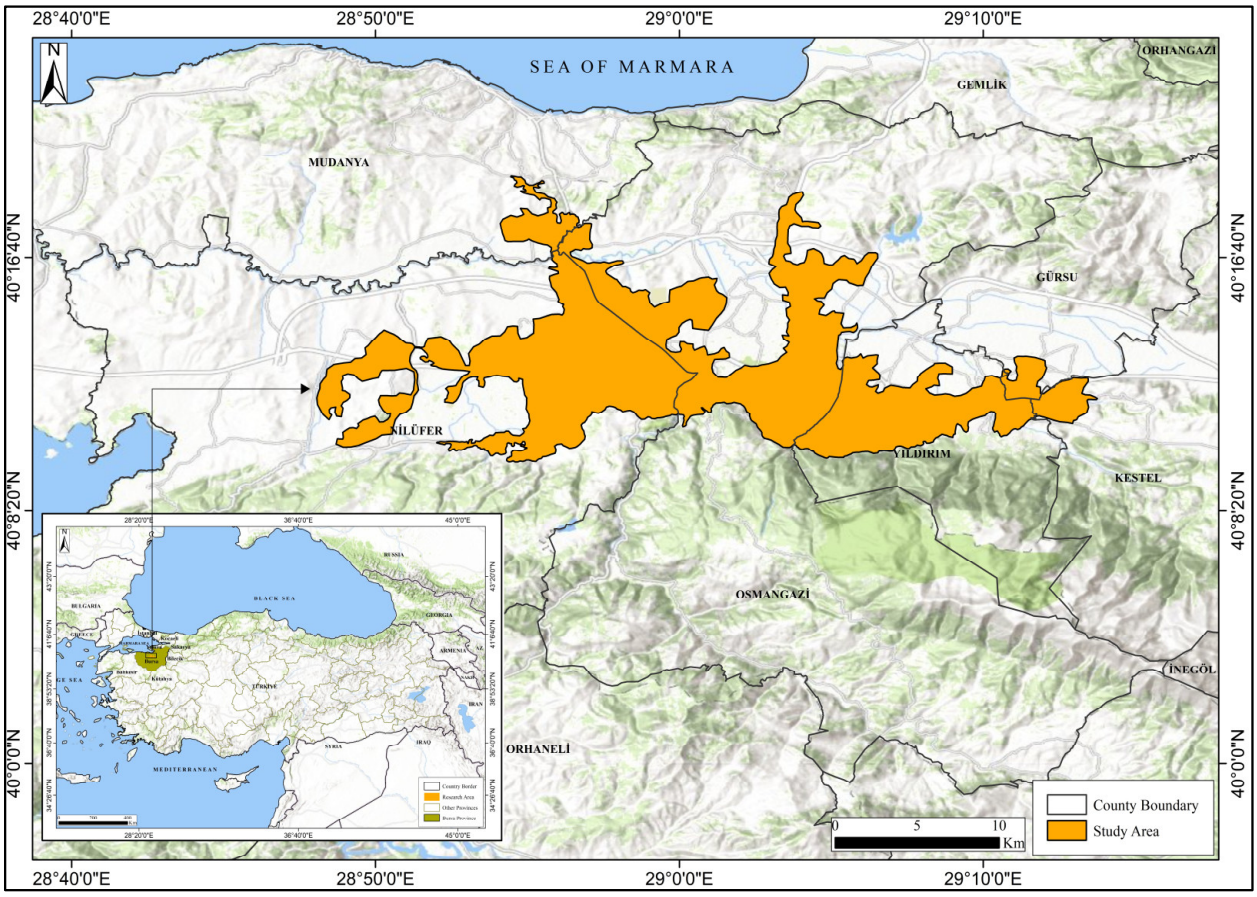


Figure 2. Study area.

2.2. Data

The data used in the research include the Spatial Address Registration System (SARS) building data, population census data, and urban fabric data (Table 1). The building data used as the basis for the study consist of building data belonging to the Osmangazi, Nilüfer, Yıldırım, Gürsu, and Kestel districts within the metropolitan area of Bursa City. According to these data, the number of buildings located in the research area is 214,983.

The predominant land use types in the research area are categorized as follows: continuous urban fabric, discontinuous high, medium, and low-density urban fabric (Figure 3). These land types constitute a significant part of the study area, and 89.5% of the population residing in the area live in these four land types. These land types are prominent not only in terms of population but also bear the burden of the city's settlement in both building and residential unit counts (Table 2).

Table 1. Data used in the research.

Data	Data Type	Location	Year	References
SARS Building	Vector (Polygon)	Bursa City	2022	Bursa Metropolitan Municipality
Population	Tabular Data	Bursa City	2022	TÜİK
Urban Fabric	Vector (Polygon)	Bursa City	2019	Republic of Türkiye Ministry of Environment, Urbanisation and Climate Change

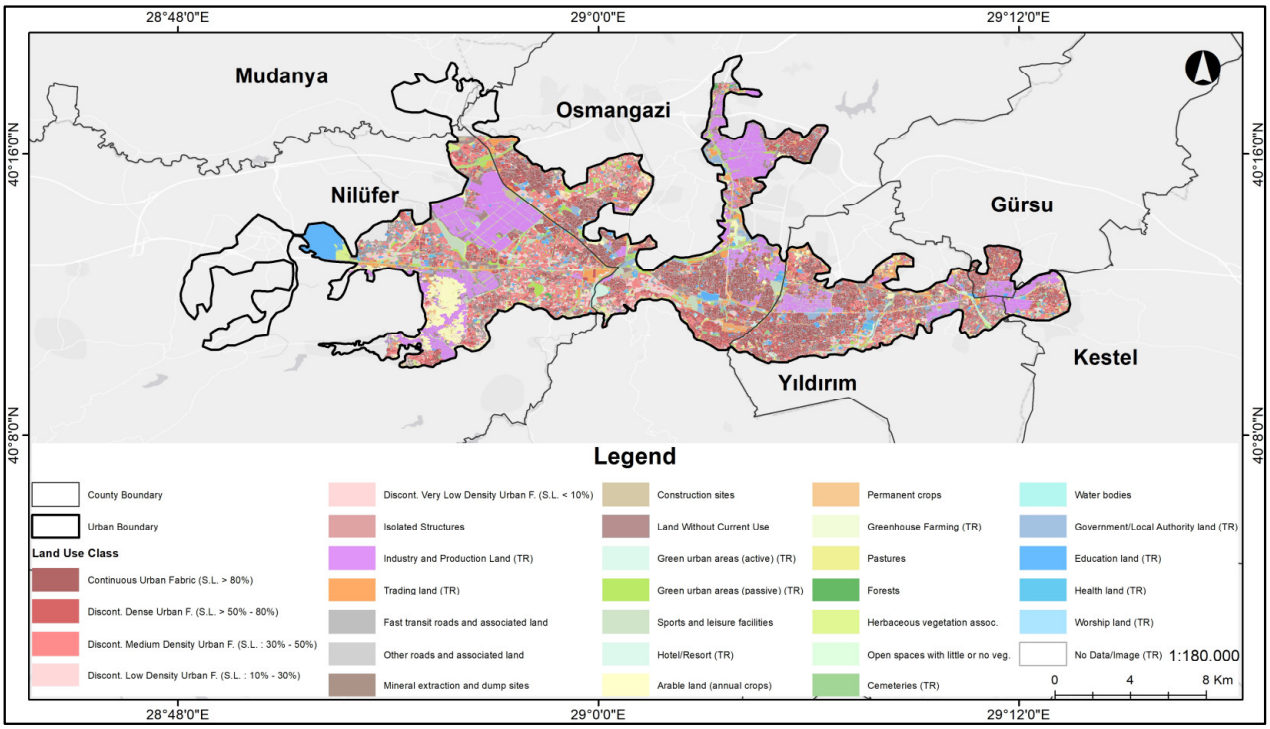


Figure 3. Distribution of urban land use types in the research area according to urban fabric data.

Table 2. Prominent land use types in terms of building, residence, and population.

Urban Fabric Class	Number of Buildings	Number of Residences	Total Population
Permanent Urban Fabric (>80%)	108,890	343,142	823,563
High-Density Discontinuous Urban Fabric (50–80%)	59,471	211,142	533,989
Medium-Density Discontinuous Urban Fabric (30–50%)	31,032	155,821	398,654
Low-Density Discontinuous Urban Fabric (10–30%)	8806	48,479	125,848
Very Low-Density Discontinuous Urban Fabric (<10%)	89	463	1191
Total	208,288	759,047	1,883,248

2.3. Methodological Approach

Previous studies, especially those based on the methods proposed by Lo [56], aimed to digitize specific geographic features and base population estimates on these features. In contrast, this study proposes using spatial statistical methods to analyze patterns, trends, and relationships in the geographic area. Thus, spatial relationships between geographic variables will emerge. Since statistical data and analyses are used in the research, this study

is quantitative research. In quantitative research, the main aspects are the research design and hypothesis. Many researchers have classified quantitative research designs in different ways. However, according to the frequently used classification, quantitative research is divided into experimental and non-experimental research designs [57]. Non-experimental research includes descriptive, survey, and correlational research. This study is an example of a correlational research type, one of the quantitative research designs. Correlational research aims to find the relationship between two different quantitative variables [58]. Hypothesizing is one of the requirements of quantitative research. Since this study is based on a positivist philosophy as a theoretical basis and uses quantitative research and statistical analysis techniques developed accordingly, it was preferred to include the null hypothesis in the research. The hypothesis of the study is stated as follows: H_0 = There is no clustering in the distribution of population at the building scale in Bursa City. In other words, there is no spatial autocorrelation. The expected value of (Moran's I) = 0<; H_1 = There is clustering in the distribution of population at the building scale in Bursa city. That is, there is spatial autocorrelation. The expected value of (Moran's I) was determined as follows: The expected value of (Moran's I) = 0>.

2.3.1. Creation of the Simple and Rapid Building Population Estimation Method

The implementation process of the research was carried out in five steps. The first step is to determine the approximate population of the buildings in the neighborhoods. The SARS Building data obtained from the Metropolitan Municipality Bursa and the 2022 Bursa neighborhood population obtained from TÜİK were matched. The SARS Building data include residential units, workplaces, and independent sections. In ArcGIS Pro, the Spatial Join tool was used to write the neighborhood population data to the building dataset. Thus, the neighborhood population data were obtained within the building dataset. This process facilitated the determination of which building belonged to which neighborhood. Subsequently, the Summary Statistics tool was used to obtain the counts of net residential units, workplaces, and shared-use independent sections in each neighborhood. When these types are divided into neighborhood populations, it has been determined how many people live, on average, in an independent unit located in a neighbourhood in the Bursa City area. The average household size calculated by TÜİK in 2022 is 3.1 in Bursa province. However, the average size of households remaining in the study area is 2.45 people. This number varies from neighborhood to neighborhood. For example, in the 30 Ağustos Zafer Neighborhood in Nilüfer district, the population multiplier is 0.93; in the Yeşilova Neighborhood of Osmangazi district, it is 1.93; in the Ulus Neighborhood of Yıldırım district, this multiplier goes up to 3.53. After determining the average household size, household sizes determined at the neighborhood scale were rewritten into building data and recalculated. Thus, the average number of residents per building was found.

2.3.2. Spatial Analysis

In the second stage, the Moran's I Analysis; in the third stage, the Anselin Local Moran's I Analysis; and in the fourth stage, the Optimized Hot Spot Analysis technique, which is underpinned by the Getis-Ord Gi* local statistic, have been used. Using the Moran's I Analysis, information about the clustering of the population at the building scale in Bursa City was obtained, while with the Anselin Local Moran's I Analysis, clustering situations were classified at a regional scale. When determining where a cluster created hot and cold spots, the Getis-Ord Gi* technique was not directly employed. Instead, the more advanced Optimized Hot Spot Analysis technique was utilized. Thus, the study attempted to determine whether clustering existed in the spatial distribution of the population, where significant and insignificant distributions occurred at a regional scale, and where hot and cold spots were formed by this distribution. What is meant to be expressed by the concept of clustering here is the close grouping of elements with similar characteristics as a result of the analysis of the dataset [26]. The formulas and application process of the analyses used in the research are explained below [25,59,60].

In the second stage, when conducting the Moran's I Analysis, the analysis was run in ArcGIS Pro 3.2.0 with the following settings for data input: Input Feature Class: SARS Building data; Input Field: Population 2022; Conceptualization: Inverse Distance; Distance Method: Euclidean. With this analysis, the presence or absence of clustering has been determined, and a distance threshold has been found. In the formula of Moran's I Analysis value, n is the number of spatial features, x_i is the feature value of feature i, x_j is the feature value of feature j, w_{ij} is the spatial weight between i and j [61]. When calculating the Moran's I Analysis value, the cross-products of the deviations from the mean of attribute values and the spatial weight matrix values are computed. The total index value resulting from these cross-products, whether it is positive or negative, indicates the spatial cluster or dispersion of features and their neighbors [29].

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \tag{1}$$

Moran's I statistic measures the strength of spatial autocorrelation. It was originally developed for binary neighborhood matrices, but it is also used in more general standardized spatial connectivity matrices [62]. This analysis provides the correlation of spatial distribution. If the resulting value approaches +1, it indicates the presence of a positive correlation, while if the value approaches −1, it indicates the presence of a negative correlation, i.e., spatial clustering [63,64]. If the resulting value is zero, it indicates that there is no clustering in the studied area, the variable is not distributed homogeneously, and the distribution in space is random [64,65]. In other words, if the Z score is greater than 2.58 and the p-value is less than 0.01, it can be concluded that there is clustering in the dataset with a confidence level above 99% [23–25].

In the third stage, the Anselin Local Moran's I Analysis was run with the following settings: Input Feature Class: SARS Building data; Input Field: Population 2022; Distance Threshold: 1724.5 This analysis was conducted to determine where clustering is significant, insignificant, and where it is an outlier. Anselin's Local Moran's I Analysis, commonly referred to as the Local Indicators of Spatial Association (LISA) analysis technique, is specifically designed to examine spatial patterns at a local scale and understand the relationships of regions with their surroundings [29,66]. The difference between LISA analysis and the Getis-Ord Local Gi* and OHSA techniques lies in the fact that LISA not only identifies similar values among points but also detects points with values different from their surrounding points. In other words, LISA analysis has been developed for the identification of spatial outliers [67]. In the Anselin formula, n represents the total number of features; w_{ij} represents the spatial weight value indicating the proximity relationship between point i and point j; z_i and z_j represent the deviation of the variable value at points i and j from the mean [66,68]. Meanwhile, the S_i^2 value was calculated using the equation below:

$$I_i = \frac{x_i - \overline{X}}{S_i^2} \sum_{j=1, j \neq i}^{n} w_{i,j} \left(x_j - \overline{X} \right) \tag{2}$$

$$S_i^2 = \frac{\sum_{j=1, j \neq i}^{n} \left(x_j - \overline{X} \right)^2}{n - 1} \tag{3}$$

where n is equal to the total number of features. The z_{Ii}-score for the statistics was computed as:

$$z_{Ii} = \frac{I_i - \mathrm{E}[I_i]}{\sqrt{\mathrm{V}[I_i]}} \tag{4}$$

where:

$$\mathrm{E}[I_i] = -\frac{\sum_{j=1, j \neq 1}^{n} w_{ij}}{n - 1} \tag{5}$$

$$V[I_i] = \mathrm{E}\left[I_i^2\right] - \mathrm{E}[I_i]^2 \quad (6)$$

The statistical values obtained from this analysis are the averages of the global Moran's I value. The maps generated from this analysis enable the testing of spatial randomness hypotheses. The results are classified based on high and low values. To do these calculations, local Moran's İndex values, z-scores, *p*-values, and a code representing the cluster type for each feature are generated. The z-scores and *p*-values represent the statistical significance of the computed index values [29,69,70]. Z-scores and *p*-values determine whether the calculated index values are statistically significant [29,69,70]. The result of this analysis yields five different codings. These include the following: high–high cluster, high–low outlier, low–high outlier, low–low cluster, and no significant. A high–high cluster indicates that a spatial entity with high value is surrounded by high values. A high–low outlier indicates that an object with a high attribute value is surrounded by elements with low values. A low–high outlier indicates that an object with a low attribute value is surrounded by objects with high values. A low–low cluster indicates that spatial entities with low values are surrounded by spatial elements with low values. No significant is common when the Local Moran's Index is close to zero [66,70,71].

In the fourth stage, the Optimized Hot Spot Analysis was utilized to create hot and cold spots. Hotspot analysis was developed by Art Getis and Keith Ord in 1995. This analysis creates a statistically significant hot and cold spot map using the Getis-Ord Gi* statistic in formula 3 [25,72–74]. As the Gi* value calculated in formula 3 approaches zero, it is understood that there are no high or low values in the neighborhood of the calculated object. With this equation, the z-score is also calculated. As the z-score increases, it is understood that the objects with high values in the geographic data are co-located or clustered. In this way, hot spots are found. As the z-score decreases, it is understood that objects with low values are located together. Accordingly, cold spots emerge. OHSA is preferred to produce the most appropriate results compared to the classical Hot Spot analysis (Getis-Ord Gi*) method. Compared to the Hot Spot Analysis (Getis-Ord Gi*) method, Optimized Hot Spot Analysis generally reduces statistically insignificant results. It calculates the optimum distance band used in the classical Hot Spot Analysis (Getis-Ord Gi*) method. In addition, this method calculates how many of its objects have less than how many neighbors based on how many meters of distance band according to the geographical objects given as input. Spatial weights were automatically assigned in this analysis to ensure optimal results. The aim of this analysis is to evaluate the spatial relationship between the value of a location in a geographic dataset and the values of surrounding locations. In this analysis, points or polygons provided as input create a map of statistically significant hot and cold spots using the Getis-Ord Gi* statistic. This analysis evaluates the characteristics of the input feature class to produce optimal results. In other words, the Optimized Hot Spot Analysis technique automatically assigns spatial weights that reflect proximity relationships. This is the difference from the Getis-Ord Gi* analysis. In this context, the formula for the Getis-Ord Gi* local statistic is as follows: n represents the number of points in the sample, x_j represents the variable value associated with point j, $w_{i,j}$ represents the spatial weights value indicating the proximity relationship between points, and S represents the standard deviation [25,73,74]. The result in this formula indicates the spatial clustering between the values of a region and those of its neighboring regions. If the Gi* value is positive and statistically significant, it indicates a high clustering of values in that region. If the value is negative and statistically significant, it indicates a low clustering of values in that region. The difference between the Getis-Ord spatial analysis and Moran's I Analysis is that the Getis-Ord analysis reveals where clusters are located. Using the Getis-Ord Gi* local statistic for all points in the sample, the "hot spots" and "cold spots" in the study area are revealed. There are 7 different classes according to the Gi* statistic. Objects with negative values can take the values -3, -2, and -1. These are called cold spots. Objects with a value of -3 (neighborhoods) represent cold spots with a 99% confidence level, while objects with a value of -2 represent cold spots with a 95% confidence level. Objects with a value of -1 are cold spots with a confidence level of 90%. A value of 0 represents objects that are not

statistically significant. Objects with a value of 1 are hot spots at a 90% confidence level. Objects with a value of 2 are hotspots with a 95% confidence level, and objects with a value of 3 are hotspots with a 99% confidence level.

$$G_i^* = \frac{\sum_{j=1}^{n} W_{i,j}\, x_j - \overline{\overline{x}} \sum_{j=1}^{n} w_{i,j}}{\sqrt{\frac{\left[n\sum_{j-1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \quad (7)$$

In the fifth stage, the population and building data were overlaid with urban fabric data. The urban fabric data were written onto the SARS Building data using the Spatial Join tool. Subsequently, the Summary Statistics tool was used to distribute the population within the building data to the urban land use types. This overlay aimed to reveal the location of clustering in urban land use. Although population estimations and analyses at the building scale using spatial statistical methods may not be widespread in the literature, various studies have been conducted utilizing these methods. The spatial statistical methods used here have been applied in various studies and provided robust results [69,75–77].

3. Results

3.1. Evaluation of the Simple and Rapid Building Population Estimation Method

The primary focus of this study is to develop a simple population estimation method using minimal data and methodology. This method offers a more accessible, applicable, and quick approach compared to complex data and methods. In our study, the accuracy rate was found to be 76%, based on the average number of households in the neighborhood and the number of dwellings in the buildings. Analyses and previous studies indicate that this simple method achieves sufficient accuracy. Furthermore, supported by real-world examples, this method demonstrates its practical usability and ability to yield real results. Therefore, the comparison of the population estimation method developed in this study, which uses minimal data and methods, with other complex methods may obscure the method's value. This is because other population estimation methods have been developed based on a significant amount of data and methods, typically utilizing satellite images. Nowadays, it is possible to achieve higher accuracy by using tools such as drones instead of satellite images. However, the entire city needs to be measured. Undoubtedly, like many approaches, this approach also has its limitations. The population estimation method proposed in this study is based on the assumption that every building with a dwelling has a population. No assumption is made that the population is evenly distributed according to the building surface area. The method applied may not always accurately reflect the actual population. This method does not consider the details at the building scale. Therefore, it may not fully demonstrate the population distribution in specific areas. Particularly in areas where population density and building characteristics vary between neighborhoods, it may not provide accurate results.

3.2. Examination of Results Using Spatial Statistics Methods

Spatial statistical methods are frequently used to conduct clustering analyses at the administrative unit level, such as neighborhoods, villages, districts, cities, and countries. However, clustering analyses based on building-level population data are not common. This paper analyzes the population calculated using the number of housing units in buildings and the household size of the neighborhood, along with urban land use types, with the help of spatial statistical methods (Local Moran's I and Hot–Cold Spot) in the case of Bursa. These analyses have aimed to address the urban population from various perspectives.

3.2.1. Moran's I Results

The spatial statistical dimension of the research began with Moran's I Analysis. As a result of the analysis, the Moran's Index value was determined as 0.155904. When Moran's Index value is greater than zero, it demonstrates that it is close to +1, and it indicates that

there is a spatial autocorrelation among the data used. According to the result, there is spatial clustering in the distribution of the population at the building scale in the study area. According to the analysis, the confidence level is 99% or higher (Figure 4). With this result, the H_0 hypothesis has been rejected, and the H_1 hypothesis has been accepted. In other words, it is determined that the population is not randomly distributed spatially, and there are clusters in certain regions. In this case, it is understood that areas with high population density are located together.

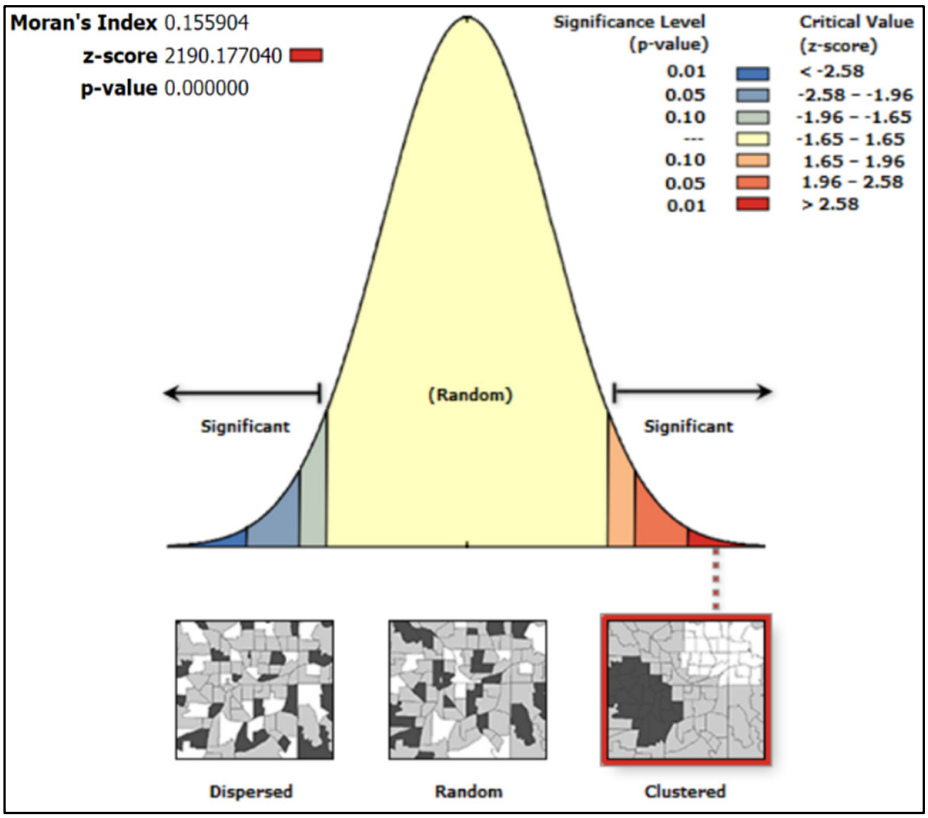


Figure 4. Moran's I analysis results.

3.2.2. LISA Results: Analysis and Implications

Moran's I analysis revealed that there is clustering. However, it did not answer the question of where there is/is not clustering. LISA analysis was used to obtain this information. With this method, the cluster and outlier analysis was carried out. This analysis examines the relationship between the value of a particular variable in a certain region and the values in neighboring regions. According to this analysis, spatial areas with high–high, low–low, and insignificant values are common. In places where a high–high cluster exists, the buildings with a high population density are located together. Görükle, Umurbey, and İstiklal Neighborhoods are examples of areas where a high–high cluster occurs. Kemerçeşme Neighbourhood and its surroundings can be given as an example of an area where a low–low cluster occurs (Figure 5). One of the interpretations that can be drawn from this analysis is the presence of a high–high cluster in some neighborhoods within the study area despite not having a high number of floors in the building. This situation can be explained by the density of the neighborhood population. İstiklal Neighborhood in the Gürsu district can be cited as an example. This may be an exceptional case. One of the general interpretations that can be drawn from here is that in spatial units classified as low–low, the socio-economic development level is weak because these areas, especially considering the eastern part of the city, are unplanned settlement locations. When it is also considered that people's socio-economic and cultural development levels determine the areas they live in, this situation becomes more understandable. Therefore, strategic

planning may be required in neighborhoods categorized as low–low, such as economic incentives and social service programs.

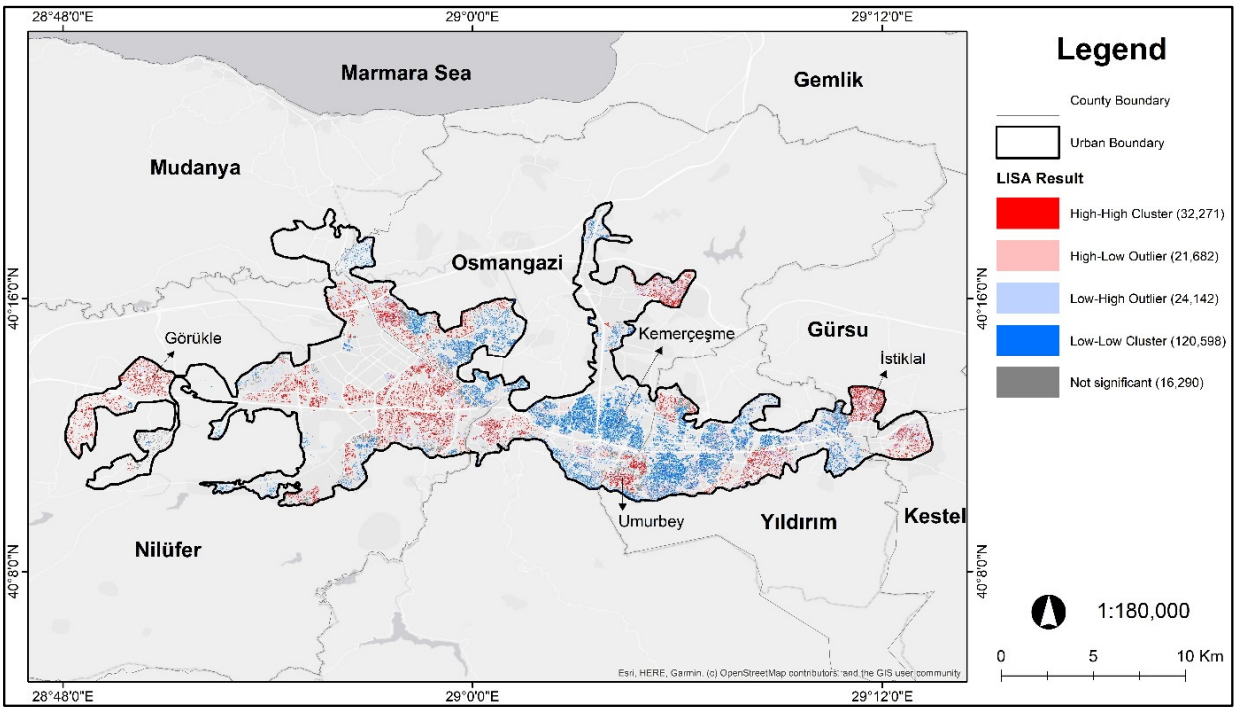


Figure 5. LISA results.

3.2.3. Analyzing Hot and Cold Spots: Results and Implications

In this stage, an Optimized Hot Spot Analysis was conducted to identify hot and cold spots within the study area. According to this analysis, cold spots are more prevalent in the eastern part of the city, while hot spots are more common in the western part (Figure 6). One of the main reasons for this is that shanty towns in the eastern part of the city are prevalent, while multi-story apartment buildings are more common in the west. Another reason is that the central and eastern parts of the city were established during an earlier period of settlement history, while the establishment and development of the western part occurred closer to the present day. Therefore, the western part of the city has more planned residential areas compared to the eastern part. The population of the Osmangazi district is 891,250; the Yıldırım district is 655,856, and the Nilüfer district is 536,365 [78]. The prominence of hot spots identified in the analysis within Nilüfer, which has a lower population compared to the three major metropolitan districts, seems to corroborate the findings mentioned above.

3.2.4. LISA and OHSA: Comparison and Implications

The LISA analysis evaluates the local dependencies of population values at the building scale and assesses similar situations among neighbors. The classification into high–high or low–low indicates whether the population distribution at the building scale exhibits a specific geographic pattern or not. The hot spot analysis assessed how much the population distribution at the building scale deviated from the mean. While LISA highlighted local dependencies and similar situations, the hot spot analysis emphasized areas that deviated from the overall trend. Accordingly, when the findings of both analyses are compared, it is observed that low–low cluster areas nearly overlap with cold spot locations, high–high cluster areas nearly overlap with hot spot areas, and areas with outliers nearly overlap with areas with no significance (Figures 5 and 6). One of the main interpretations that can be drawn from this is that in areas where high–high cluster areas overlap with hot spot areas, there may be homogeneity in terms of the population status. The overlap between

outliers identified in the LISA results and the insignificant values obtained from the hot spot analysis can be explained by the fact that the building or region exhibits significantly different population behaviors compared to others.

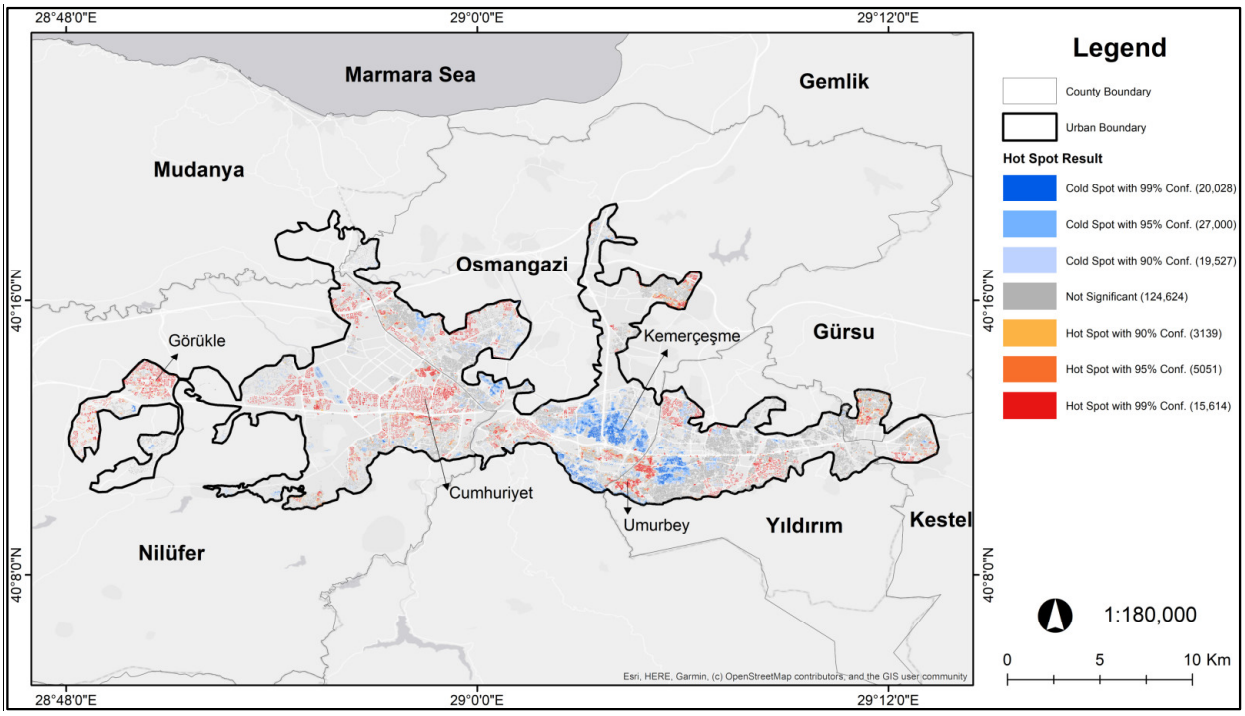


Figure 6. Hot and cold spots in the study area according to optimized hot spot analysis.

3.3. Examination of the Population Estimation Method through Urban Land Use Types and Comparison with LISA and OHSA Results

The population data in the building dataset have been distributed among the urban land types. Thus, the results obtained through spatial statistical methods can be viewed in terms of urban land types; 64.6% of the population (2,101,581) in the study area is located in the continuous urban fabric (>80%) and discontinuous high-density urban fabric (50–80%) classes. In the continuous urban fabric covering 168,208.34 m^2 within the city, 823,708.5 people reside in 105,501 buildings (Appendix A Table A1, Appendix B Table A2, Appendix C Table A3). The results of the LISA analysis applied in the research were blended with the urban fabric and 2022 population data. According to this, the urban land types where high–high cluster was observed in the study area stood out as discontinuous medium-density urban fabric (30–50%), discontinuous high-density urban fabric (50–80%), and continuous urban fabric (>80%), respectively. The areas where the low–low cluster was observed were determined, respectively, as follows: continuous urban fabric (<80%), discontinuous high-density urban fabric (50–80%), and discontinuous medium-density urban fabric (30–50%); 30% of the urban population (2,101,581.46) resides in the high–high cluster areas of prominent urban land types, while 28.6% live in the low–low cluster areas (Appendix D Table A4). When the results of the LISA analysis, the urban fabric, and building data are blended, the first three urban land types where high–high and low–low clusters are observed are the same for both cluster classes. These cluster areas were identified as continuous urban fabric (>80%), discontinuous high-density urban fabric (50–80%), and discontinuous medium-density urban fabric (30–50%) (Appendix E Table A5). When the optimized hot spot analysis results were matched with the 2022 census data and urban fabric data, urban land types where hot spots were distributed at a 99% confidence level were highlighted, respectively, as follows: discontinuous medium-density urban fabric (30–50%), discontinuous high-density urban fabric (50–80%), and continuous urban fabric (>80%). The distribution of cold spots at a 99% confidence level was determined,

respectively, as follows: continuous urban fabric (>80%), discontinuous high-density urban fabric (50–80%), and discontinuous medium-density urban fabric (30–50%). While 18.57% of the population (2,101,581.46) in the city resides in the hot spot areas of prominent urban land types, 3.9% are located in cold spot areas (Appendix F Table A6). When the optimized hot spot results, building data, and urban fabric data were blended, the distribution of hot spots at a 99% confidence level was concentrated, respectively, as follows: discontinuous medium-density urban fabric (30–50%), discontinuous high-density urban fabric (50–80%), and continuous urban fabric (>80%). The distribution of cold spots at a 99% confidence level stood out, respectively, as follows: continuous urban fabric (>80%), discontinuous high-density urban fabric (50–80%), and discontinuous medium-density urban fabric (30–50%) (Appendix G Table A7). In the distribution of urban land types where LISA results are scattered and the distribution of urban land types where hot spot analysis results are scattered, there are similarities in terms of population but differences in terms of structure. For example, when LISA and hot spot analysis results are blended with the urban fabric and population data, it is observed that discontinuous medium-density urban fabric stands out both in terms of high–high clusters and hot spots in both analyses. When LISA and hot spot analysis results are compared with the building data and the urban fabric data, it is observed that while continuous urban fabric stands out in high–high cluster areas in LISA analysis, discontinuous medium-density urban fabric is prominent in hot spot areas.

4. Discussion

4.1. Main Findings and Implications of This Study

The main innovation of the study is to create a simple and useful population estimation method using a minimum of data and methodology. This study aimed to provide a more accessible, feasible, and fast approach without the need for complex data and methods. Analyses and previous studies show that this simple method has a sufficient level of accuracy. İt is possible to see studies in the literature that estimate and analyze building populations at the micro-scale using various methods. These works focus on some factors, such as population estimation at the micro level, location, size, number of floors, and intended use of a building. In other words, one of the main objectives is to describe the buildings. While these studies in the literature focus on estimating and analyzing the population on a building basis, especially through area and volume measurements, this study has developed a more useful population estimation method with minimum data and methods. In addition, previous studies have primarily focused on detailed aspects within buildings, whereas this study has a broader perspective, specifically addressing general urban areas and population clusters within these areas [4,8,12,14]. Many research studies conducting population estimation analyses often include accuracy rates. These types of analyses explain the relationship between the reference population and the estimated population. Geographic Information Systems (GISs) or statistical methods can be used to calculate accuracy rates. Accuracy rates are important for demonstrating the reliability of analyses. Chen et al. [12] obtained an accuracy rate of 65% as a result of using the Random Forest Algorithm (RF) model. Wang et al. [4] conducted fine-scale population estimation through 3D reconstruction of urban residential buildings. As a result, they achieved an average accuracy rate of 83%. Lu et al. [14] used an area and form-based approach and achieved an accuracy rate of 80%. Shang et al. [15] proposed a new method for population estimation at the building scale by integrating multi-source GIS data, such as UFZ, POI data, general land use planning data, building vector data, and green coverage vector data. This method significantly improved the accuracy of population estimation, achieving an accuracy rate of 94%. In their study, Shang et al. [15] used multi-source GIS data to exclude non-residential buildings and then categorized residential buildings into four categories to account for the spatial heterogeneity of the population related to buildings. In our study, using the average household size of the neighborhood and the number of residential units in buildings, an accuracy rate of 76% was found. This rate is considered a satisfactory accuracy achieved with minimal data and the simplest

method. Finding accuracy rates using the average household size of the neighborhood and the number of residential units in buildings is a simpler and faster approach compared to complex methods. For example, one of the main positive aspects that differentiate the results of this study from the study by Shang et al. [15] is its lower cost and faster applicability. Additionally, working with minimal data enhances its applicability even in areas with limited data access. This aspect allows our proposed method to be applied across a wide range of cities, making it a more flexible and practical tool for urban planners. The application of population estimation methods using complex data and methods requires specialized software, hardware, advanced knowledge, and technical skills. However, since our method is a simple algorithm or calculation method, it can be easily applied by a wider range of users. This method can be effective even in small municipalities or regions with limited technical capacity. It should not be forgotten that simplicity is an important tool in the production of scientific knowledge as long as it is accurate and testable. Sometimes, simplicity can even be a key to understanding more complex systems.

(1) Using this population estimation method, various spatial analyses were performed in the study area. According to the LISA analysis, spatial regions with high–high, low–low, and insignificant values were found to be common in the study area. In the regions where high–high clustering is observed, buildings with high population values are located together. For example, Görükle, Umurbey, and İstiklal neighborhoods are included in such clustering areas. Kemerçeşme Neighborhood and its surroundings are examples of areas where low–low clustering is common (Figure 5). In the next stage, Optimized Hot Spot Analysis was performed to identify hot and cold spots in the study area. According to the results of the analysis, it was determined that cold spots are more common in the eastern part of the city, while hot spots are more common in the western part (Figure 6). One of the main reasons for this situation is the prominence of slum areas in the eastern part of the city and the prevalence of multi-story apartment blocks in the west. In addition, while the city center and the eastern part of the city were established at an earlier date, the establishment and development of the western part of the city coincide with a more recent period. Comparing the results of both analyses, it is seen that low–low clustering areas and cold spots, high–high clustering areas and hot spots, and outlier areas and meaningless areas overlap to a great extent. One of the main interpretations that can be drawn from this is that the population may have a homogenous structure in the regions where high–high clustering areas and hot spots overlap. The overlap between the outliers in the LISA analysis and the insignificant values detected in the hot spot analysis can be explained by the fact that the relevant building or region exhibits significantly different population behavior from the others.

(2) In the last stage of the research, the population based on building data was distributed to urban land types. Thus, the results obtained by spatial statistics methods were analyzed using urban land types. In the distribution of LISA and hot spot analysis results with urban land types, similarities were observed in terms of population, and differences were observed in terms of structure. For example, when LISA and hot spot analyses are combined with urban atlas data and population data, it is found that medium-density discontinuous urban areas stand out in terms of both high–high clustering and hot spots in both analyses. When the results of LISA and hot spot analyses are compared with the building data and urban atlas data, it is seen that in the LISA analysis, continuous urban areas are more prominent in high–high clustering areas, while medium-density discontinuous urban areas are more prominent in hot spot areas. These results provide important clues in understanding the spatial and structural diversity of urban areas. The fact that LISA and hot spot analyses yield similar results in terms of population density and distribution may indicate a homogenous population structure in these areas. However, the differences in terms of structure data emphasize the diversity in the physical structure of urban areas and how this diversity affects the population distribution. In particular, the

prominence of medium-density discontinuous urban areas in terms of both high–high clustering and hotspots suggests that such areas should be given more consideration in urban planning and the distribution of social services. The prominence of continuous urban areas in the LISA analysis indicates that these areas may have a more dense and coherent structure in terms of population and structure. These analyses provide important data that can be used in different stages of urban planning. Both the spatial statistical methods and the relationship between urban land types, which are based on the population estimation method, can play a critical role in determining urban development strategies.

(3) This study differs from its counterparts both with the systematic template it uses and the population estimation method it has developed in the context of data. Many studies in the literature have developed population estimation methods by using data that are not always accessible everywhere. The requirements such as data, methods, hardware, software, and qualified manpower used by these researchers weaken their applicability in regions with limited opportunities (Table 3). This study aimed to test the accuracy and efficiency of the population estimation method for Bursa City based on minimum data and methods. This focus has enabled a detailed evaluation of the method within the framework of available data sources and time constraints. This method is flexible enough to meet the needs of local governments and urban planners, especially in developing countries and rapidly urbanizing regions. The recent widespread use of building-scale population estimation methods in China indicates how these methods can be effective in areas such as urbanization, infrastructure planning, and disaster management. The integration of the population estimation method used in the research into spatial analyses not only determines the clustering of the population but also provides the opportunity to examine the effects of urban dynamics and socio-economic processes on the spatial structure in more depth. These analyses can provide important data to decision-makers in cities experiencing rapid urbanization processes. Analyzing population estimates at the building scale according to urban land use types sheds light on urban growth processes at the micro level. The methodology and results show that this study is applicable not only to a specific geographical context but also to regions with different urban structures and population dynamics around the world. It is thought that the population estimation method put forward in this study will be a useful approach in many situations that require rapid analysis, especially for decision-makers and in underdeveloped regions with limited opportunities. In order to evaluate the generalizability of our method and its applications in other cities, it is recommended to test it in different cities in future studies. This will help us to understand how the method has a wide range of applications and how it works in different contexts. If the problems related to data limitations are overcome in the future and the transferability of the method is demonstrated by us, it is aimed to name this method the “Minimum Data-Based Population Estimation (MDB-PE) Method”.

Table 3. Main features of some papers using population estimation methods.

Authors	Study Area and Year	Data	Method	Limitations	Accuracy Rate (%)	Strengths
Wang et al. [4]	Chaoyang District, Beijing, China (2016)	Chinese No. 3 Resources Satellite (ZY-3), high-resolution satellite imagery	3D building reconstruction, dasymetric mapping, morphological analyses	There may be less certainty when there is a lack of data in complex urban areas	83	High accuracy in fine-scale population estimation with 3D building reconstruction
Chen and et al. [12]	Huangpu District, Shanghai, China (2021)	LiDAR, NTL, POI	RF	Uneven population distribution, LiDAR data is not easy to obtain in every region unavailability	65	More accurate population estimation at building scale with LiDAR and multi-data integration
Lu et al. [14]	Denver, Colorado, USA (2010)	QuickBird imagery, LiDAR	Area and volume-based approaches, regression analysis	The volume-based approach is more prone to classification errors to be sensitive	80	Ensuring high accuracy by using LiDAR data
Shang et al. [15]	Ningbo, China (2021)	UFZ	RF	Model accuracy when spatial heterogeneity is not treated may decrease	94	Population estimation at the building scale by taking into account spatial heterogeneity, more accurate and widespread application possibility
Xu et al. [79]	Chaoyang District, Beijing, China (2020)	ZY3-02 High-Resolution Satellite	Stereo pair analysis method	Lack of detail, general data deficiencies and methodological there may be limitations	92	Claimed potential for sensitivity for high-level population estimation
Mei et al. [80]	Wuhan, China (2022)	POI	RF, Cross-Scale Feature Construction (CSFC) method using pixels (100 m, 200 m, 500 m)	No details provided; general data gaps and methodological limitations may exist	93	Fine-scale population spatialization

4.2. Limitations

Scientific research is undoubtedly conducted within the framework of certain limitations. Limitations are one of the natural elements of scientific research. These limitations are important for guiding future studies. One of the reasons why the entire province of Bursa was not chosen as the study area in the research is that the SARS Building data at this level were not supplied by the authorized institutions. The suggested population estimation method in this study is based on the hypothesis that there is a population in every building with residential units. Due to this hypothesis, there may be a margin of error in the estimation. Even though independent units are included in the system in areas where the construction and occupancy processes have not been completed yet, the margin of error increases because people have not moved into these areas. Therefore, it is believed

that the accuracy rate may be higher in areas with fewer new constructions. In addition, the margin of error may increase due to student dormitories that appear as single housing units in a building or buildings that are in a dilapidated condition.

The building data used in the research belong to the urban area covering the districts of Osmangazi, Nilüfer, Yıldırım, Gürsu, and Kestel. Although there are building data for settlements such as Mudanya, Gemlik, and Inegol districts of Bursa province, these settlements could not be reflected in the study. The reason for this is the inadequacy of the current technological infrastructure (a server with 48 GB RAM) for conducting spatial statistical analyses. When the study area was selected as the urban fabric, this limitation was eliminated. However, since there are no urban fabric data for the entire study area, especially the areas in the western part of the city, it could not be evaluated in terms of urban land use. The reason for this situation is the use of the urban fabric data prepared by the Ministry of Environment, Urbanization, and Climate Change in Türkiye. These data provide more detailed land use classes compared to the data provided by the Copernicus Land Monitoring Service (CLMS).

Researchers' access to data or the timeliness of the data they access can vary from region to region, country to country, city to city, and even from district to district. In this study, the most recent urban land use data are from 2019, while the building-level housing data are from 2022. To check the accuracy of the urban land use data, 2022 satellite images and Google Street images were verified using 100 random sample points. Accordingly, the accuracy or unchanged rate is 99%. In this respect, urban fabric data are usable for this study. The lack of more recent urban land use data with the same detail is a limitation of this study. Another limitation of this study is that the simple method used for population estimation is not compared with the methods in the literature. One of the main reasons for this is that this study pursues the question of how population estimation can be performed in a simple and fast way with minimum data and methods. The time-consuming and costly nature of the other methods, which were developed by using very complex data and analyses, made it difficult to make comparisons. The population estimation method used in this study was aimed to be used in small (Bilecik, Düzce), medium (Sakarya, Eskişehir), and large cities (Istanbul, Izmir) in Türkiye and to make a comparison with Bursa. However, actual building population data for these cities could not be obtained. Due to the data shortage encountered, this method was not tried in small, medium, and large cities.

Spatial statistical methods are off-the-shelf methods, and their accuracy has been proven. In this study, after the population estimation method was created, the results obtained were evaluated using spatial statistics methods. Population clustering/hot spot maps obtained using different spatial statistics methods (LISA and OHSA) were compared. However, since it is not common to evaluate spatial statistics analyses in similar studies using the population estimation method, the spatial statistics results in this study could not be compared with the literature.

5. Conclusions

This research stands out for its unique aspects because it not only predicts population using neighborhood average household size and the number of residences in buildings but also conducts spatial clustering analysis at the building scale and discusses this analysis from the perspective of urban land types. The accuracy rate of the population estimation method used in the study is 76%. Considering that the method used is simple and fast, this rate is acceptable compared to the accuracy rates of complex and difficult-to-apply methods in the literature. The population estimation method developed at the building scale in the research can be used in other cities with minimal data and methods requirements. However, the applicability and accuracy of the method depend on the availability of similar types and quality of data in other cities, the demographic structure of the cities, and the suitability of urban land use types. To ensure that the method produces accurate and valid results in other cities, results should be compared with accuracy rates in the literature. Undoubtedly,

local governments' perspectives on scientific research, planning processes, and data access facilities may also affect the applicability of the method.

In this study, micro-scale spatial clustering analysis was conducted in the city of Bursa, and the analysis determined where the clusters were high and low and identified where hot and cold spots were formed. In the subsequent stage, the emerging clustering situation was explained by matching it with urban land types. In this context, there is a positive clustering in the distribution of population at the building scale. According to the LISA analysis, high–high clusters are observed in areas where neighborhood populations are dense. According to the hot spot analysis, clusters are generally seen as hot spots in the western parts of the city; on the other hand, they emerge as cold spots in the eastern parts. When the results of LISA and hot spot analyses are paired with urban land types, it is understood that there are similarities in terms of population but differences in terms of structures. There are various benefits of determining the distribution of population at the building scale and matching the results with urban land types. This analysis can provide insights to decision-makers regarding the efficient use of resources and planning urban areas in terms of housing, transportation, health, and energy. For example, in the area of housing, it helps to identify where new housing should be built by showing which areas are densely populated. In transport, revealing the relationship between population density and urban land use helps to plan the necessary infrastructure investments to reduce traffic congestion and optimize public transport systems. In healthcare services, it helps identify the need for more hospitals and clinics in densely populated areas, thereby increasing access to healthcare services. In energy, it forecasts energy demand in different regions, optimizing the planning of energy distribution networks and the integration of renewable energy sources. In summary, the planning of urban areas in terms of population and land use is crucial for the management of cities' present and future state. This study can guide decision-makers toward making urban areas more functional and utilizing resources more efficiently.

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Appendix A

Table A1. Distribution of urban land use types in metropolitan provinces in m^2.

Urban Fabric Classification	Gürsu	Kestel	Nilüfer	Osmangazi	Yıldırım
Permanent Urban Fabric (>80%)	513,286	243,028	1,639,366	9,289,178	5,135,974
Other Roads and Related Areas	704,189	587,983	6,140,572	8,664,372	6,105,154
Industry and Production Areas	651,793	1,304,682	12,354,607	7,397,760	2,463,461
High-Density Discontinuous Urban Fabric (50–80%)	1,094,057	562,255	3,329,130	6,759,313	4,623,290
Medium-Density Discontinuous Urban Fabric (30–50%)	300,032	584,279	8,222,616	4,858,842	3,672,111
Areas with No Current Use	367,105	260,929	5,833,295	3,666,845	2,439,774
No Data (No Image)	0	0	1,7089,308	3,099,932	51,057

Table A1. *Cont.*

Urban Fabric Classification	Gürsu	Kestel	Nilüfer	Osmangazi	Yıldırım
Trade Areas	85,339	52,793	1,980,744	2,732,009	1,382,867
Low-Density Discontinuous Urban Fabric (10–30%)	5,429	184,940	3,239,223	2,716,462	1,368,016
Urban Green Spaces (Passive)	52,160	45,355	2,693,714	2,325,793	1,069,049
Public Spaces	12,250	49,698	354,081	1,533,134	768,276
Arable Areas	162,390	92,499	5,007,722	1,445,840	599,564
Education Areas	90,023	87,565	3,295,168	1,310,851	877,029
Maki or Herbaceous Plants	21,067	255,652	1,405,818	1,178,250	1,080,012
Sports and Entertainment Areas	11,929	81,976	1,214,096	1,152,864	353,403
Rapid Transit Routes and Related Areas	12,706	64,023	688,344	1,143,093	356,240
Continuous Products	32,457	52,354	370,710	1,022,429	681,102
Green Areas in the City (Active)	39,893	109,51	702,121	977,547	808,861
Cemetery Areas	5758	27,130	148,982	356,918	131,449
Construction Areas	327	13,401	767,093	353,180	61,696
Places of Worship	16,315	11,047	156,155	254,030	214,904
Water Areas	0	6005	137,926	196,679	129,063
Pasture Areas	0	44,645	14,508	181,728	82,442
Railways and related Areas	11,968	21,467	239,325	178,085	132,275
Forests	0	370	108,568	175,729	142,429
Health Areas	4455	35,241	143,245	150,018	118,501
Areas with Little or No Vegetation	0	0	0	140,690	0
Mine Quarry and Discharge Sites	0	0	20,025	107,112	22,969
Airports	0	0	0	92,827	0
Hotel/Resort	0	634	24,110	88,469	477
Very Low-Density Discontinuous Urban Fabric (< 10%)	0	715	9,651	80,357	5531
Fruit Gardens	0	0	0	675	0
Isolated Structures	0	0	0	309	1034
Greenhouse Areas	1255	2347	10,842	15	2861

Appendix B

Table A2. Population living in metropolitan districts by urban land use types.

Urban Fabric Classification	Gürsu	Kestel	Nilüfer	Osmangazi	Yıldırım
Permanent Urban Fabric (>80%)	28,360	10,529	73,098	433,907	277,813
High-Density Discontinuous Urban Fabric (50–80%)	44,711	19,533	80,618	207,584	182,080
Medium-Density Discontinuous Urban Fabric (30–50%)	11,041	17,304	158,437	104,272	108,910
Low-Density Discontinuous Urban Fabric (10–30%)	49	3749	51,050	40,323	31,032
Industry and Production Areas	38	30	2826	8826	9560
Trade Areas	2806	203	4096	8012	5560
No Data (No Image)	0	0	100,304	7940	201
Areas with No Current Use	1689	491	13,838	6304	6000
Public Spaces	0	69	12	1677	1583
Other Roads and Related Areas	449	60	794	1111	3202
Very Low-Density Discontinuous Urban Fabric (<10%)	0	0	36	1083	70
Continuous Products	0	156	128	854	102
Urban Green Spaces (Passive)	19	0	635	577	8485
Places of Worship	8	14	34	435	337
Construction Areas	0	178	8063	410	357
Maki or Herbaceous Plants	5	445	497	387	1529
Health Areas	5	85	120	367	380

Table A2. *Cont.*

Urban Fabric Classification	Gürsu	Kestel	Nilüfer	Osmangazi	Yıldırım
Education Areas	31	2	235	301	564
Sports and Entertainment Areas	112	0	410	170	160
Arable Areas	517	90	186	135	107
Airports	0	0	0	108	0
Green Areas in the City (Active)	10	0	82	90	114
Hotel/Resort	0	0	0	57	0
Rapid Transit Routes and Related Areas	0	0	0	25	0
Pasture Areas	0	2	0	12	9
Cemetery Areas	0	0	7	6	0
Mine Quarry and Discharge Sites	0	0	0	3	0
Fruit Gardens	0	0	0	2	0
Forests	0	0	42	2	8
Isolated Structures	0	0	0	0	3
Greenhouse Areas	0	43	0	0	0

Appendix C

Table A3. Number of buildings in metropolitan districts by urban land use types.

Urban Fabric Classification	Gürsu	Kestel	Nilüfer	Osmangazi	Yıldırım
Permanent Urban Fabric (>80%)	2619	954	6664	60,516	34,748
High-Density Discontinuous Urban Fabric (50–80%)	3794	1673	5562	24,409	20,660
Medium Density Discontinuous Urban Fabric (30–50%)	975	872	8792	9680	8986
Low-Density Discontinuous Urban Fabric (10–30%)	9	230	2543	2914	2466
No Data (No Image)	0	0	5576	1699	24
Industry and Production Areas	4	3	382	1225	1822
Trade Areas	155	13	100	1120	448
Areas with No Current Use	80	26	540	328	244
Other Roads and Related Areas	32	9	43	240	317
Public Spaces	0	7	2	109	45
Places of Worship	2	3	10	101	71
Urban Green Spaces (Passive)	1	0	28	84	535
Very Low-Density Discontinuous Urban Fabric (<10%)	0	0	6	59	12
Education Areas	3	1	29	50	43
Maki or Herbaceous Plants	2	21	78	43	51
Continuous Products	0	7	19	43	24
Health Areas	1	10	6	41	40
Green Areas in the City (Active)	1	0	7	25	16
Sports and Entertainment Areas	5	0	7	22	5
Airports	0	0	0	21	0
Arable Areas	21	4	66	18	13
Hotel/Resort	0	0	0	15	0
Construction Areas	0	8	196	12	4
Cemetery Areas	0	0	2	3	0
Rapid Transit Routes and Related Areas	0	0	0	2	0
Pasture Areas	0	1	0	1	2
Mine Quarry and Discharge Sites	0	0	0	1	0
Fruit Gardens	0	0	0	1	0
Forests	0	0	6	1	1
Isolated Structures	0	0	0	0	1
Greenhouse Areas	0	2	0	0	0

Appendix D

Table A4. Distribution of LISA results by urban land use types at a population scale.

Urban Fabric Classification	High–High Cluster	High–Low Outlier	Low–High Outlier	Low–Low Cluster	Not Significant
Medium-Density Discontinuous Urban Fabric (30–50%)	255,239	40,931	24,328	55,165	24,301
High-Density Discontinuous Urban Fabric (50–80%)	199,401	94,193	52,934	150,982	37,016
Permanent Urban Fabric (>80%)	175,932	150,241	47,410	395,621	54,501
No Data (No Image)	85,821	2110	3458	9159	7895
Low-Density Discontinuous Urban Fabric (10–30%)	78,768	17,715	5530	14,694	9495
Areas with No Current Use	18,787	5920	899	872	1843
Trade Areas	9263	4375	983	4427	1628
Construction Areas	8397	257	171	6	177
Industry and Production Areas	1685	5648	1176	12,586	187
Other Roads and Related Areas	1661	1175	364	1794	622
Maki or Herbaceous Plants	1508	769	163	154	268
Urban Green Spaces (Passive)	834	53	91	44	64
Very Low-Density Discontinuous Urban Fabric (<10%)	759	87	77	58	207
Continuous Products	740	77	66	135	223
Arable Areas	723	73	39	129	70
Sports and Entertainment Areas	659	121	10	61	1
Public Spaces	546	1935	49	150	659
Health Areas	253	245	127	278	53
Education Areas	242	395	71	263	162
Green Areas in the City (Active)	75	42	57	98	22
Greenhouse Areas	43	0	0	0	0
Places of Worship	11	46	133	570	68
Airports	0	0	0	108	0
Hotel/Resort	0	10	2	44	0
Forests	0	0	0	10	42
Pasture Areas	0	12	2	9	0
Cemetery Areas	0	0	7	6	0
Isolated Structures	0	0	0	3	0
Fruit Gardens	0	0	0	2	0
Rapid Transit Routes and Related Areas	0	24	1	0	0
Mine Quarry and Discharge Sites	0	0	0	0	3

Appendix E

Table A5. Distribution of LISA results by urban land use types at a building scale.

Urban Fabric Classification	High–High Cluster	High–Low Outlier	Low–High Outlier	Low–Low Cluster	Not Significant
Permanent Urban Fabric (>80%)	9401	11,512	7503	70,634	6451
High-Density Discontinuous Urban Fabric (50–80%)	8684	6178	8649	28,289	4298
Medium-Density Discontinuous Urban Fabric (30–50%)	8297	2275	4967	10,815	2951
Low-Density Discontinuous Urban Fabric (10–30%)	2046	712	1223	3177	1004
Industry and Production Areas	104	276	224	2792	40
No Data (No Image)	2694	113	840	2784	868
Trade Areas	264	236	193	971	172
Other Roads and Related Areas	49	49	77	395	71
Areas with No Current Use	434	170	205	214	195
Places of Worship	1	4	32	135	15
Education Areas	10	15	23	60	18
Maki or Herbaceous Plants	33	14	37	59	52
Health Areas	9	12	20	48	9
Public Spaces	18	82	10	40	13
Arable Areas	29	5	16	39	33
Continuous Products	24	6	15	35	13
Green Areas in the City (Active)	3	4	14	22	6
Sports and Entertainment Areas	10	3	4	21	1
Airports	0	0	0	21	0
Hotel/Resort	0	1	1	13	0
Very Low-Density Discontinuous Urban Fabric (<10%)	22	6	15	12	22
Urban Green Spaces (Passive)	17	2	21	11	8
Cemetery Areas	0	0	2	3	0
Construction Areas	120	5	50	2	43
Pasture Areas	0	1	1	2	0
Forests	0	0	0	2	6
Isolated Structures	0	0	0	1	0
Fruit Gardens	0	0	0	1	0
Greenhouse Areas	2	0	0	0	0
Rapid Transit Routes and Related Areas	0	1	1	0	0
Mine Quarry and Discharge Sites	0	0	0	0	1

Appendix F

Table A6. Distribution of optimized hot spot results by urban land use types at a population scale.

Urban Fabric Classification	Cold Spot with 90% Confidence	Cold Spot with 95% Confidence	Cold Spot with 99% Confidence	Hot Spot with 90% Confidence	Hot Spot with 95% Confidence	Hot Spot with 99% Confidence	Not Significant
Medium-Density Discontinuous Urban Fabric (30–50%)	6727	7264	4307	11,855	24,267	196,123	149,420
High-Density Discontinuous Urban Fabric (50–80%)	23,238	20,209	15,187	14,777	26,556	114,299	320,259
Permanent Urban Fabric (>80%)	74,110	107,323	64,610	16,920	24,910	79,825	456,006
Low-Density Discontinuous Urban Fabric (10–30%)	1950	1385	272	3223	6803	76,294	36,275
No Data (No Image)	2444	857	417	3775	9203	62,974	28,772
Areas with No Current Use	115	32	16	1025	1694	16,281	9158
Construction Areas	34	74	22	2	359	8170	347
Trade Areas	609	847	124	673	1030	6674	10,718
Urban Green Spaces (Passive)	74	153	0	380	1148	5578	2382
Industry and Production Areas	2590	2259	321	96	93	2176	13,746
Other Roads and Related Areas	203	231	290	141	324	1717	2710
Maki or Herbaceous Plants	22	10	41	149	278	1292	1070
Public Spaces	6	6	4	324	386	1210	1403
Continuous Products	7	0	0	17	91	684	442
Sports and Entertainment Areas	0	4	0	0	22	673	153
Very Low-Density Discontinuous Urban Fabric (<10%)	0	0	0	79	219	412	479
Arable Areas	2	3	7	117	73	335	498
Education Areas	24	41	3	24	145	151	742
Health Areas	59	27	4	71	85	113	598
Green Areas in the City (Active)	2	15	1	0	0	62	215
Places of Worship	35	115	90	0	17	39	531
Cemetery Areas	0	0	0	0	0	4	9
Rapid Transit Routes and Related Areas	0	0	0	0	0	1	24
Airports	56	31	0	0	0	0	20
Hotel/Resort	19	1	0	10	0	0	26
Isolated Structures	0	0	0	0	0	0	3
Mine Quarry and Discharge Sites	0	0	0	0	0	0	3
Pasture Areas	0	0	0	0	0	0	24
Fruit Gardens	0	0	0	0	0	0	2
Forests	0	0	0	0	0	0	53
Greenhouse Areas	0	0	0	0	0	0	43

Appendix G

Table A7. Distribution of optimized hot spot results by urban land use types at a building scale.

Urban Fabric Classification	Cold Spot with 90% Confidence	Cold Spot with 95% Confidence	Cold Spot with 99% Confidence	Hot Spot with 90% Confidence	Hot Spot with 95% Confidence	Hot Spot with 99% Confidence	Not Significant
Permanent Urban Fabric (>80%)	11,775	19,196	13,866	1120	1516	3304	54,724
High-Density Discontinuous Urban Fabric (50–80%)	4148	4142	4143	923	1492	3391	37,859
Medium Density Discontinuous Urban Fabric (30–50%)	1567	2057	1356	630	1153	4899	17,643
No Data (No Image)	669	325	288	189	397	1656	3775
Other Roads and Related Areas	47	57	96	6	18	35	382
Low-Density Discontinuous Urban Fabric (10–30%)	529	385	88	156	296	1654	5054
Industry and Production Areas	535	534	76	4	5	23	2259
Trade Areas	146	176	32	35	50	119	1278
Maki or Herbaceous Plants	8	7	23	3	8	17	129
Places of Worship	8	32	23	0	5	8	111
Construction Areas	13	35	20	1	14	114	23
Arable Areas	2	3	7	4	3	13	90
Areas Without Current Use	45	16	4	40	58	290	765
Public Spaces	1	2	2	18	18	14	108
Education Areas	7	9	2	1	5	9	93
Green Areas in the City (Active)	1	5	1	0	0	4	38
Health Areas	7	4	1	2	3	2	79
Green Areas within the City (Passive)	23	42	0	30	68	245	240
Continuous Products	1	0	0	1	3	18	70
Very Low Density Discontinuous Urban Fabric (<10%)	0	0	0	4	6	17	50
Sports and Entertainment Areas	0	2	0	0	1	9	27
Rapid Transit Routes and Related Areas	0	0	0	0	0	1	1
Cemetery Areas	0	0	0	0	0	1	4
Airports	10	8	0	0	0	0	3
Isolated Structures	0	0	0	0	0	0	1
Mine Quarry and Discharge Sites	0	0	0	0	0	0	1
Pasture Areas	0	0	0	0	0	0	4
Fruit Gardens	0	0	0	0	0	0	1
Forests	0	0	0	0	0	0	8
Hotel/Holiday Village	8	1	0	1	0	0	5
Greenhouse Areas	0	0	0	0	0	0	2

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