DOKUZ EYLÜL UNIVERSITY

GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

EXAMINING THE RELATIONSHIP BETWEEN THE SOCIOECONOMIC STRUCTURE AND THE EFFICIENCY OF URBAN TRANSPORT NETWORK IN URBAN AREAS USING THE DEGREE OF CIRCUITY

by

Elif Su KARAASLAN

July, 2021

İZMİR

EXAMINING THE RELATIONSHIP BETWEEN THE SOCIOECONOMIC STRUCTURE AND THE EFFICIENCY OF URBAN TRANSPORT NETWORK IN URBAN AREAS USING THE DEGREE OF CIRCUITY

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by

Elif Su KARAASLAN

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İZMİR

M.Sc THESIS EXAMINATION RESULT FORM

We have read the thesis entitled **"EXAMINING THE RELATIONSHIP BETWEEN THE SOCIOECONOMIC STRUCTURE AND THE EFFICIENCY OF URBAN TRANSPORT NETWORK IN URBAN AREAS USING THE DEGREE OF CIRCUITY"** completed by **ELİF SU KARAASLAN** under supervision of **PROF.DR. KEMAL MERT ÇUBUKÇU** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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ABSTRACT

Equally distributed, accessible, and available urban public services should be for every individual living in the city. Although urban areas are heterogeneous it does not justify providing services at different levels. This study aimed to reveal the disadvantaged urban areas by determining where the urban public transport network is sufficient/insufficient and to reveal whether relationships exist in the efficiency levels of public transportation and the socioeconomic variables.

In this research, *circuity degree* was used to reveal the efficiency of public transportation systems. The linkage between the efficiency of public transportation systems and the socioeconomic characteristics was investigated in the İzmir metropolitan area and *per capita income* and *population density* were used as socioeconomic variables. Analyzes were done with using Geographical Information Systems. *Global Moran's I* and *Anselin Local Moran's I statistics* were used to investigate the spatial distribution of the efficiency; to reveal the relationship between efficiency and the socioeconomic variables, *bivariate Global Moran's I* and *bivariat*e *Anselin Local Moran's I* were used.

The results are statistically significant at the 0.05 level. It is revealed that the socioeconomic characteristics and the efficiency of the public transportation systems are significantly related and differentiated spatially. This study provides a worthy approach in spatially determining the urban public transport efficiency in urban areas and proved that the socioeconomic variables that affected the efficiency levels can be obtained spatially. The methods used in this research are easily applicable and provide results for the improvement of the public transportation network.

Keywords: Circuity, network efficiency, public transportation, socioeconomic structure, Moran’s I, spatial autocorrelation

KENTSEL ALANLARDA SOSYOEKONOMİK YAPI İLE KENTSEL ULAŞIM AĞI VERİMLİLİĞİ ARASINDAKI İLİŞKİNİN SAPAK ENDEKSİ (CIRCUITY DERECESİ) KULLANILARAK İNCELENMESİ

ÖZ

Eşit olarak dağıtılmış, erişilebilir ve kullanıma hazır kentsel kamu hizmetleri, kamu yararını dikkate alarak şehirde yaşayan her birey için sağlanmalıdır. Kentsel alanlar heterojendir ancak bu durum, farklı düzeylerde hizmet sunulmasını haklı çıkarmaz. Bu çalışma, kentsel toplu taşıma ağının yeterli ve yetersiz olduğu alanları belirleyerek, dezavantajlı kentsel alanları ve toplu taşıma sistemlerinin verimlilik düzeyleri ile sosyoekonomik değişkenler arasında mekânsal ilişkiler olup olmadığını ortaya çıkarmayı amaçlamaktadır.

Bu araştırmada, verimlilik değerlendirme ölçüsü olarak *sapak endeksi* kullanılmıştır. Toplu taşıma sistemlerinin verimliliği ile sosyoekonomik özellikler arasındaki bağlantı, İzmir metropoliten alanındaki 348 mahalleyi kapsayarak kurgulanmış, sosyoekonomik yapıyı değerlendirmek için *kişi başına düşen gelir* ve *mahallelerin nüfus yoğunluğu* kullanılmıştır. Kentsel ulaşım ağındaki verimliliğin/verimsizliğin mekânsal dağılımını ve bunların sosyoekonomik değişkenlerle ilişkisini görmek için Coğrafi Bilgi Sistemleri kullanılmıştır. Sapak endeksi değerlerinin mekânsal dağılımını incelemek amacıyla, *tek değişkenli mekânsal otokorelasyon analizleri* olan *Global Moran's I* ve *Anselin Yerel Moran's I*; sapak endeksleri ve sosyoekonomik değişkenler arasındaki ilişkiyi incelemek amacıyla *iki değişkenli mekânsal otokorelasyon analizleri* olan *iki değişkenli Global Moran's I* ve *iki değişkenli Anselin Yerel Moran's I* istatistikleri kullanılmıştır.

Sonuçlar, 0,05 düzeyinde istatistiksel olarak anlamlıdır. Toplu taşıma sisteminin verimliliği ve sosyoekonomik özellikler arasında, mekânsal olarak anlamlı bir ilişki olduğu; bu ilişkinin mekânsal olarak farklılaştığı ve yoğunlaştığı ortaya çıkmıştır. Bu çalışma, kentsel toplu taşıma ağının yeterli ve yetersiz olduğu alanlarının, mekânsal olarak belirlenmesinde değerli bir yaklaşım ortaya koymakta, verimliliği etkileyen sosyoekonomik değişkenlerin mekânsal olarak tespit edilebileceğini kanıtlamaktadır. Bu araştırmada kullanılan yöntemler, toplu taşıma hizmetlerinin planlanmasında kolayca uygulanabilir bir yaklaşım sunmakta ve iyileştirilmesinde kullanılabilecek sonuçlar sağlamaktadır.

Anahtar kelimeler: Circuity, ağ verimliliği, toplu taşıma, sosyoekonomik yapı, Moran’s I, mekânsal otokorelasyon

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CHAPTER 1
INTRODUCTION

Cities are dynamic, living systems and have been investigated by many urbanists, sociologists, economists, and other various related scientific fields. In the statement of Wirth (1938), he argued it may be proper to define a city as a large-sized, dense, and heterogenous social entity. Social, economic, demographic, historical, topological structures differ within a city and even between cities. The socioeconomic aspects and the spatial arrangements in a city were concerned and many researchers have studied the connections between public services as an urban policy and the equality in accessing them.

The statement of Jacobs (1961) “Cities have the capability of providing something for everybody, only because, and only when, they are created by everybody” was formed the initial thoughts of this research as a baseline. Urban equality as a basic yet important concern is related to all branches of the urban planning discipline. Equally distributed, accessible, and available urban public services should be for every individual living in the city by enhancing the public interest.

In his book in 1970, Henri Lefebvre pointed out that different social groups interact with each other, and create and exist in their own places so that the general form of the city shaped by their interactions and characteristics (Lefebvre, 2013). It can be said that the different social groups are located in different parts of the city. In the light and ideology of Marx and Engels, Smith (2010) points to the uneven development in a spatial context formed by social inequality in a city. Spatial segregation is relevantly a crucial concern and according to Musterd (2005), it is highly related to social inequality. In this perspective, the distribution of public resources should be considered. It has been investigated that the inequalities in accessing the public services in the city over the years. The notion that citizens do not benefit equally from the distribution of public services, has been widely accepted by scholars and the general public (Lineberry, 1974).

The concept of the right to the city as the statement of Henri Lefebvre in his book back in 1968, has been studied and debated in the urban planning discipline since then. With embracing the initial point of the right to the city, many socio-spatial problems can be argued. Harvey (2013) stated that Lefebvre’s right to the city concept was framed with the earlier works of Marx and stated that the right to the city is a demand and an outcry. Public services must be provided for all citizens in an adequate and efficient way. The demand for taking efficient service is a legal right. Urban public services are mostly provided by public authorities using public resources. In this case, access to urban transport services, which is one of the basic public services, and is very important for all city residents to meet their daily mobility needs. Participating the urban mobility which shapes the lives of the inhabitants is the basic right for everybody. That is the secondary initial concern for this research’s to be formatted.

Dikeç (2005) argues that on occasions where inequality increases, then we discuss the ‘exclusion’ and ‘excluded’ rather than uneven development and exploitation. There are socio-economic, topographic, physical, and cultural differences, but these differences do not justify providing services to urban areas at different levels. In this case, taking into account the study of Dikeç (2005), it can be said that conscious segregation in providing services may be an issue.

It has been observed that basic public services such as public transportation are unequally distributed in different parts of a city. This study aimed to reveal the urban areas with services disadvantages by determining the areas where the urban public transport network is concentrated and insufficient. In this perspective, socioeconomic characteristics play an important role in this way. Omer & Goldblatt (2011) found segmentation or separation in a city accounts for the differentiation in socio-economic structure. There are many studies that suggested the direct relation between the socioeconomic structure and public transportation (Galster & Killen, 1995; Krizek, 2003; Pucher & Renne, 2003; Renne & Bennett, 2014).

This thesis mainly centered on examining the efficiency of public transportation systems by using *circuity degree* as the efficiency assessment measure. The linkage between the efficiency of public transportation systems and the socioeconomic characteristics was formed. Previously mentioned spatial segregation, spatial inequality, and the right to the city concepts were internalized and discussed with the relationship efficiency in public transportation services.

Although, there is intense literature focusing on socioeconomic disparities between neighborhoods, and studies examined the public services and public transportation systems; none of them has provided a method for spatially investigating the efficiency of the public transportation systems and the spatially reveal the relationship between socioeconomic structure. This study is unique in focusing on the circuity degree as the measure of the efficiency and the neighborhoods with their differences in terms of socioeconomic characteristics.

It was examined if there are any relationships between public transportation efficiency and the socioeconomic structures at the neighborhood level in İzmir. Two variables were used to assess the socioeconomic structure such as per capita income levels and population density levels of the neighborhoods. Differentiation of the circuity level as the determiner of the efficiency was calculated as the first step for the later analyzes. Due to see the spatial distribution of the efficiencies/inefficiencies and their relationship with the socioeconomic variables, several spatial analyzes used in this study using the Geographical Information Systems.

In *Spatial Autocorrelation techniques*, each of the observed data is being analyzed regarding their attributes to reveal if there is a relationship between them. Spatial autocorrelation analyzes were applied in many studies in different fields such as zoology, ecology, marine aquaculture, engineering services, and indeed, urban planning. There are spatial autocorrelation techniques such as univariate, bivariate, and multivariate. Univariate spatial autocorrelation analyzes can be performed only with one variable while bivariate spatial autocorrelation analyzes can be performed with two variables. In this study, *the Global Moran's I* and *Anselin Local Moran's I* statistics were used to identify if there is a relationship between the circuity levels of the neighborhoods in univariate and bivariate ways. Univariate and bivariate analyzes of Global and Local Moran were performed at the neighborhood level in İzmir. Univariate spatial autocorrelation analyzes used to investigate the spatial distribution of the circuity degrees. This analyzes identified spatially where the efficiencies and deficiencies located. The bivariate spatial autocorrelation analyzes were performed between circuity and the socioeconomic variables separately. With the help of the bivariate spatial autocorrelation analyzes the relationship between the mentioned variables obtained in İzmir.

This study has put forth a worthy approach in spatially determining the urban areas that receive an efficient public transportation service and the urban areas that have service deficiencies and/or insufficiencies. Also, this study proved that with the bivariate analysis the socioeconomic variables that affected the efficiency can be obtained spatially. The several methods that shaped this research, easily applicable, and provide results that are really can help the overall improvement of the public transportation systems. The findings can be beneficial for the decision-makers and practitioners of the city in providing more inclusive decisions and enhancing the public interest. This study suggests that with further improvements in the data collection processes and technical adjustments, the efficiency of the public transportation systems and the relationship with the socioeconomic structure can be correctly and practically obtained by the method methods provided in this research.

The overall study was organized as follows: Chapter 2 presents the literature review, Chapter 3 contains the methodology with the stages that built up this research, Chapter 4 presents the data used, Chapter 5 contains the analysis and results of the research, and the last section Chapter 6 presents the discussion and conclusions of this thesis.

CHAPTER 2
LITERATURE REVIEW

2.1 The Degree of Circuity and The Public Transportation Systems

Network structures shape cities, orientate the development processes and provides mobility. Since the roads mainly direct the transportation, urban public transportation systems also depend on the network structure in terms of efficiency and inclusiveness. The network structures in urban areas are various. The internal network structure of the city characterized by its topography, design standards, population density (Levinson, 2012). Planning the network structures must be considered to sustain efficiency in urban transportation and for the sake of every individual living in the city.

Euclidean distance and network distance have been concerned in the past decades in various studies. In their work, Haggett & Chorley (1967) had early thoughts and discussions about the Euclidean distance and the network distance which they were used in their model proposals. The difference between these two measures of distance is an important matter, especially in spatial sciences and analysis. The relation between the Euclidean distance and the network distance was also argued by Barbour (1977). In his work Barbour (1977) performed and compared theoretical and real network structures with rural road length and farm-market distances to investigate the efficiency of the road system and to determine what types of road patterns minimize road costs. He concluded that an optimum and efficient road system can be more logical to spend the public funds more carefully (Barbour, 1977). The search for efficiency has been an initiator in the research and development of the degree of circuity.

The circuity index has been used in studies and applications in many different fields especially it has been widely used in network analysis. It is calculated with two distance variables which are Euclidean distance and network distance. Circuity is the ratio of the shortest path distance over the Euclidean distance, and it is using for the measurement of network efficiency (Levinson & El-Geneidy, 2009; Parthasarathi, Levinson & Hochmair, 2013; Huang & Levinson, 2015; Giacomin & Levinson, 2015). A circuity factor cannot be less than 1 (Ballou, Rahardja & Sakai, 2002). Since network distances are greater than the Euclidean distances between the two locations, a circuity factor should be greater than one. The circuity value is equal to 1.000 if the network has a perfect connection (Giacomin & Levinson, 2015).

O'Sullivan & Morrall (1996) calculated the average circuity for the transit stations' service areas with the purpose of understanding the pedestrian behavior about the walking distance to LRT transit stops. They aimed to see the relationship between the service area defined in general guidelines of transit stops and the transportation activity may be helpful to increase the usage and effectiveness of urban transit systems (O'Sullivan & Morrall, 1996). The average circuity was found as 1.21-to-1.24 in Calgary, Canada and it was seen that the degree of circuity is a significant tool for transit catchment areas and understanding the pedestrian behavior (O'Sullivan & Morrall, 1996). Their study is a valuable work as it attaches great importance and contributes to the development of public transportation and the provision of public services to the citizens more efficiently. Ballou et al. (2002) comprised the road networks of 26 countries and determined the circuity levels varying from 1.12 to 2.10. Their research was determined that the factors affecting the circuity levels. They stated that directly connected high-level roads show quite lower circuity levels than the cities with low-density road networks with poor connection and obstacles. They concluded that the average circuity can be used as a multiplier in designing the urban networks, or other spatial applications based on networks as it is a proper measure in assessing the efficiency of road networks (Ballou et al., 2002).

Circuity factors also related to individuals and travel behaviors. Levinson & El-Geneidy (2007) investigated the work-home locations and used the circuity factor. They found that individuals' route selections are 0.056 smaller than the random routes, so they consciously choose routes with lower circuity levels. Therefore, they stated that the efficiency of a network is directly related to the travelers' usage of the network. According to Levinson & El-Geneidy (2009) workers choose to reside in the areas, where the home-to-work routes have lower circuity levels. They concluded that network efficiency must be assessed regarding travelers' behavior and that maximizing land while minimizing commute time is an important factor in urban location.

Boscoe et al. (2012) hypothesized that network distances give more advanced and precise results than straight-line distances in seeking the most efficient route for the hospitals. They used the circuity index and compare travel time and travel distance. They stated that both can be used instead of straight-line distance (Boscoe et al., 2012). Levinson (2012) determined the transportation performance by analyzing the accessibility and network structure of 50 US cities by using the measures of connectivity, treeness, accessibility, entropy, and circuity. The study finds out due to a high correlation between automobile and transit accessibility, large cities have both high automobile and transit accessibility, consequently, the transit mode share increases with the accessibility levels, in contradistinction to the automobile mode share (Levinson, 2012). The study provides a perspective about understanding transportation performance by analyzing the internal and external network structures. Giacomin & Levinson (2015) calculated the circuity levels for different time periods and found that circuity was significantly increased over the years and became less efficient less well-connected than before.

Parthasarathi et al. (2013), hypothesized that the perception of travel time of individuals is related to the street network. They used the circuity index and calculated it with the travel times. They stated that the travel time cognition and the street network structure have a relation, and street network structure has effects on travelers' perception (Parthasarathi et al., 2013). Their work proved that travel time gives accurate results in calculating the degree of circuity and that this index can be used successfully applied in other studies. Nagne & Gawali (2013), stated that as a measure of the efficiency in road networks, it is convenient to use the degree of circuity for transportation purposes. They stated that because the service areas of transportation systems are extensive, it is powerful to use the circuity degree in efficiency purposes at wide spatial coverage like a city or a region (Nagne & Gawali, 2013).

Huang & Levinson (2015) calculated the circuity levels by using the unweighted travel time as the shortest route in the calculation of the degree of circuity to comprehend the performance of urban public transportation systems and explain the mode share. They find out travel time by transit and the circuity degree of the transit are negatively correlated. As mentioned earlier, the comparison of the circuity degrees between transit and automobile trips shows how transit systems serve and explain the travel behavior of individuals. Their study (Huang & Levinson, 2015) creates a ground for using the travel times of different mode share which is useful in assessing efficiency in public transit networks.

The usage of circuity in assessing public transportation efficiency has been an enlightening development in the fields of public transportation services and urban and transportation planning. Owen & Levinson (2015) calculated circuity with using travel times by transit and the travel times by auto and compared the accessibility of transit and auto mode shares. They argued that circuity and accessibility are negatively correlated, and circuity level has effects on selecting the mode share (Owen & Levinson, 2015). Boeing (2019) determined the relationship between walkable and driveable urban networks by using the circuity index. Investigating network efficiency has been widely considered in earlier studies. In his study, he concluded that urban travel and access studies should be used network-based distances rather than straight-line and it is important to note that different types of places have various network circuities. (Boeing, 2019). The network structures and the efficiency in transportation systems has been studied in many different contexts. Çubukçu (2020) performed a ring-based analysis and states that circuity is diverse through different parts of the city, and it can be useful in assessing the network efficiency by being a guide for policymaking in the planning. It is reasonable to use circuity for transport efficiency purposes, in this manner it can assess the network measures tacitly in a travel route or origin-destination pair (Çubukçu, 2020).

As stated earlier, the circuity index can be used for the purpose of assessing the network efficiency (Levinson & El-Geneidy, 2009; Parthasarathi, Levinson and Hochmair, 2013; Huang & Levinson, 2015; Giacomin & Levinson, 2015). Many studies investigated the performance and efficiency in public transportation systems with the degree of circuity (Huang & Levinson, 2015; Nagne & Gawali, 2013; Owen & Levinson, 2015). Nagne & Gawali (2013), stated that because the service areas of transportation systems are extensive, it is powerful to use the circuity degree in efficiency purposes at wide spatial coverage like a city or a region. Additionally, Huang & Levinson (2015) calculated the circuity levels by using the unweighted travel time as the shortest route in the calculation of the degree of circuity to comprehend the performance of urban public transportation systems, and Owen & Levinson (2015) calculated circuity with using travel times by transit and the travel times by auto and compared the accessibility of transit and auto mode shares. It is as a measure of the efficiency in road networks, it is convenient to use the degree of circuity for seeking efficiency in public transportation purposes (Nagne & Gawali, 2013).

Public transportation systems are mainly crucial for sustainable, inclusive, and efficient urban mobility in cities. These studies have provided a series of conclusions that have contributed to the concern of efficiency in public transportation services for improvement in the field of urban transportation services. It is aimed to find out if any differentiation between the neighborhoods in terms of giving public transportation services regarding their socio-economic characteristics. In the light of this literature review, this study investigated the efficiency of public transportation services using the circuity index. The relationship between the socio-economic variables such as population density and per capita income and circuity levels of the neighborhoods as the efficiency determiner was further analyzed in the study.

2.2 Per Capita Income and Public Transportation

This literature review has been conducted to see previous researches focused on the effect of per capita income on public transport services. As stated earlier, the relationship between per capita income and the efficiency of public transportation services were examined spatially in this study.

Urban and rural areas show different characteristics in terms of their social, economic, demographic, historical, topological structures. Cities are heterogenic in many aspects; they have changed over the years by the interference of their residents and the public authorities. Since this differentiation is important in terms of development and public services, the studies investigating urban equity, inclusiveness, and urban services have been developing for years. Many studies investigated the issue of income levels of households and their spatial and social existence in the city.

Omer & Goldblatt (2011) found that segmentation or separation in a city accounts for the differentiation in socio-economic structure. Differentiation in social structure has a significant relationship with spatial segregation in a city (Omer & Goldblatt, 2011). Galster & Sharkey (2017), stated that spatial segregation is directly related to economic inequality. Their study showed that there is a distinct relationship between household income and location choice (Galster & Sharkey, 2017). It is common knowledge to think of suburban residents have higher socio-economic status. Brueckner & Rosenthal (2009) investigated the income and the age of the housing stock with a spatial perspective and found that the income level is increasing with the distance from the city center.

The socio-economic structures of a city differentiated and studied in terms of urban services. The notion that citizens do not benefit equally from the distribution of public services, has been widely accepted by scholars and the general public (Lineberry, 1974). Lineberry (1974) argued that equal social standards must be applied in order to enhance equality in terms of basic needs. Miller & Roby (as cited in Lineberry, 1974, p. 26) argue that income may refer as a “hidden multiplier” of public services. Lineberry (1974) investigated the spatial arrangements and capacities of the libraries as public services and found that wealthier urban areas get more sufficient services such as the capacity, the density of the population served. It is highly agreed that equal access to public resources is required for sustainable development (Kawabata & Shen, 2007).

Public transportation is one of the main urban services and it is crucial for urban mobility. It must in service for everybody living in the city. Galster & Killen (1995) stated that higher-income households are more advantaged in giving adequate public services. Additionally, Pucher (1982) suggests that neighborhoods with lower income have been giving insufficient public transportation service with high fares contradiction to the unqualified and crowded travel supply. Public transportation times are longer in the low-income urban areas, due to the service mostly provided by bus transit (California Department of Transportation, 2001). It can be interpreted as a service deficiency for low-income urban areas.

It has long been a concern and studied many times that the public transportation systems may affect the location choice of households (LeRoy & Sonstelie, 1983). Glaeser, Kahn & Rappaport (2008) investigated the poverty rates and the public transportation services spatially, they find out that the low-income groups tend to locate in central city neighborhoods because of their dependence on public transportation. The expansion or upgrading in the public transportation system was led to the increase in the low-income relocation towards the service innovations (Glaeser et al., 2008).

The need for mobility demand is essential because daily activities such as work, school, leisure are the basic daily needs. Urban mobility needs are affected by the presence of an adequate and efficient public transportation system. There is a relationship between the three variables which are socio-economic characteristics, travel behavior, and land use. It is common knowledge in the urban planning discipline that socioeconomics has impacts on travel behavior. Stead (2001) claims that the travel behavior of households often influenced by socio-economic characteristics. Concurrently, Krizek (2003) find out that socio-demographic conditions are significantly affecting travel behavior. Furthermore, Renne & Bennet (2014) stated that daily travel with different mode choice decisions is related to household economics, demographic characteristics, and the overall system design.

The mobility rates are differentiated regarding the socio-economical structure. Low-income households have narrow possibilities, and they have to travel less than other parts of the society (Guiliano, 2005). In their research, Pucher & Renne (2003) argue that lower-income households make shorter and fewer trips per day rather than high-income households. It can be also related to urban mobility, that households in urban areas with less accessibility meet their multiple needs in one trip (Krizek, 2003). California Department of Transportation (2001) suggested that generally low-income households that used public transportation-related with less and short trips. These arguments show that mobility is limited in some urban areas and the income level has a hold on it. Renne & Bennet (2014) noted that because the travel costs are all paid by the travelers, the income becomes the essential variable for the mobility needs. California Department of Transportation (2001) remarked that due to the limited facilities, low-income groups have fewer trips, which is not their preference. Pucher & Renne (2003) stated that it is an indication of inequality in a public transportation system that low-income citizens have lower mobility levels. Public transit has a high level of urgency for the mobility of the low-income and the elderly aged households (Guiliano, 2005). Public transportation systems must be in the use of every citizen and equally distributed in terms of accessibility to the system.

California Department of Transportation (2001) assessed that the poor and low-income households tend to use public transportation regularly when the transit system exists. Concurrently, Rosenblatt & DeLuca (2012) reported that public transportation existence is a significant factor for households, especially those living in low-income urban neighborhoods. Pathak, Wyczalkowski & Huang (2017) examined whether there is an impact on the residential location choices of the low-income households caused by the shifts in the bus transportation system. The lower-income groups tend to locate near CBD in order to use public transportation and have easier access to amenities and jobs in the city center (Brueckner & Rosenthal, 2009). Pathak et al. (2017) concurred with the findings of Glaeser et al. (2008) and Brueckner & Rosenthal (2009) and further stated that public bus transportation access is an important indicator for those households with lower-income level.

Since car ownership has a relationship with income level, it can be stated that mobility which is "a function of resources" is related to the travel behavior of households (California Department of Transportation, 2001). Low-income households commonly do not own a car and abstain to relocate due to their dependence on public transportation (Rosenblatt & DeLuca, 2012). Dong (2017) stated that lower-income areas with lower car ownership in the city are more interacting with the public transportation services. As it is expected households that do not have cars tend to use public transportation (California Department of Transportation, 2001). Consequently, low-income households do not prefer to make long trips with expensive and long suburban public transportation without owning private cars, so they tend to stay inner city (Clampet-Lundquist, 2004). It was concluded that the location choice of the low-income households in urban areas can be affected by the changes in the service quality of public transportation systems (Pathak et al., 2017). Schouten (2019) stated that the absence of a private vehicle in low-income households makes public transportation crucial and steers them to locate in inner-city rather than moving to newly developed residential areas. Kawabata (2003) remarked that old and compact urban metropolitan areas have more enhanced public transportation systems which may compete with the car-dependent areas of the city.

From a different point of view, researchers found significant correlations between new investments in the public transportation networks and gentrification or upgrading in the economic and physical structures in low-income areas (Immergluck, 2008; Dukakis Center for Urban and Regional Policy, 2010). Immergluck (2008) investigated the development project which is called Atlanta Beltline and found significant changes in estate values after the implication of the project in the area. The study concludes that it must be comprehensively thinking and planned to develop such projects which can lead to gentrification and consequently to a displacement of the residents (Immergluck, 2008). Dukakis Center for Urban and Regional Policy (2010) also mentioned the risk for the investment in public transportation could lead to differentiation of the surrounding neighborhood and this may consequently be against the individuals living there. They stated that the risks such as displacement and gentrification of the area should be prevented with planning tools and policies by forecasting the side-effects for the low-income and disadvantaged groups (Dukakis Center for Urban and Regional Policy, 2010). It can be predicted that the existence of an efficient and adequate public transportation system is a wanted and speculative feature for the surrounding neighborhoods, but the negative effects are crucial for the locals who could be displaced.

Pucher & Renne (2003) argue that public authorities and decision-makers disregard the demand for public transportation of the low-income groups. Taylor (1991) stated that the public transit service funding has canceled in low-income areas in the city and the funds were used for the low-density high-income suburban areas instead. The decision of the abolition of the transit line is not fit the service efficiency concerns and the need for transit has economic and political sides (Taylor, 1991). Manville, Beata & Shoup (2013) investigated the relationship between private car usage, parking, transit usage, and the socio-economic characteristics in the USA, they stated that high-income households use the public transportation system less. Nevertheless, Giuliano (2005) stated that public transportation services are improving in the urban areas with no crucial dependency rather than the highly demanded urban parts. California Department of Transportation (2001) stated that suburban commuters may prefer public transportation due to high car-parking charges. In the research of Renne & Bennet (2014), it was stated that only high-income households prefer the commuter rail system applied in the wealthier suburban areas. Ignoring the high implementation costs of such systems with limited users may lead to financial losses. Guiliano (2005) stated that it would be more operative if a properly scheduled public transportation system applied to high-density with low-income and poor urban areas in a city. Especially in inner-city low-income neighborhoods, the demand for public transportation is important. Indeed, it would be an overall advantage for all workers to develop more efficient and connected public transportation systems, not only for the low-income, low-skilled, and those with dependence on public transit (Kawabata, 2003). Lower-income neighborhoods are more dependent on the existence of an adequate public transportation system.

2.3 Urban Population Density and The Public Transportation

This literature review has been conducted to see the previous literature focused on the effect of population density on public transport services. In the light of this literature review, this study examines the relationship between population density and the efficiency of public transportation services spatially.

In the literature, population and residential density has been widely investigated. Burgess (1925) determined the central growth with a well-known model called the “concentric zone model” which is generally known by many urban researchers. He hypothesized that the socio-economic characteristics and status affect the form of the city and residential areas. Individuals with high socio-economic status live in the low-density residential areas (suburban or commuters’ zone) while the low socio-economic status (immigrants or workers) locate in the central city with high-density urban neighborhoods (Burgess, 1925). The concentric zone model has created a basis for the growth and form of the cities, regarding the density and the social segregation concerns.

Population density, land use, and street characteristics show differences among the neighborhoods (Khattak & Rodriguez, 2005). Density is differentiated among the neighborhoods, and it is related to the household demographics. Anderson & Egeland (1961) stated that high-socio economic status residents locate less dense residential settlements like single-family households, sub-urban settlements, or commuter residential areas located outwards of the city center. Levinson & Wynn (1963) concurrently stated that population density tends to decrease outwards of the highly dense city center. Low-income households tend to reside in high-density urban neighborhoods in the metropolitan areas (California Department of Transportation, 2001). Concurrently, Manville et al. (2013) found that population density has a strong negative correlation with the income level of households.

Many studies found a positive relationship between public transportation usage and population density (Ewing & Cervero, 2001; Frank & Pivo, 1994; Kitamura, Mokhtarian & Laidet, 1997; Zhang, 2004). Walking, mode choice, and population density have significant associations (Frank & Pivo, 1995). These all create a demand for transportation and mobility. Frank & Pivo (1995) stated that population density positively correlated with public transportation usage. Chen, Gong & Paaswell (2008) and Zhang (2004) noted that compact urban forms are associated with density and the existence of a public transportation system.

High-density urban areas generally have a high demand for transportation services. People use public transportation regularly when their jobs located in high-density central urban areas (California Department of Transportation, 2001). The installment of public transportation services between the high-density urban areas especially with CBD would create a magnetic effect for transit (Levinson & Wynn, 1963). Levinson & Wynn (1963) stated that public transportation should be enhanced with higher capacities for high-density urban areas. California Department of Transportation (2001) argue that residents of a high-density residential area with available public transportation services are more likely to be regular users.

Levinson & Wynn (1963) stated that there is a strong positive correlation between public transportation system occupancy and high-density. California Department of Transportation (2001) stated that households that has a dependency on public transportation presumed to reside in high-density neighborhoods rather than low-density suburbs. Local urban population densities are directly related to the public transportation systems, with the second variable of mixed land use (Ewing & Cervero, 2001, 2010). Kitamura et al. (1997) stated that lower-income, smaller houses, less private car ownership and mix land used urban areas address the higher-densities but also more enhanced public transportation service level. Ewing & Cervero (2001) investigated the elasticity in built urban environment characteristics and the travel patterns with mode choice decisions. Highly dense urban areas with mixed-uses have high accessibility with shorter travel times (Steiner, 94; Ewing & Cervero, 2001, 2010). Schouten (2019) argued that in an urban metropolitan area, mixed-use highly dense urban residential neighborhoods are higher levels of public transportation accessibility besides other parts of the city. Urban mobility is one of the crucial concerns and has relations with the income levels of households and eventually the population densities of the neighborhoods. ECOTEC (1993) reported that the population density, average income levels, and car ownership is related to each other and has an impact on the travel behaviors of individuals.

Holtzclaw (1994) assessed the relationship between population density and the travel distances within a year and concluded that there is a negative correlation between the population density and the travel distances. Behaviors of every individual in terms of mobility can affect the public services related and dependent on each other. Transportation patterns are affected by the trip lengths and the efficiency of the public transportation systems thus the urban density is an important manner (Kenworthy & Laube, 1999). Concurrently, Stead (2001) argues that there is a significant relationship between population density and the travel distances of individuals. Population density has a negative correlation with the distance traveled (Stead, 2001). Néchet (2012) studied the spatial correlation between urban spatial structure and daily mobility and suggested that the population density and income levels of the inhabitants are correlated with daily mobility (Néchet, 2012).

It can be assumed that car ownership is related to the household income level as a piece of general knowledge. Since having a private car is expensive, low-income families cannot be able to afford it. Households that reside in high-density neighborhoods are less likely to have a private car (Ewing & Cervero, 2010). Levinson & Wynn (1963) stated that employment and commercial activities are located in the high-density urban central areas due to the availability of public transportation system with less dependency on private cars. Kitamura et al. (1997) stated that people live in higher-density residential areas are more likely to use public transportation systems and other modes rather than the private car. Schouten (2019) argued that households which were moved from their resident often choose to relocate in high-density inner-city neighborhoods and avoid to having a car instead.

On another side, Erwing & Cervero (2001) suggested that in high-density urban areas the car ownership may be discouraging due to parking and congestion problems.

Zhang (2004) and Hamidi, Ewing, Preuss & Dodds (2015) discussed that due to the traffic and car parking problems, people in dense urban areas generally tend to use public transportation system rather than private cars which is one of their findings in the research, density is negatively correlated with the car owner.

Steiner (1994) assessed that in high-density areas it may be easier to find affordable housing for low-income households. High-density with low-income urban areas are adequate for such system can be efficient, but also it must be considered that the low-income households living outside the high-density inner cities (Giuliano, 2005). Since the regions outside the suburban with low-density population, transportation can be a problem for the people living in that kind of rural area. Schouten (2019) argued that there is low public transportation access in the outlying rural areas that sparsely populated.

People who live in residents located in lower-population density areas have lower levels of public transportation usage (Manville et al., 2013). In the literature, low-density residential areas such as suburban settlements are generally associated with high-income households with private car access. Kenworthy & Laube (1999) stated that the higher costs are applied to the public transportation fares especially in low-density, highly private car-dependent areas because they have low occupancy rates. Giuliano (2005) stated that many studies in the past showed that it is more effective to offer low fares in the public transportation system and install them in the areas where the continuous service could be sustained, would increase the usage.

Saghapour, Moridpour & Thompson (2016) argued that the population density in urban areas has been neglected in concerning the accessibility to the public transportation systems in previous studies. Indeed, the effect of income level must be assessed in such cases. Levinson & Wynn (1963) noted that transportation needs must be evaluated by taking the density into the account. Barthélemy (2011) stated that the characteristics of neighborhoods such as population, density, and street network structure are connected with the average travel time. In this case, the view of

Barthélemy (2011) is valuable due this research uses the travel times for calculating the main variable: the circuity index.

CHAPTER 3
METHODOLOGY

This research was carried out in stages using multiple spatial analyzes. In this chapter, the methodology was presented and listed in stages. The methodology was carried out in connection with the literature review.

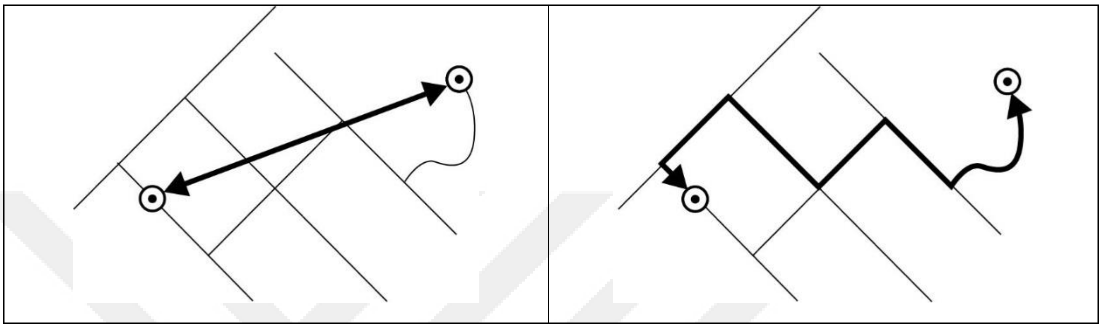
The ability to use geographic information science and systems to solve transportation problems and perform several network operations is one of the most substantial applications in GIS technologies today (Fischer, 2003). The geographical information system software has many capabilities and benefits such as mapping, assessing, modeling, visualizing, and analyzing spatial data with various tools. In this research, the analyzes and techniques conducted by using geographical information system technologies. The procedures that configure this research has been examined under two headings and are as follows: circuity analysis of the public transportation system at the neighborhood level in İzmir province, and spatial analysis of the neighborhoods. These analyzes explained in detail in this chapter.

3.1 Circuity Analysis of the Neighborhoods

In order to perform an accurate circuity analysis, several steps were done. The analyzes of the research began with the mean center analysis of the neighborhoods. The neighborhoods were then matched with the destination points using the closest facility analysis. Finally, the circuity degree was calculated among these origins and destinations. Each of the following steps was explained in detail.

3.1.1 Circuity

There are several methods to calculate the efficiency of the networks. One of them is *the circuity index* and it has been used in studies and applications in many different fields. The degree of circuity has also been widely used in network analysis. It is calculated with two distance variables which are Euclidean distance and network distance as shown in Figure 3.1. Circuity is the ratio of the shortest path distance over the Euclidean distance, and it is using for measurement of network efficiency (Levinson & El-Geneidy, 2009; Levinson et.al., 2013; Huang & Levinson, 2015; Giacomin & Levinson, 2015). In this study, the circuity index is used to determine the efficiency of public transportation systems.



Euclidean Distance	**Network Distance**

Figure 3.1 Difference between Euclidean distance and network distance (Adopted and formatted from Levinson & El-Geneidy, 2009)

The circuity is calculated as:

$$\frac{D_{ij}^{n}}{D_{ij}^{e}} = C_{ij} \tag{3.1}$$

D_{ij}^{n} represents the network distance and D_{ij}^{e} represents the Euclidean distance where the i as the origin, and j as the destination while the C_{ij} denotes the circuity level (Huang & Levinson, 2015).

This study, it is aimed that to assess the efficiency of the urban public transportation network and reveal its relationship with the socio-economic structure by using the degree of circuity to measure the efficiency of public transportation systems. It is reasonable to use circuity for transport efficiency purposes, in this manner it can assess the network measures tacitly in a travel route or origin-destination pair (Çubukçu, 2020).

Circuity can be assessed by using travel time (Huang & Levinson, 2015). As an example, in their study, Huang & Levinson (2015) investigate correlations among automobile circuity, transit circuity, and accessibility of automobile and transit circuity and stated that circuity and accessibility have a possible correlation between each other. Thus, Owen & Levinson (2015) calculated circuity by using travel times by transit and the travel times by auto and compared the transit and auto mode shares. They argued that circuity and accessibility are negatively correlated, and circuity level has effects on selecting the mode share.

In this study, since "travel time" is used to calculate the degree of circuity, the following formula was used to estimate the circuity:

$$\frac{T_{ij}^{t}}{T_{ij}^{a}} = C_{ij} \tag{3.2}$$

T_{ij}^{t} represents the travel time by transit and T_{ij}^{a} represents the travel time by automobile where the *i* as the origin, and *j* as the destination while the C_{ij} denotes the circuity level.

3.1.2 Mean Center

The mean center analysis is the most known and widely used method in central tendency analysis. The geographic center or the center of concentration for a group of features is defined by the mean center (Esri, 2021a). The mean center analysis gives the average location of the given spatial attributes that have been calculated. Çubukçu (2015) stated that the mean center in spatial statistics corresponds to the average value in classical statistics. The averages of the coordinates (x_i, y_i) of the attributes are used in the mean center analysis.

$$(\bar{x}_{mc}, \bar{y}_{mc}) = \left(\frac{\sum_{i=1}^{n} x_i}{n}, \frac{\sum_{i=1}^{n} y_i}{n}\right) \quad (3.3)$$

Attribute values can also be added to entities that can be expressed with points (Çubukçu, 2015). In this research, *the Mean Center* method was performed in ArcGIS's ArcMap version 10.5 software (Figure 3.2).

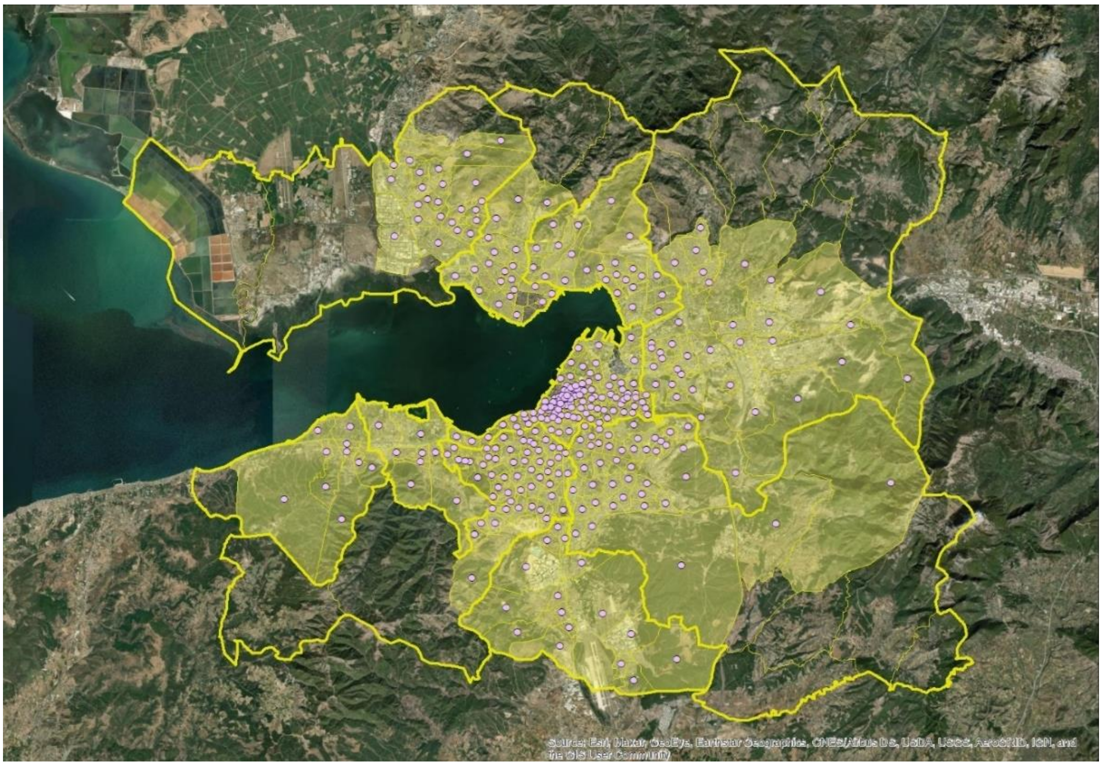


Figure 3.2 Mean Centers of the neighborhoods presented on a satellite imagery (Esri Imagery Basemap accessed in 24.04.2021 edited by the author, 2021)

In this research, *mean center analysis* was created from the polygon attributes of the neighborhoods. These mean centers of the neighborhoods were set as the origin locations for the circuity analysis between Origin-Destination pairs. Thus, the mean center points were used in the retrieval of the travel time data for circuity analysis as origin coordinates.

3.1.3 Digitizing Destination Locations

Geographical information system software has many capabilities and benefits such as mapping, assessing, modeling, visualizing, and analyzing spatial data with various tools. Circuity index was calculated with the travel time by public transportation and the travel time by automobile in this research. The origin locations of the routes were identified with the mean center analyzes as stated in the previous subsection. To define destinations several things were concerned.

The destination points were determined regarding the geographical structure of İzmir. Boscoe, Henry & Zdeb (2012) noted the physical structures that cannot be passed over like rivers, mountains, and rural areas can cause errors in the calculation of the circuity.

In this case, since the shoreline is a massive restriction in calculating the circuity, the decision of the destination locations was critical. The characteristics of the destinations were specified with regarding these requirements:

- Being a multimodal public transportation hub,
- Having the characteristics of a transfer location,
- Accessible by the pedestrians.

With the *Create Feature* tool individual features can be created in point, line, or polygon feature class in a vector format (Esri, 2021b). The *Create Feature* method was performed in ArcGIS's ArcMap 10.5software.

The coordinate system used was a projected coordinate system. Since the distance accuracy is crucial for this study, the projected coordinate system selected is a Transverse Mercator. The characteristics of the adequate coordinate system are as follows:

Projected Coordinate System: ITRF96
Projection: Transverse_Mercator

False_Easting:500000,00000000

False_Northing: 0,00000000

Central_Meridian: 27,00000000

Scale_Factor: 1,00000000

Latitude_Of_Origin: 0,00000000

Linear Unit: Meter

Geographic Coordinate System: GCS_WGS_1984

Datum: D_WGS_1984

Prime Meridian: Greenwich

Angular Unit: Degree

The points that created as the representations of the destinations were created as points and stored in a shapefile format (Figure 3.3). These locations were set as the destination locations for the circuity analysis between Origin-Destination pairs. Thus, the destination points were used in the retrieval of the travel time data for circuity analysis as destination coordinates.

Figure 3.3 Destination locations of the neighborhoods presented on a satellite imagery (Esri Imagery Basemap accessed in 24.04.2021 edited by the author, 2021)

3.1.4 Closest Facility

In recent years, with the development in GIS technology, network analyzes are being done in the GIS software. The ability to use geographic information science and systems to solve transportation problems and perform several network operations is one of the most substantial applications in GIS technologies today (Fischer, 2003).

The shortest destination location for an origin was determined with ArcGIS's Network Analyst extension using the *Closest facility* method. The cost of traveling between two locations and the determination of the shortest network distance between locations can be determined by the closest facility tool as shown in Figure 3.4 (Esri, 2021c). Lehtonen (2021) examined the accessibility of schools as road distances with an aim to reveal the effects of school closures on the rural development in Finland with the shortest path distance calculation.

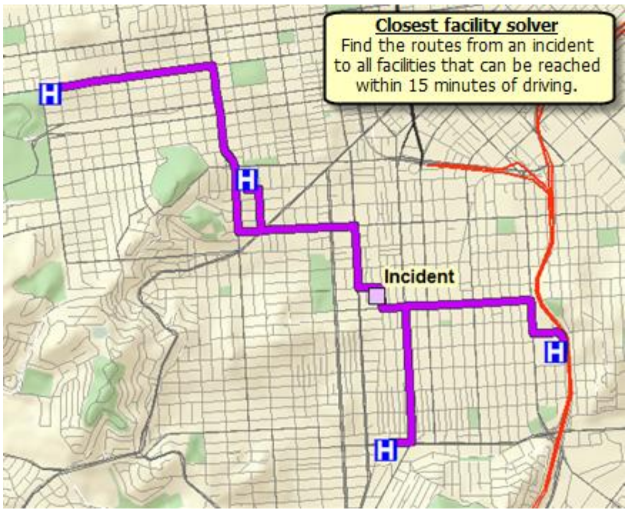


Figure 3.4 The shortest network distances from an incident point as the origin to hospitals within 15-minutes driving time (Esri, 2021c)

The original *Dijkstra's Algorithm* solves the shortest path from a starting point to a destination Esri, 2021d). The algorithm basically selects the path with the minimum total length in several stages. The shortest length of the branches between the nodes is selected by promptly investigating every vertex starting with the assigned origin to the destination (Dijsktra, 1959). Dijkstra's algorithm calculates the most suitable route over a road network (Nicoară & Haidu, 2014).

ArcGIS provides a Network Analyst extension that contains a collection of analysis tools. *The Closest Facility* calculation on the ArcGIS's Network Analyst extension is based on the Dijkstra algorithm (Esri, 2021c). Since Dijkstra's algorithm uses vertexes and lines, the existence of a network feature is required. In ArcGIS software, a network feature is transforming the network data such as the road structure of a city and creates nodes in the intersection points and lines with the capability of restoring the attribute data of them.

Circuity index is calculating between two locations such as origin-destination pair. In the analysis, the origins refer to the neighborhoods' mean centers and the destination points are the locations that were selected according to the city's geographical features. Every origin location must be connected to a destination point. In this research, a network feature was created and the Closest Facility tool was performed over a road network feature. Origins and destinations were matched according to the shortest network distance between them over a road network feature on ArcGIS software.

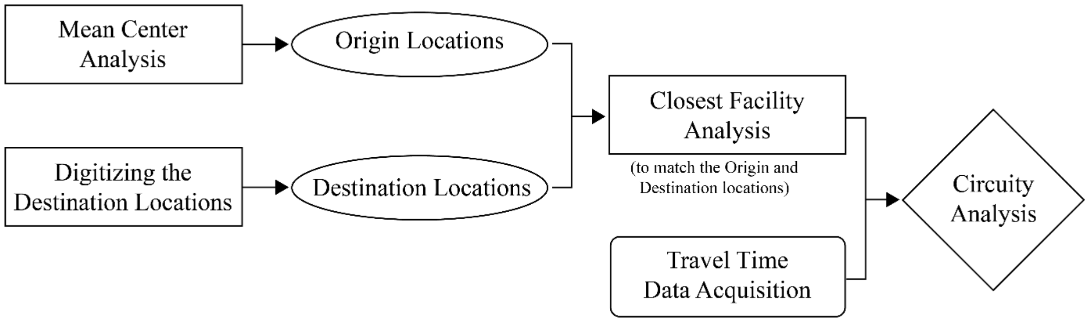


Figure 3.5 Summative flow chart for the circuity analysis

In the circuity analysis section of the methodology for this research, multiple methods were combined. The final circuity analysis was performed with a system such as an input-output chain with the analyzes explained earlier, as seen in Figure 3.5 above.

3.2 Spatial Analysis of the Neighborhoods

The analysis of the spatial distribution of the phenomena's has been widely concerned and investigated over the years. The distribution of assets can be performed in different ways under the Point Pattern Analysis such as Nearest Neighborhood Analysis, Quadrant Analysis, and the Spatial Autocorrelation Analysis. The spatial distribution or the spatial pattern of the investigated point features can be determined using the Nearest Neighborhood Analysis and the Quadrant Analysis. Nevertheless, in these analyzes calculations are made by considering only the locations of the observed data, they disregard the attributes of the data (Çubukçu, 2015). Only the distribution characteristic can be identified by applying the Point Pattern Analysis. Çubukçu (2015) stated that in spatial sciences it can be aimed to investigate the attributes of the spatial data, but in the Nearest Neighborhood Analysis and the Quadrant Analysis, the attributes of the investigated points are not be evaluated.

In Spatial Autocorrelation, each of the observed data is being analyzed regarding their attributes to reveal if there is a relationship between them. The term "spatial autocorrelation" was first described by a geographer named Michael F. Decay (Çubukçu, 2015). The studies of Patrick A. P. Moran and Robert C. Geary have created the basis for spatial autocorrelation techniques. Global Spatial Autocorrelation techniques were improved and Local Spatial Autocorrelation techniques were developed by Getis & Ord (1992) and Luc Anselin (1995).

Spatial autocorrelation analyzes were applied in many studies in different fields such as zoology, ecology, marine aquaculture, engineering services, and indeed, urban planning. In this study, the Global Moran's I and Anselin Local Moran's I statistics were used to identify if there is a relationship between the circuity levels of the neighborhoods.

3.2.1 Univariate Global Spatial Autocorrelation (Global Moran's I)

Global Spatial Autocorrelation techniques were developed by Patrick A. P. Moran in 1948 and Robert C. Geary in 1954. *Moran's I Index* (Moran, 1948) and *Geary's C Ratio* (Geary, 1954) are the most known global spatial autocorrelation techniques for the overall spatial distribution investigation. The idea behind this is to investigate if there is a significant pattern for the attributes in a spatial context. It is a well-known spatial autocorrelation technique in analyzing the spatial patterns of attributes. Moran's *I* index was firstly introduced by Moran (1948, 1950). In their work in 1973, Cliff and Ord clarify and further developed the original classic study of Patrick A. P. Moran (Getis, 2008).

Global Moran's *I* Index was used widely in various fields especially related to geographics and geographic information science. In their study, Chakravorty (2003) investigated the industrial clustering, and performed the Global Moran's I statistic for the hypothesis test. Yang et al. (2011) investigated the population density at the country level in four years period by using the Global Moran's I statistic. More recently, Jossart, Theuerkauf, Wickliffe &Morris Jr. (2020) used the Global Moran's *I* statistic in their study on aquaculture treatment with using the climatological data.

The Moran's *I* statistic for spatial autocorrelation equation is written below:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \bar{x}) (x_j - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{3.4}$$

In the equation above, where *n* is the number of spatial points; x_i is the value of the variable *i*; x_j is the value of the variable *j*; $\bar{x}$ is the mean of *x*; w_{ij} is the element of the spatial weight matrix and S_0 is the sum of the values in w_{ij} matrix. The spatial weight is a value for describing the relationship between the points *i* and *j* (Çubukçu, 2015). There are different formulas for using as a weight due to the aims and structure of the study. Lee & Wong (2001) noted that the weight matrix is created regarding the distances as it is an influential measure for defining a relationship between points one to another and stated as:

$$w_{ij} = \frac{1}{d_{ij}} \tag{3.5}$$

It can be also stated as:

$$w_{ij} = \frac{1}{d^2{}_{ij}} \tag{3.6}$$

Çubukçu (2015) argued that $\frac{1}{d^2{}_{ij}}$ formula usage is common in the studies related to geography.

The I value that is calculated needs to be compared with the Expected Value of Moran's I. The expected value is the cases when there is no spatial autocorrelation under the null hypothesis and the formula of the Expected Value of Moran's I is:

$$E\,(I) = \frac{-1}{N-1} \tag{3.7}$$

Global Moran's I statistics point out the distribution patterns of the observed data as shown in Figure 3.5. The value of I ranges from -1 to +1. The observed spatial distribution is:

- Clustered, if $I > E\,(I)$;
- Random, if $I \approx E\,(I)$;
- Uniform/Dispersed, if $I < E\,(I)$.

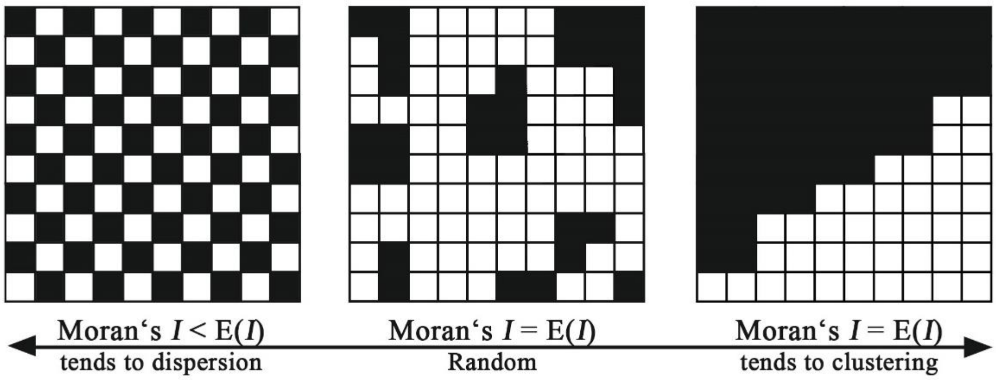


Figure 3.6 Global Moran's I statistics distribution patterns example (Adopted and formatted from Grekousis, 2020)

The hypothesis test is conducted whether the foregoing evaluation is significant for observed spatial distribution. The following are the hypotheses:

H_0: The spatial distribution being analyzed is randomly distributed.
H_A: The spatial distribution being analyzed is not randomly distributed.

The Moran's *I* value must be transformed into a z-score to interpret the spatial distribution as significant or not significant. Below is the formula for the calculation of the z-score:

$$z_I = \frac{I - E(I)}{\sqrt{V(I)}} \tag{3.8}$$

In the formula above, *I* is the Moran's value that calculated; *E(I)* is the expected value of the Moran's *I*; *V(I)* is the Variance value. The following formula is for the calculation of the variance:

$$V(I) = E(I^2) - [E(I)]^2 \tag{3.9}$$

The calculated z-score for the case must ensure the z-value for the significance level at α under the normal distribution for the z-scores values. The following condition must be satisfied:

$$|z_I| \geq z_\alpha \tag{3.10}$$

In this research, the Global Moran's *I* Index was calculated on the ArcGIS 10.5 software with the *Spatial Autocorrelation* tool under the Spatial Statistics toolbox. Below in the Table 3.1 shows the critical p-values for different intervals of z-score calculated in the software:

Table 3.1 Standard deviations, probability and confidence level (Adopted from Esri, 2021e)

z-score (Standard Deviations)	**p-value (Probability)**	**Confidence Level**
< -1.65 or > +1.65	< 0.10	90%
< -1.96 or > +1.96	< 0.05	95%
< -2.58 or > +2.58	< 0.01	99%

3.2.2 Univariate Local Spatial Autocorrelation (Anselin Local Moran's I)

The Local Spatial Autocorrelation techniques are differentiated from the Global Spatial Autocorrelation techniques. As stated in the previous subsection, Global techniques such as *Moran's I Index* and *Geary's C Ratio* both have one index value and one z-score for the overall spatial distribution. In some instances, it is important to detect the clusters with similar attribute values in the spatial context (Çubukçu, 2015). Çubukçu (2015) points out that the indexes and z-scores are calculated for each observed point in local spatial autocorrelation techniques.

Anselin Local Spatial Autocorrelation technique was developed by Luc Anselin in 1995 based on the previous studies of Patrick A. P. Moran in 1948 and 1950. Luc Anselin (1995) outlined the statistical techniques called *LISA (Local Indicators of Spatial Association)*. The purpose behind the study was to describe the "outliers" and assess the effects of specific spatial attributes on global statistics (Anselin, 1995). There are a lot of studies in various fields that used the Local Spatial Autocorrelation technique. Chakravorty (2003) investigated the industrial clustering and performed local Moran's *I* analysis for three cities to reveal the industrial clustering spatially over workers and firms. Yang et al. (2011) determined the local spatial autocorrelation of the population density at the country level in four years period by using the index of Local Moran's *I*. Local indicators of spatial association was used in various disciplines and scientific researches, for example Jossart et al. (2020) aimed to find the most suitable locations for aquaculture treatment with Local Moran's I statistic.

Anselin Local Moran's *I* statistic for local spatial autocorrelation equation is written below:

$$I_i = z_i \sum_j w_{ij} z_j \qquad (3.11)$$

In the equation above, where w_{ij} is the element of the spatial weight matrix; z_i is the in deviation of the variable *i* from the mean; z_j is the in deviation of the variable *j* from the mean. Wong & Lee (2005) stated that the equation for the z_i as the in deviation of the variable *i* from the mean is:

$$z_i = (x_i - \bar{x}) / \delta \tag{3.12}$$

In the equation above, where x_i is the value of the variable *i*; $\bar{x}$ is the mean of *x*; δ is the standard deviation of x_i .

For all the observations that being analyzed, Anselin Moran's *I* statistic must be calculated for every one of them. High and positive I_i values are indicated the existence of a spatial clustering where similar *i* values (the values may be high or low) coexist; high and negative *i* values are indicated that *i* is a spatial outlier where *i* values coexist with dissimilar (i. e. high values surrounded by low values) values (Anselin, 1995). The Moran Scatter Plot has quadrants and the interpretation of the Local Moran's *I* offer the spatial clusters (High-High or Low-Low) or the spatial outliers (High-Low or Low-High) as shown in Figure 3.6 (Anselin, 1995).

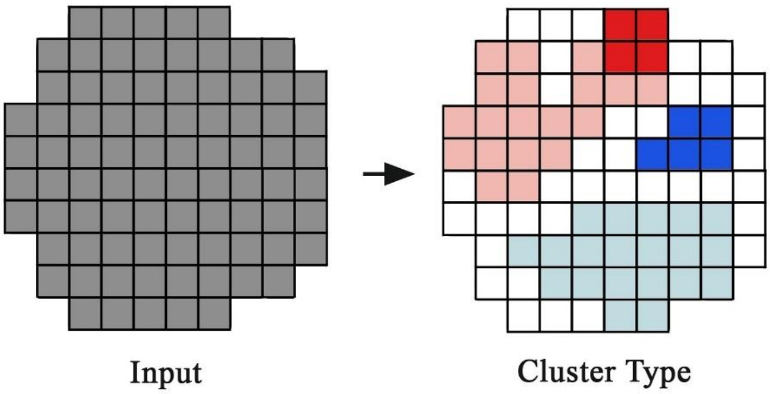


Figure 3.7 Anselin Local Moran's I cluster output example

The hypothesis test is conducted to whether the foregoing evaluation is significant for observed Anselin Local Moran's *I* statistic. The following are the hypotheses (Anselin, 1995):

H_0: There is no local spatial association between the investigated variable and its neighbors,

H_A: The is a local spatial association between the investigated variable and its neighbors.

The Anselin Local Moran's *I* value for i must be transformed into a z-score to interpret the spatial distribution as significant or not significant. Below is the formula for the calculation of the z-score:

$$Z_i = \frac{I - E(I_i)}{\sqrt{V(I_i)}} \tag{3.13}$$

In the formula above, *I* is the Anselin Local Moran's *I* value that calculated; $E(I_i)$ is the expected value of the Moran's *I*; $V(I_i)$ is the Variance value. The following formula is for the calculation of the Expected Value of Anselin Local Moran's *I*:

$$E(I_i) = -\frac{\sum_j w_{ij}}{(n-1)} \tag{3.14}$$

The Variance value for the Anselin Local Moran's *I* is stated as (Anselin, 1995):

$$V(I_i) = \frac{w_{i(2)}(n-b_2)}{(n-1)} + \frac{2w_{i(kh)}(2b_2-n)}{(n-1)(n-2)} - \frac{w_i^2}{(n-1)^2} \tag{3.15}$$

Since the Anselin Local Moran's *I* statistic was performed in the ArcGIS 10.5 software in this research; below is the equation of the variance that performed in the software (Esri, 2021):

$$V(I_i) = \frac{w_{i(2)}(n-b_2)}{(n-1)} - \frac{2w_{i(kh)}(2b_2-n)}{(n-1)(n-2)} - \frac{w_i^2}{(n-1)^2} \tag{3.16}$$

In the equation above, where $V(I_i)$ is the Variance value of the Anselin Local Moran's *I*; w_i^2 is the square of the sum of row *i* of the weight matrix; $w_{i(2)}$ is the of the sum of row *i* of the weight matrix; $2w_{i(kh)}$ is the sum of the values different than itself of the weight matrix that the initial point is *i*. Finally, below is the formula of b_2 (Çubukçu, 2015):

$$b_2 = \frac{m_4}{m_2} \tag{3.17}$$

Above the formula, m_4 as the fourth moment and m_2 as the second moment:

$$m_2 = \sum_i \frac{z_i^2}{n} \tag{3.18}$$

$$m_4 = \sum_i \frac{z_i^4}{n} \tag{3.19}$$

As mentioned in the Global Moran's *I* same conditions apply: the calculated z-score for the case must ensure the z-value for the significance level at α under the normal distribution for the z-scores values. The following condition must be satisfied:

$$|z_I| \geq z_\alpha \tag{3.20}$$

In this research, The Anselin Local Moran's *I* Index was calculated on the ArcGIS 10.5 software with the *Cluster and Outlier Analysis (Anselin Local Moran's I)* tool under the Spatial Statistics toolbox. Below in the Table 3.2 shows the critical p-values for different intervals of z-score calculated in the software:

Table 3.2 Standard deviations, probability and confidence level (Adopted from Esri, 2021e)

z-score (Standard Deviations)	**p-value (Probability)**	**Confidence Level**
< -1.65 or > +1.65	< 0.10	90%
< -1.96 or > +1.96	< 0.05	95%
< -2.58 or > +2.58	< 0.01	99%

3.2.3 Bivariate Global Spatial Autocorrelation (Bivariate Global Moran's I)

Spatial associations and patterns of the observed variables have been long considered. Further thinking of the spatial autocorrelation techniques, the multivariate concept over the spatial correlation analysis was firstly mentioned by Daniel Wartenberg (1985). Wartenberg (1985) introduced a new analytical perspective about multivariate correlation and spatial dependence. Lee (2001) stated that the spatial relation between two variables can only be interpreted by a bivariate spatial association and offered a bivariate spatial association calculation method. He integrated the non-spatial Pearson's correlation coefficient and the spatial aspect that wanted to investigate.

The concept of *Bivariate Global Moran's I* was developed and introduced by Luc Anselin, Ibnu Syabri, and Oleg Smirnov in their study in 2002. They extended a previous study of the Moran Scatter Plot and aimed to develop furthermore. They extended the Moran Scatter Plot in a different bivariate concept. The idea behind the Bivariate Moran Scatterplot is that the extending Moran Scatterplot with two variables: one as the x-axis and its spatial lag as y-axis which is a different variable (Anselin Syabri & Smirnov, 2002). It analyzes whether two variables are in the same location at the same time. Bivariate spatial correlation identifies if there is a relation and which degree between the investigated variable and a different variable at the surrounding neighbors of it (Anselin, 2019).

There are a lot of studies in various fields that used the Bivariate Global Spatial Autocorrelation technique. Cheng (2016) performed a bivariate analysis with the purpose to investigate the correlation between the environmental pollutants over the manufacturing agglomeration. Bivariate Global Moran's I statistics were used to reveal the spatial correlation between the pollutants and the agglomeration (Cheng, 2016). More recently, Song et al. (2020) used Bivariate Global Moran's I statistics to reveal the spatial correlation between air pollution and the per capita GDP levels.

The equation for Bivariate Moran Scatterplot is written below (Cheng, 2016; Anselin, 2019):

$$I = \frac{n}{(n-1)} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \bar{x}) (y_j - \bar{y})}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \tag{3.21}$$

In the equation above, where *n* is the number of spatial points; x_i is the value of the first variable *i*; y_j is the value of the second variable *j*; $\bar{x}$ is the mean of *x*; w_{ij} is the element of the spatial weight matrix. The Bivariate Moran Scatterplot gives a linear regression, and the slope of this linear regression is equal to the observed value of Bivariate Moran's *I* (Anselin et al., 2002). In the Bivariate Moran's I statistic, *x* values are fixed in location, but the *y* values are permuted randomly (Anselin, 2019).

Bivariate Moran's *I* statistic ranges from -1 to 1. As the value is getting closer to -1 or 1, it means that the bivariate spatial autocorrelation is getting stronger. Between the variables investigated, there is:

- Positive spatial autocorrelation, if $I > 0$,
- No spatial autocorrelation, if $I = 0$,
- Negative spatial autocorrelation, if $I < 0$.

In the case of Bivariate Moran's *I*, the spatial autocorrelation tests are performed between an *x* value at the location *i* and a *y* value as the neighbors of it (Anselin, 2019). In this perspective, the hypotheses are:

H_0: The spatial distribution of the y values is random.
H_A: The spatial distribution of the y values is not random.

By implementing the permutation approach on software, the significance of the analysis can be sustained (Anselin et al., 2002). GeoDa 1.18.0.0 software, which is open-source software and it was developed by Luc Anselin and his colleagues back in 2003. The software provides many spatial data analysis techniques with mapping, visualizing, interpreting advantages.

In this research, Bivariate Moran's I analysis was performed in the GeoDa 1.18.0.0 software with the *Bivariate Moran's I tool* under the Moran Scatter Plot. As an output the Bivariate Moran Scatter Plot consisted of the x-axis, y-axis as its spatial lag that is a different variable and the observed Moran's I value. The significance obtained by the approach of permutations.

3.2.4 Bivariate Local Spatial Autocorrelation (Bivariate Anselin Moran's I)

As it was mentioned in the previous subsection, spatial autocorrelation techniques in the multivariate concept over the spatial correlation analysis were firstly mentioned by Daniel Wartenberg (1985). Wartenberg (1985) introduced a new analytical perspective in the global multivariate statistic context. Lee (2001) offered a bivariate Moran-like spatial association calculation method with integrated the non-spatial Pearson's correlation coefficient. Luc Anselin, Ibnu Syabri, and Oleg Smirnov (2002) extended a previous study of Moran Scatter Plot developed Bivariate Moran's I and Bivariate Local Moran's I statistics. Anselin (2019) offered a multivariate concept by extending the Local Geary's C Index.

The concept of *Bivariate Local Moran's I* was developed and introduced by Luc Anselin, Ibnu Syabri, and Oleg Smirnov in their study in 2002. In their study, both the Global and the Local Bivariate associations were mentioned. By extending the earlier study of Anselin (1995), Local Indicator of Spatial Association (LISA) was improved to a bivariate context. The idea behind the study was to describe the "outliers" and assess the effects of specific spatial attributes on global statistics (Anselin, 1995).

There are a lot of studies in various fields that used the Bivariate Global Spatial Autocorrelation. Gutiérrez & Delclòs (2016) compared the socio-economic characteristics and the foreign immigrant population in Catalonia using the Bivariate Local Moran's statistics to see if the foreign population concentrated in cities. Cheng (2016) performed a bivariate analysis with the purpose to investigate the correlation between the environmental pollutants over the manufacturing agglomeration. Bivariate Local Moran's *I* statistics were used to reveal the spatial clusters and outliers between the pollutants and the agglomeration into a map (Chang, 2016).

Bivariate Local Moran's *I* statistic for bivariate local spatial autocorrelation equation is written below (Anselin, 2020):

$$I_i^B = cx_i \sum_j w_{ij} y_i \tag{3.22}$$

In the equation above, where w_{ij} is still the element of the spatial weight matrix; c is a constant scaling factor; z_j is the in deviation of the variable *j* from the mean (Tao & Thill, 2020).

Bivariate Local Moran's *I* statistic measures the linear association between an *x* value at the location *i* and the average of different variables as the neighboring locations of *x* it is *y* (Anselin et al., 2002). The linear association may be positive or negative, High similarity and high dissimilarity values indicate a strong relationship. Positive similarity exposes spatial clustering with similar values; likewise, negative values expose spatial clustering with dissimilar values (Anselin et al., 2002). As in the Moran Scatter Plot has quadrants and the interpretation of the Local Moran's I offer the spatial clusters (High-High or Low-Low) or the spatial outliers (High-Low or Low-High) (Anselin, 1995); there is a Bivariate Local Moran's Scatter Plot statistic presenting the if there are spatial clusters and/or spatial outliers. In this perspective, the hypotheses are:

H_0: There is no local spatial association between the variables: *x* and its neighbors as *y*.
H_A: There is a local spatial association between the variables: *x* and its neighbors as *y*.

By implementing the permutation approach on software, the significance of the analysis can be sustained (Anselin et al., 2002). As mentioned in the subsection "Bivariate Global Statistic"; in this research, Bivariate Local Moran's t analysis was performed in the GeoDa 1.18.0.0 software with the *Bivariate Moran's I* tool under the Moran Scatter Plot.

The analysis tool offers choices to select the wanted outputs. A Moran Significance Map can be created as an output for the analysis and the significance obtained by the approach of permutations. Additionally, a Bivariate LISA Cluster Map can be created that shows the clusters (High-High or Low-Low) or the outliers (High-Low or Low-High) spatially. Another output, the Bivariate Moran Scatter Plot consisted of the four quadrants, x-axis, y-axis as its spatial lag that is a different variable and the observed Moran's I value can be created.

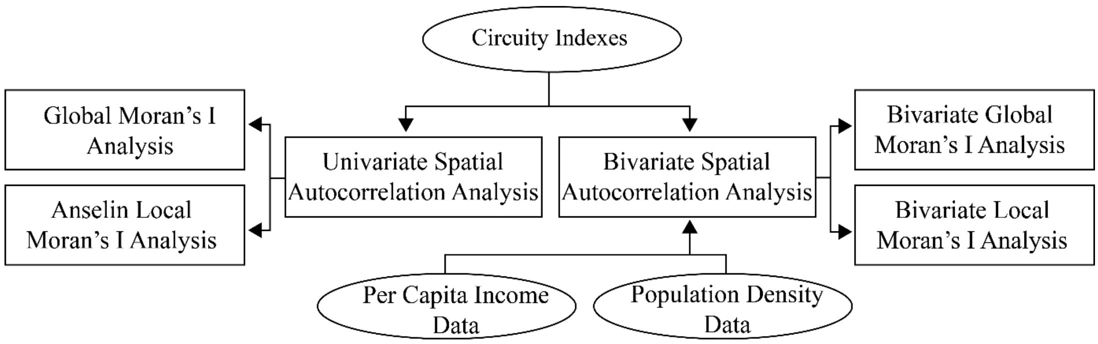


Figure 3.8 Summative flow chart for the spatial autocorrelation analysis

Multiple methods were combined for the spatial autocorrelation analysis in this research. As it was explained earlier in this section, the overall spatial analysis was performed with the output of the circuity analysis: with the circuity indexes of the neighborhoods. Along with the circuity indexes, socio-economic variables were used as inputs within a system such as an input-output chain with the specified analyzes, as seen in Figure 3.8 above.

CHAPTER 4
DATA

This chapter provides information about the data for the analyzes used in this research. Brief information about the geographical and urban characteristics of the study area in İzmir city was given. The data were categorized into two. The circuity data and the socio-economic variables data. Since this research mainly focused on the circuity degree of the public transportation systems, the study mainly focused on the data of circuity times for public transportation systems. The income level and the population density of studied neighborhoods were calculated from the data which are derived from Turkish Statistical Institute (TUIK) and Endeksa. Endeksa formats and redistributes the original Turkish Statistical Institute (TUIK) data.

4.1 Study Area

4.1.1 İzmir City

İzmir city is one of the most populated and largest cities in Western Anatolia. With its long history from ancient times until today, the gulf with a famous port the commercial activities had a big role on the city's urbanization processes.

A rapid industrialization process was continued to grow faster in the '50s and triggered rapid urbanization in cities of Turkey (Tekeli, 1998). Tekeli (1998) discussed that migration to cities from the rural was observed and this process caused the emergence of squatter settlements and the working class has settled in the city centers in Turkey. He also stated that this rapid urbanization in city centers led to deficiencies in public services and especially in transportation systems. İzmir city also experienced the same processes of rapid migration and urbanization starting with its dense traditional city center (Karadağ & Mirioğlu, 2011). Izmir has 30 districts with 1306 neighborhoods with the last changes in 2020 and covers nearly 11952 square kilometers area (Figure 4.1).

Figure 4.1 Location and borders of İzmir city on a satellite imagery and its location in Turkey (Esri Imagery Basemap accessed in 24.04.2021 edited by the author, 2021)

4.1.2 Neighborhoods

The spatial location choice is mainly shaped by topographical structures in İzmir for this reason the urban macroform has shaped as axial development and centralization in the sub-region (Partigöç Aydın & Tarhan, 2017). The population density, residential density, urban mobility, and the public transportation network are mainly concentrated in the metropolitan area (10 districts and 377 neighborhoods) in İzmir city. This research was conducted in a metropolitan area with 10 districts. As Şenbil, Yetişkul & Gökçe (2020) stated that in the metropolitan area of Izmir, the population increase rates are differentiated. Regarding this heterogenic population distribution, the public transportation systems also have a different dynamic in some neighborhoods. Correlatively, 23 neighborhoods were determined that contradict the purpose.

Since this research is mainly focused on the circuity analysis because the closeness to a transportation hub may cause errors, 6 neighborhoods were obtained that also contradict the purpose. In line with the aim of the study, 29 neighborhoods in total were excluded from the analysis in order to prevent these differences from creating an error for the entire study. The research was conducted with 348 neighborhoods in the metropolitan area regarding the macroform and the urban continuity (Figure 4.2).

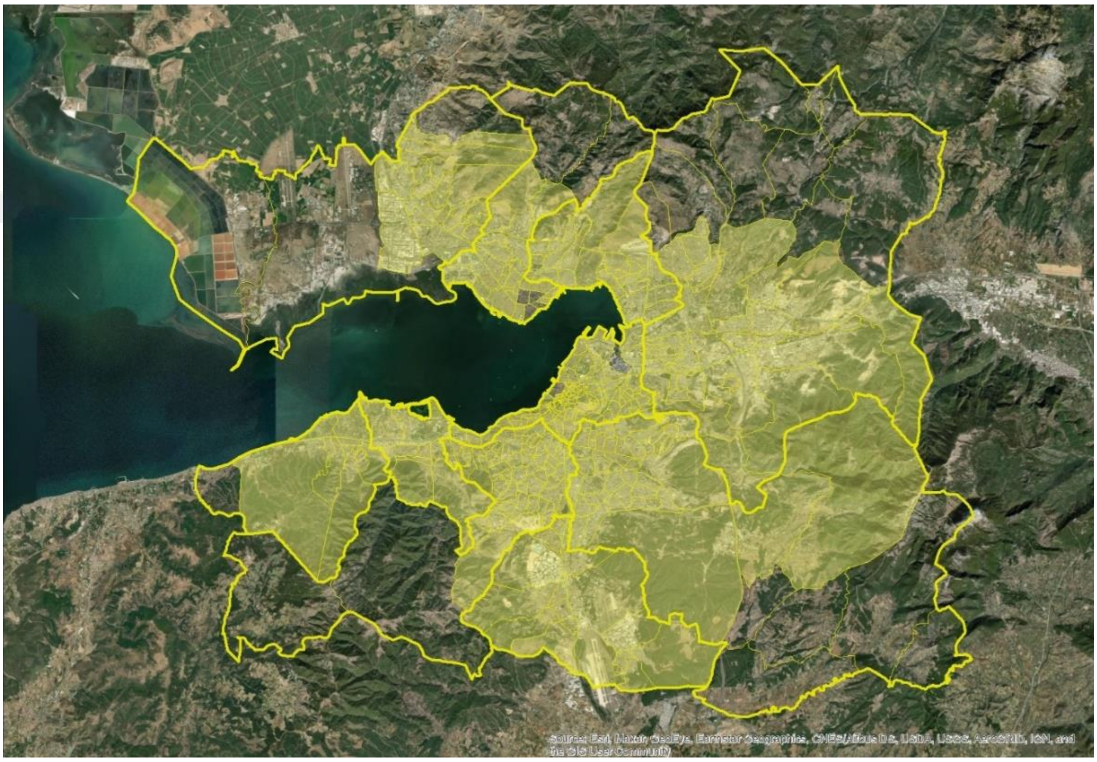


Figure 4.2 Location and borders of the study areas on a satellite imagery (Esri Imagery Basemap accessed in 24.04.2021 edited by the author, 2021)

4.2 Circuity

This research is predominantly concentrated on circuity degree for the analysis of the public transportation system efficiency in İzmir. The circuity levels are differentiated among the neighborhoods. For this reason, the collection and the accuracy of the circuity data are crucial for this study. The circuity data collection was carried out by personal efforts. A database was created, and the data was stored. This database used in a table format for the further analysis performed in GIS software and shown below in Figure 4.3.

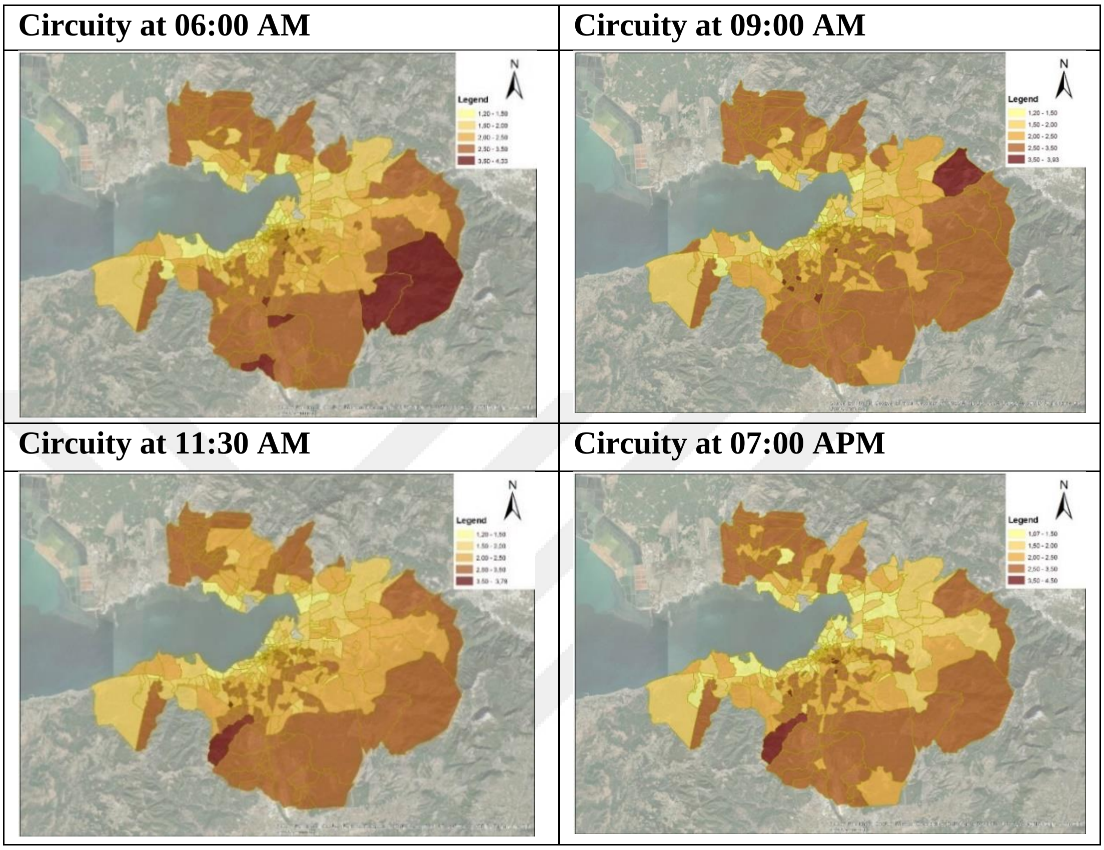


Figure 4.3 Spatial distribution of the circuity levels of neighborhoods

The descriptive statistics were performed and analyzed in SPSS software. The summary of the statistics shown below in Table 4.1:

Table 4.1 Descriptive statistics of the circuity indexes in time-of-day variations

	Neighborhoods	Minimum	Maximum	Mean	Median	Std. Deviation
Circuity Index at 06:00 AM	348	1.2	4.330	2.332	2.333	0.587
Circuity Index at 09:00 AM		1.2	3.930	2.411	2.444	0.576
Circuity Index at 11:30 AM		1.2	3.780	2.304	2.300	0.552
Circuity Index at 07:00 PM		1.07	4.500	2.257	2.278	0.589

4.2.1 Travel Length

There are several methods to calculate the efficiency of the networks and it was stated previously that the degree of circuity has been widely used in network analysis. As was also mentioned earlier in this study, the circuity index is used to determine the efficiency of public transportation systems. Circuity can be assessed by using travel time (Huang & Levinson, 2015). In this research, "travel time" is used to calculate the degree of circuity. Travel time was obtained on a “minute” basis. The descriptive statistics were performed and analyzed in SPSS software, the summary of the statistics shown below in Table 4.2:

Table 4.2 Descriptive statistics of the population density at the neighborhood level

	Moovit Public Transportation Travel Length				**Google Maps by Auto Travel Length**			
Neighborhoods	348				348			
Time-of-Day	6:00 AM	9:00 AM	11:30 AM	7:00 PM	6:00 AM	9:00 AM	11:30 AM	7:00 PM
Minimum	6	6	6	6	4	4	4	5
Maximum	84	85	89	90	22	30	28	35
Mean	27.04	29.78	27,75	30.84	11.37	12.15	11.85	13.63
Median	25	28	26	28	10.50	12	12	12
Std. Deviation	12.69	13.47	12.49	14.24	3.77	4.14	3.84	5.19

4.2.2 Time-of-Day Variations

Time-of-day variations have been long considered and used in transportation studies over the years (Austin & Zegras, 2012; Polzin, Pendyala & Navari, 2002; Zeng, Fu, Arisona, Erath & Qu, 2014; Alexander, Jiang, Murga & Gonzale, 2015). Polzin et al. (2002) expressed that time-of-day distribution has substantial effects on public transportation services in specifying the travel demand within a day. In this research, travel time for public transportation systems and the travel time for automobiles were obtained at four different times in a day. The time-of-day selections were obtained under two categories:

- Off-peak hours,
- Peak hours.

Bowman (1998) described the time periods of a day in terms of activity patterns. According to his claims on five time periods in a day shown below in Table 4.3:

Table 4.3 Five time-of-day periods (Bowman, 1998)

1	Early	03:00 AM to 06:59 AM
2	AM Peak	07:00 AM to 09:29 AM
3	Midday	09:30 AM to 03:59 PM
4	PM Peak	04:00 PM to 06:59 PM
5	Late	07:00 PM to 02:59 AM

Since the rapid growth in technology, urbanization processes and the migration in cities are the main factors affecting the transportation systems and traffic situations and vary across the cities, the peak and off-peak times may differentiate regarding the characteristics of cities. In this case, the traffic conditions of the İzmir city were examined specifically. In their research, Elbir et al. (2010) determined the air quality by investigating the traffic in İzmir city. Since the data acquisition was held on January 2021, their statement for winter season was considered. They stated that AM peak is between 08:00 – 09:00 and PM peak is between 18:00-19:00 for the winter season (Figure 4.4).

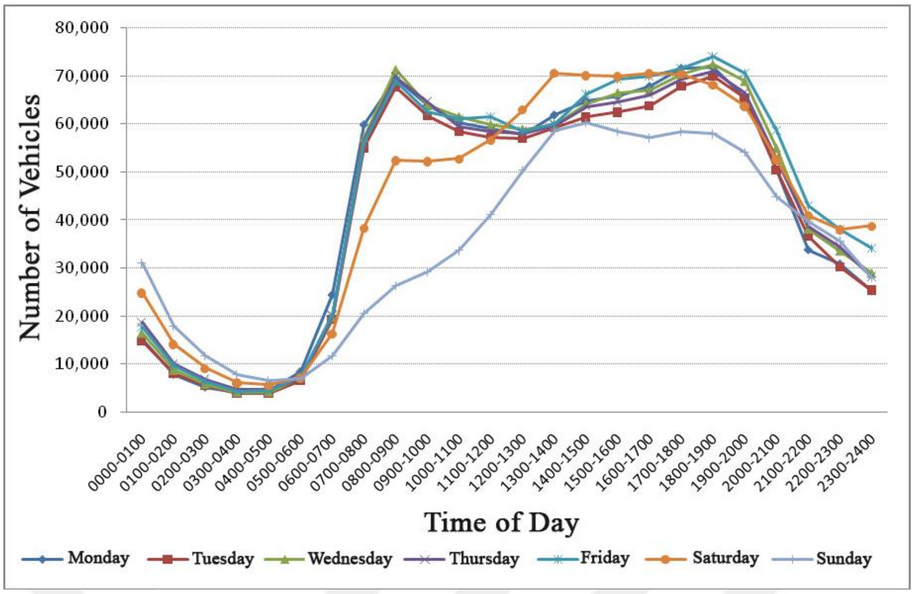


Figure 4.4 Change of the total number of vehicles according to time periods in the winter season, vehicle/hour (Adopted and translated from Elbir et al., 2010)

İZUM (Izmir Transportation Center), Google Maps and Yandex Maps are providing real-time traffic data and they provide it as open-source. In this direction, the peak and off-peak periods of İzmir were compared with the previous work of Elbir et al. (2010).

Considering the studies of Bowman (1998) and Elbir et al. (2010) as a basis, the real-time data comparisons were conducted examining the peak and off-peak hours from İZUM (Izmir Transportation Center), Google Maps, and Yandex Maps. In order to see the differences in the efficiency between peak and off-peak times, two off-peak times were determined according to the traffic levels. For the analyzes of the circuity level, the travel time data was acquired at four time-of-day periods for public transportation systems and automobiles. The time periods are defined as below in Table 4.4:

Table 4.4 Four time-of-day periods defined for the analysis

1	AM Off-Peak	06:00 AM
2	AM Peak	09:00 AM
3	Midday Off-Peak	11:30 AM
4	PM Peak	07:00 PM

4.2.3 Data Collection

Circuity analyzes in this study were conducted between the neighborhoods as the origins and the four selected destination points as the destinations. The travel time data for the circuity level analyzes were acquired from two online services Google Maps and Moovit.

Online mapping technologies have been widely used increasingly in GIS-based analyzes and researches. Google Maps services were introduced in 2005 and provide a free-to-use online mapping service (Vandeviver, 2021). It also provides extra services such as route planner for several modes of transportation regarding the departure or arrival time options. Hadas (2013) used Google Transit data and examined PT networks to provide a method for the analyzes in PT. Since Google Transit services are locally differentiated unfortunately there was not complete public transportation data for the İzmir city. In this research, Google Maps services were used in creating the shortest path to get the "shortest travel time by automobile" by using the "Directions" option.

"Mobility as a Service (MaaS) is the integration of various forms of transport services into a single mobility service accessible on-demand" (MaaS Alliance, 2021). Moovit (2021) defines itself "Mobility as a Service (MaaS) solutions provider and creator of the #1 urban mobility app". It was introduced in 2012 and provides free-to-use MaaS (Moovit, 2021). Moovit app can be used by public transportation users to get possible routes from origin to destination, transfers with travel times, also, it can calculate it with regarding the departure or arrival time options.

The data acquisition was held in January 2021. The travel time data for the circuity level analyzes were taken simultaneously from two online services Google Maps and Moovit. The weather forecasts of İzmir in January 2021 listed below in Table 4.5:

Table 4.5 Monthly weather forecasts of İzmir in January 2021 (Adopted and formatted from Freemateo, 2021)

Description	**Value**
The Average High-Temperature (°C)	14.355
The Average Low-Temperature (°C)	7.194
Average Monthly Total Precipitation (mm)	4.635

Since the data retrieval has been carried out in the winter season, it needs to point out that the traffic levels and individual travel behaviors can be changed seasonally. It must be pointed out that the weather conditions may have effects on traffic flow. Due to the pandemic of COVID-19 and the quarantines and the seasonal effects on the traffic levels during the pandemic, it can be stated that the traffic was not on its usual volume levels for İzmir city.

In this research, the data acquisition from Google Maps and Moovit services was performed with the determined time-of-day times as the departure time. The collected travel time data were stored in a database for all the neighborhoods.

4.3 Socio-economic Variables

In this study, it was mainly aimed to investigate the public transportation efficiency among the neighborhoods to see if there are any differences and patterns. A socio-economic structure is unique for each neighborhood and shows different characteristics.

The socio-economic variable data used in this research was acquired from Endeksa (2021). Endeksa formats and redistributes the original Turkish Statistical Institute (TUIK) data. Raw data taken from Endeksa (2021) consists of the districts and neighborhoods of İzmir. It was categorized eliminated into the context of this study regarding the determined 10 districts with 348 neighborhoods. The variables were calculated at the neighborhood level.

4.3.1 Per Capita Income at Neighborhood Level

Per capita income data at the neighborhood level was acquired from Endeksa (2021) for 348 neighborhoods in this research. The descriptive statistics were performed and analyzed in SPSS software, the summary of the statistics shown below in Table 4.6:

Table 4.6 Descriptive statistics of the per capita income at the neighborhood level

	Neighborhoods	**Minimum**	**Maximum**	**Mean**	**Median**	**Std. Deviation**
Per Capita Income	348	2858	6499	3962.609	3862	703.168

4.3.2 Population Density

In this study, Neighborhood population data and the neighborhood shapefile formatted data were taken from İzmir Metropolitan Municipality Department of Cartography and Geographical Information Systems. The population density was calculated considering the urbanized areas of the neighborhoods. Net density contains the residential uses with local roads (Landcom, 2011). Below the formula for calculation of the population density:

$$\text{Population Density} = \frac{Number\ of\ Individuals\ in\ a\ Neighborhood}{Residential\ Land\ Area\ (in\ square{-}km)} \qquad (4.1)$$

The population density was calculated by dividing the population of the neighborhood by the residential area of the neighborhoods in ArcMap 10.5. software with the ITRF96 projected coordinate system. The descriptive statistics were performed and analyzed in SPSS software, the summary of the statistics shown below in Table 4.7:

Table 4.7 Descriptive statistics of the population density at the neighborhood level

	Neighborhoods	**Minimum**	**Maximum**	**Mean**	**Median**	**Std. Deviation**
Population Density	345	440.627	77704	21.624	20765.550	11583.538

CHAPTER 5
ANALYSIS AND RESULTS

In this research, spatial analyzes were conducted under four main categories. The relationship between the efficiency of public transportation with using circuity and the selected socio-economic variables were tested using the spatial autocorrelation statistics. This chapter provides and presents the results of the performed univariate and bivariate spatial analyzes.

5.1 Spatial Univariate Analyzes of Circuity

This research is mainly focused on the circuity index. The circuity was calculated with four time-of-day variations, for each of the 348 neighborhoods in the metropolitan area of İzmir. The calculated circuity values were examined under two spatial autocorrelation techniques such as Global Moran's I Statistic and Anselin LISA Statistic.

5.1.1 Global Spatial Autocorrelation (Global Moran's I Statistic)

Global Moran's *I* statistic is a well-known spatial autocorrelation technique in analyzing the spatial patterns of attributes. The idea behind this is to investigate if there is a significant pattern for the attributes in a spatial context. The significance and the z-score of the analyzes were given in the report to assess the spatial distribution and fulfillment of the hypothesis. In this case, the hypotheses for the Univariate Global Moran's I analysis are:

H_0: The spatial distribution of the circuity index is randomly distributed.
H_A: The spatial distribution of the circuity index is not randomly distributed.

In this research, the Global Moran's *I* Index was calculated on the ArcGIS 10.5 software. *Spatial Autocorrelation* tool from Analyzing Patterns sub-group under the Spatial Statistics toolbox. It calculates the Global Moran's I statistic and reveals the spatial autocorrelation based on feature locations and attribute values (Esri, 2021f). As an output, the Global Moran’s I Spatial Autocorrelation Report was created.

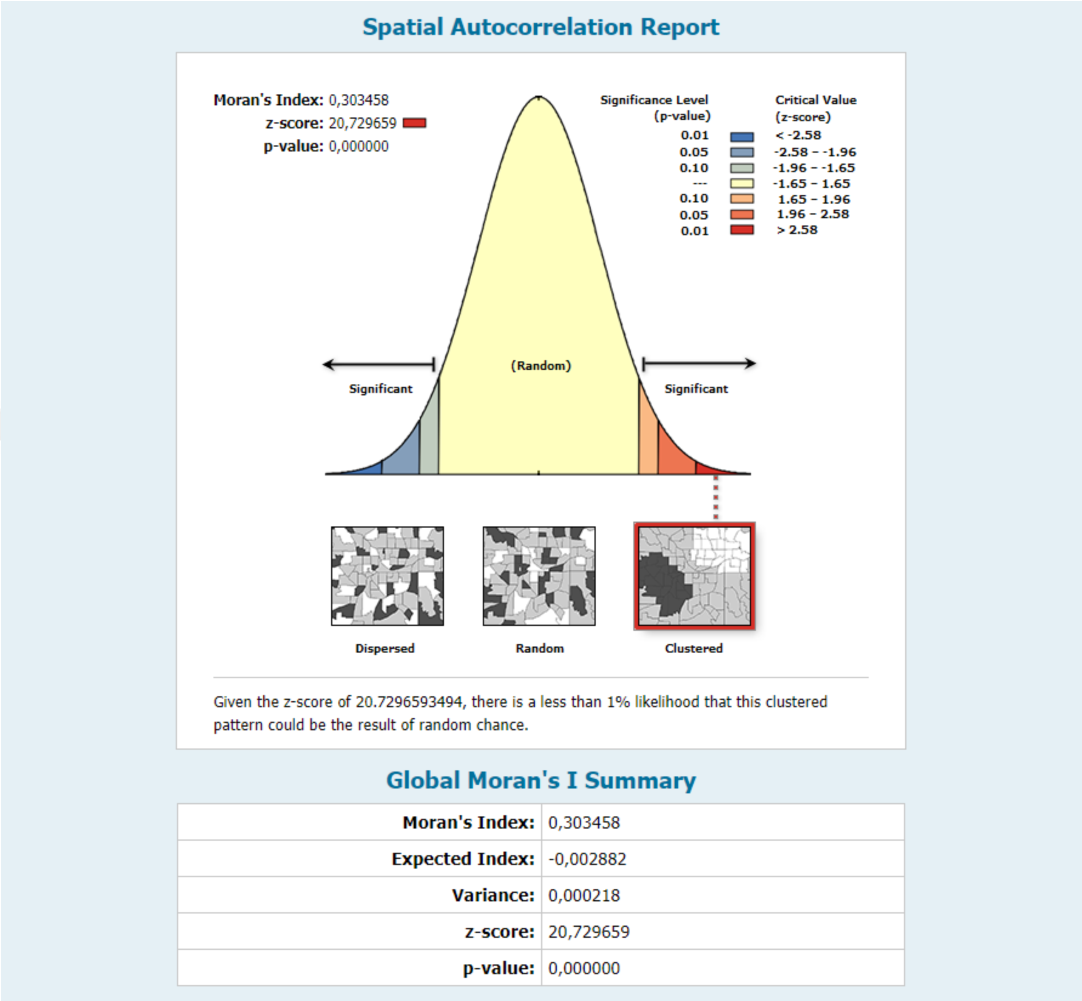
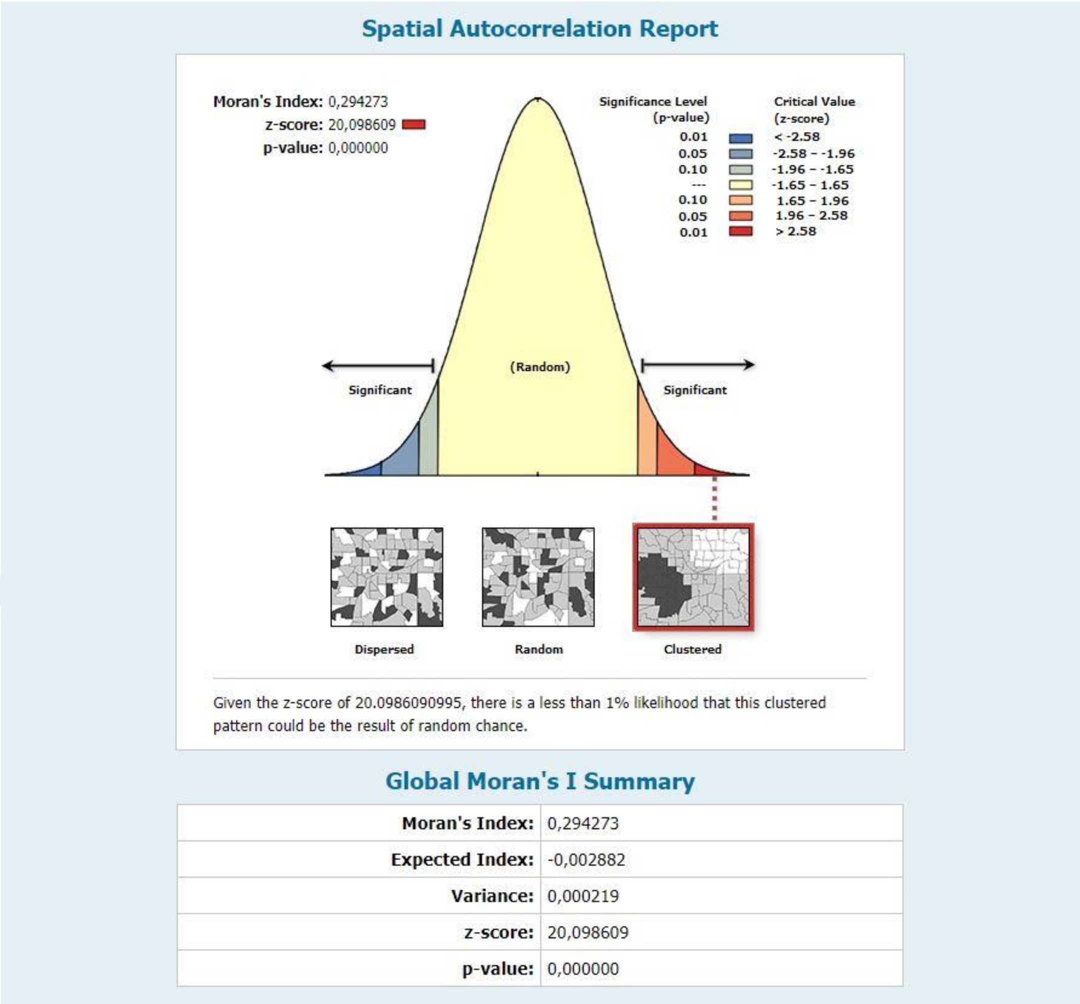


Figure 5.1 Spatial autocorrelation report, circuity index at 06:00 am as the input

The results of the Global Moran’s *I* Analysis revealed that the circuity level at 06:00 am of 348 neighborhoods shows a clustered pattern in İzmir as presented in Figure 5.1. This finding is statistically significant at α=0.01 level. The z-score of the analysis was calculated as 20.729659. Observed Moran’s *I* index and Expected Moran’s *I* index were calculated as 0.303458 and -0.002882 respectively.

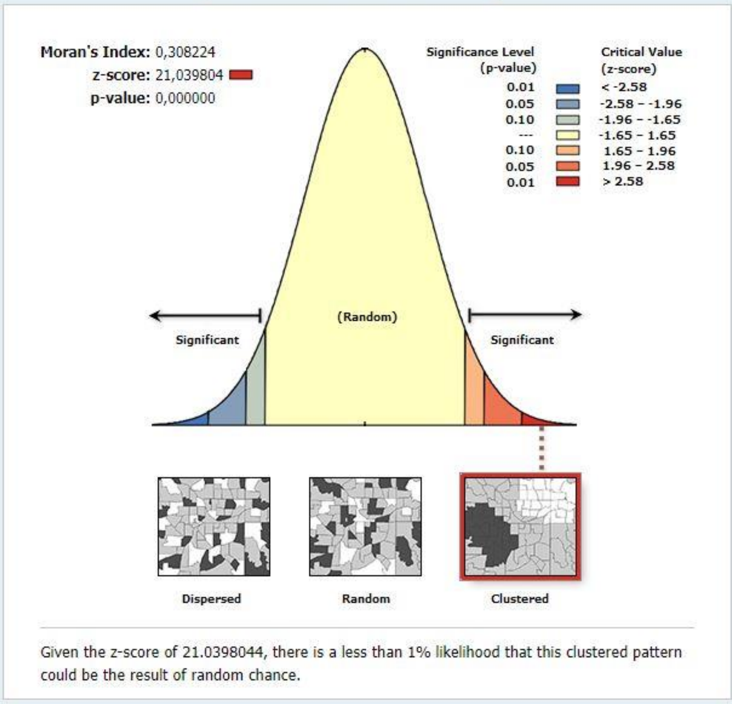


Moran's Index:	0,294273
Expected Index:	-0,002882
Variance:	0,000219
z-score:	20,098609
p-value:	0,000000

Figure 5.2 Spatial autocorrelation report, circuity index at 09:00 am as the input

The results of the Global Moran's *I* Analysis revealed that the circuity level at 09:00 am of 348 neighborhoods shows a clustered pattern in İzmir as presented in Figure 5.2. This finding is statistically significant at α=0.01 level. The Z-score of the analysis was calculated as 20.098609. Observed Moran's *I* index and Expected Moran's *I* index were calculated as 0.294273 and -0.002882 respectively.

Spatial Autocorrelation Report

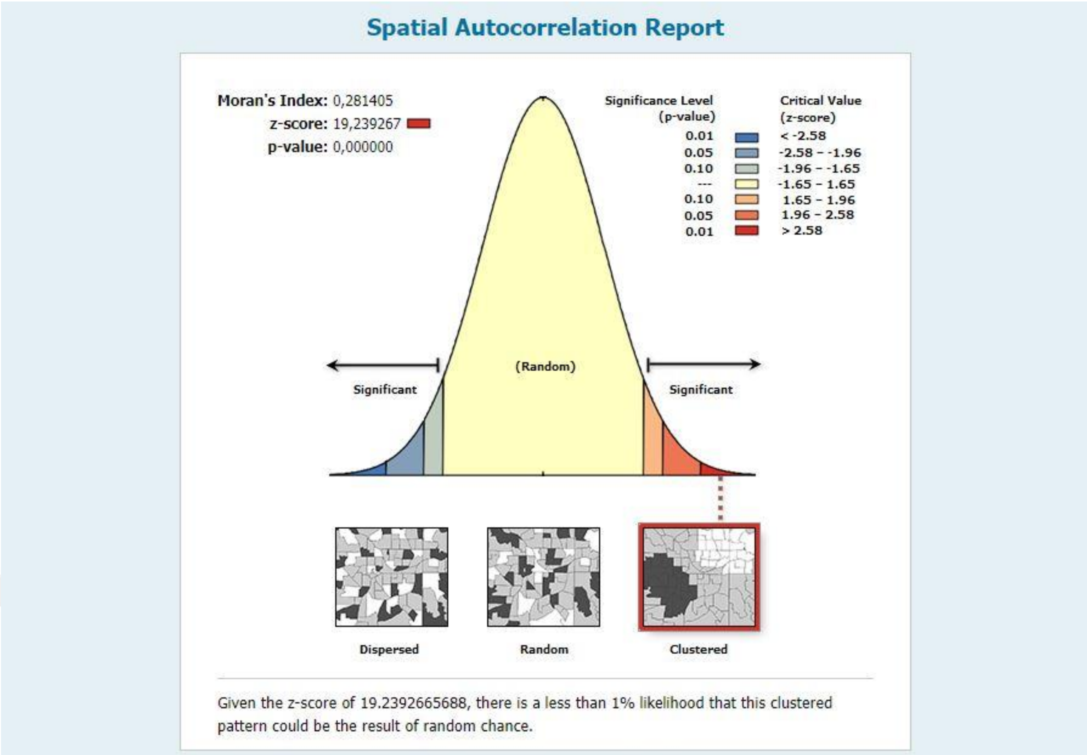


Global Moran's I Summary

Moran's Index:	0,308224
Expected Index:	-0,002882
Variance:	0,000219
z-score:	21,039804
p-value:	0,000000

Figure 5.3 Spatial autocorrelation report, circuity index at 11:30 am as the input

The results of the Global Moran's *I* Analysis revealed that the circuity level at 11:30 am of 348 neighborhoods shows a clustered pattern in İzmir as presented in Figure 5.3. This finding is statistically significant at α=0.01 level. The Z-score of the analysis was calculated as 21.039804. Observed Moran's *I* index and Expected Moran's *I* index were calculated as 0.308224 and -0.002882 respectively.



Global Moran's I Summary

Moran's Index:	0,281405
Expected Index:	-0,002882
Variance:	0,000218
z-score:	19,239267
p-value:	0,000000

Figure 5.4 Spatial autocorrelation report, circuity index at 07:00 pm as the input

The results of the Global Moran's *I* Analysis revealed that the circuity level at 07:00 pm of 348 neighborhoods shows a clustered pattern in İzmir as presented in Figure 5.4. This finding is statistically significant at α=0.01 level. The z-score of the analysis was calculated as 19.239267. Observed Moran's *I* Index and Expected Moran's *I* Index were calculated as 0.281405 and -0.002882 respectively.

5.1.1.1 Summative Assessment of Univariate Global Spatial Autocorrelation Analyzes

The results from the two univariate spatial analyzes such as Global Moran's *I* and Local Moran's *I* statistic were explained in detail earlier. The overall spatial distribution pattern was detected by Global Moran’s I Statistic. Four different analyzes were performed for four time-of-day circuity index variations. The results and spatial distribution patterns obtained from the Global Moran’s I analyzes were presented in a summary Table 5.1 below:

Table 5.1 Summary table of Univariate Global Moran’s I statistics for circuity index

	Moran's I Index	**Expected Index**	**Variance**	**z-score**	**p-value**	**Distribution Pattern**
Circuity Index at 06:00 AM	0.303	-0.003	0.002	20.730	<0.01	Clustered
Circuity Index at 09:00 AM	0.294	-0.003	0.002	20.099	<0.01	Clustered
Circuity Index at 11:30 AM	0.308	-0.003	0.002	21.040	<0.01	Clustered
Circuity Index at 07:00 PM	0.281	-0.003	0.002	19.233	<0.01	Clustered

As it was represented above in Table 5.1 all of the spatial distribution patterns were clustered for the four analyzes. All the four analyzes were statistically significant at α=0.05 level. This finding revealed that neighborhoods with similar circuity indexes tend to be located in the urban areas close to each other. If we interpret these results from a different perspective, the efficiencies or deficiencies of public transportation systems tend to concentrate with a clustered pattern in İzmir.

5.1.2 Local Spatial Autocorrelation (Anselin Moran’s I Statistic)

The Anselin Local Moran’s *I* Index was calculated on the ArcGIS 10.5 software. “Cluster and Outlier Analysis (Anselin Moran’s I)” tool from Mapping Clusters sub-group under the Spatial Statistics toolbox. It calculates the Anselin Local Moran's *I* statistic and reveals the spatial clusters and outliers based on feature locations and attribute values (Esri, 2021g).

The neighborhoods represented with light blue and light red show the clustered patterns with Low-Low and High-High clusters respectively. High-High clusters are the neighborhoods that have High values surrounding by High values. Low-Low outliers are the neighborhoods that have Low values surrounding by Low values. The neighborhoods represented with dark red and dark blue show the locations with High-Low and Low-High spatial outliers respectively. High-Low outliers are the neighborhoods that have High values surrounding by Low values. Low-High outliers are the neighborhoods that have Low values surrounding High values.

In this case, the Anselin Local Moran's *I* analysis was measured circuity levels of the investigated neighborhood. As mentioned above Anselin Local Moran's I offer the spatial clusters (High-High or Low-Low) or the spatial outliers (High-Low or Low-High). High-High clusters present the neighborhoods with high circuity levels surrounding by high circuity levels. High-Low outliers present the neighborhoods with high circuity levels surrounding by low circuity levels. To recap, high circuity values indicate lower public transportation efficiency. Low-Low clusters present the neighborhoods with low circuity level income surrounding by low circuity levels. Low-High outliers present the neighborhoods with low circuity levels surrounding high circuity levels. To recap, low circuity values indicate higher public transportation efficiency.

In ArcGIS, the significance can be assessed with the False Discovery Rate Correction (FDR). FDR correction may or may not be applied. Applying the FDR correction provides the statistical significance level for α=0,05 level, or else the significance level of the analysis appears with α=0,05 level or fewer p-values (Esri, 2021e). In this perspective, the hypotheses are:

H_0: There is no local spatial association between the circuity index and its neighbors,

H_A: There is a local spatial association between the circuity index and its neighbors.

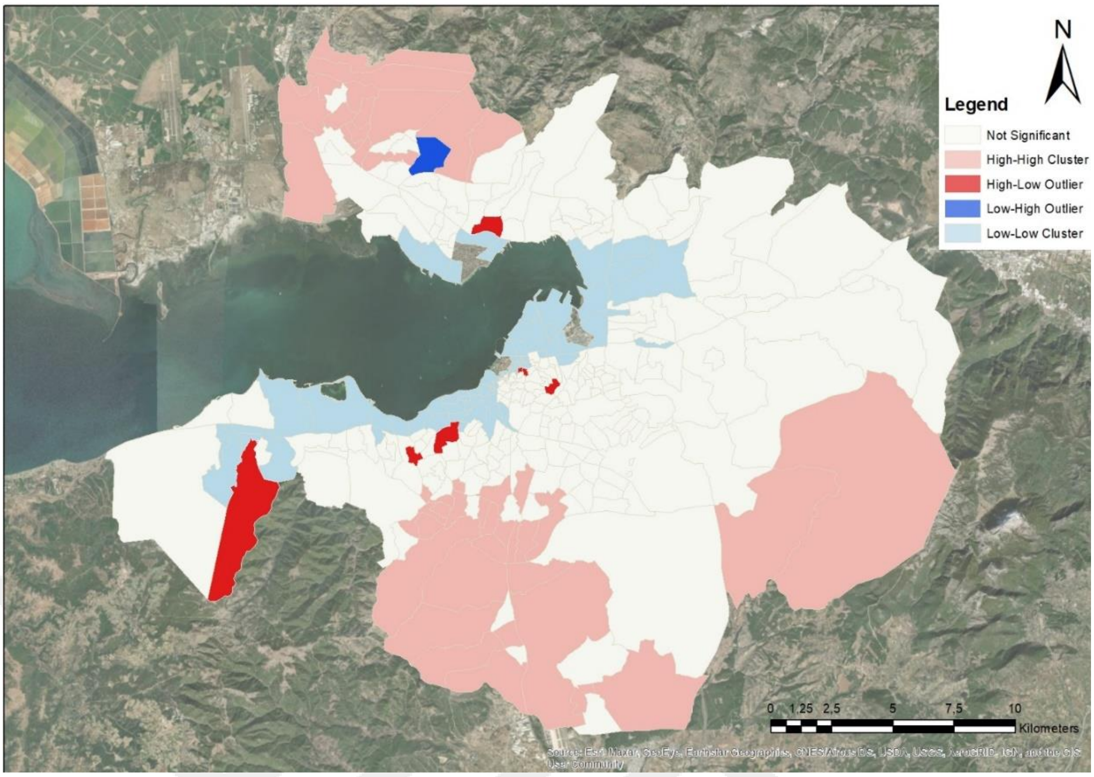


Figure 5.5 Anselin Local Moran's I clusters and outliers, circuity index at 06:00 am as the input

The results of the Anselin Local Moran's *I* Analysis show where the clustered patterns are obtained for the circuity level at 06:00 am of 348 neighborhoods in İzmir (Figure 5.5). This cluster map shows the statistically significant clusters at $\alpha=0.05$ level with FDR correction.

The four categories were represented. The neighborhoods represented with light blue and light red show the clustered patterns with Low-Low and High-High clusters respectively. It is observed that the Low-Low clusters were mostly concentrated in areas close to the seashore among the İzmir Gulf where the High-High clusters located away from the seashore clustered in the North-South and East directions for the circuity index at 06:00 am. The neighborhoods represented with dark red and dark blue show the locations with High-Low and Low-High spatial outliers respectively.

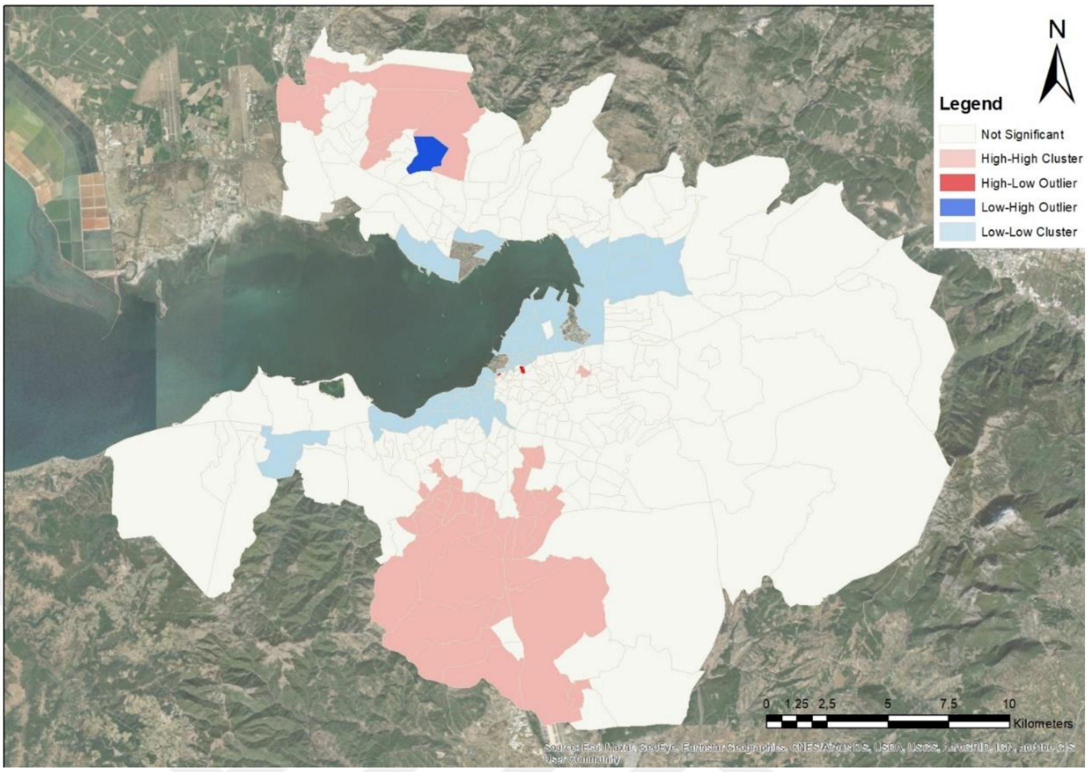


Figure 5.6 Anselin Local Moran's I clusters and outliers, circuity index at 09:00 am as the input

The results of the Anselin Local Moran's *I* Analysis show where the clustered patterns are obtained for the circuity level at 09:00 am of 348 neighborhoods in İzmir (Figure 5.6). This cluster map shows the statistically significant clusters at α=0.05 level with FDR correction.

The four categories were represented. The neighborhoods represented with light blue and light red show the clustered patterns with Low-Low and High-High clusters respectively. It is observed that the Low-Low clusters were mostly concentrated in areas close to the seashore among the İzmir Gulf. The High-High clusters located away from the seashore clustered in the North-South direction for the circuity index at 09:00 am. The neighborhoods represented with dark red and dark blue show the locations with High-Low and Low-High spatial outliers respectively.

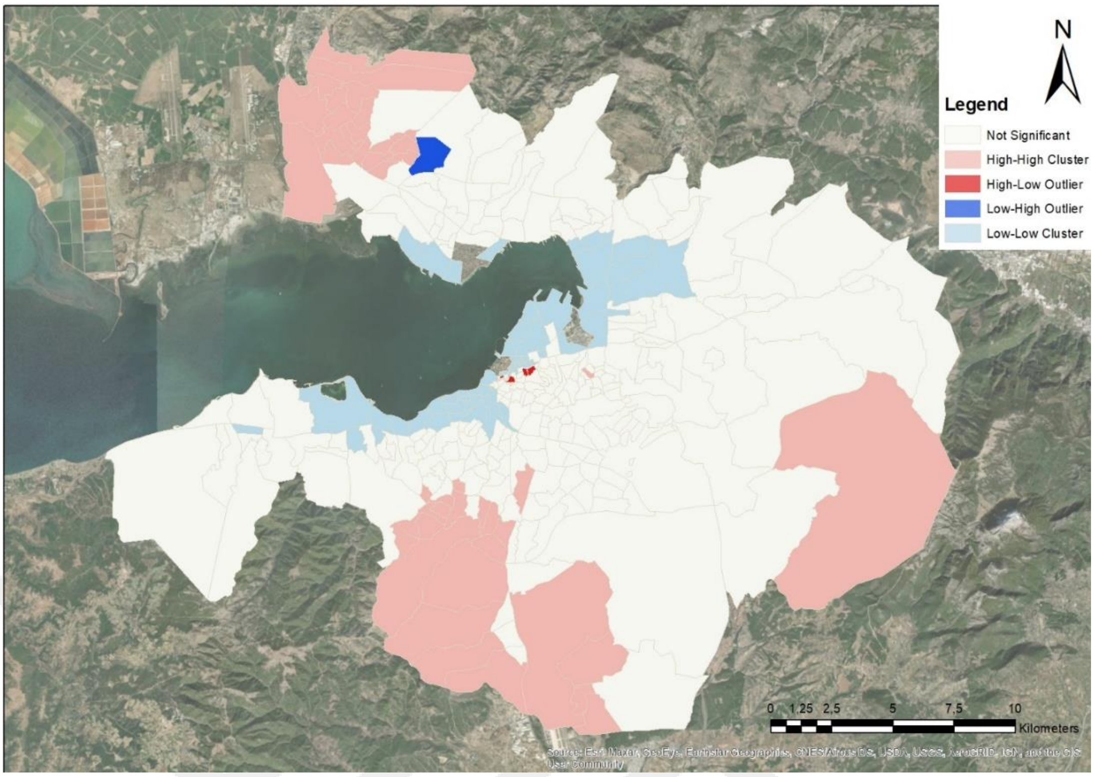


Figure 5.7 Anselin Local Moran's I clusters and outliers, circuity index at 11:30 am as the input

The results of the Anselin Local Moran's *I* Analysis show where the clustered patterns are obtained for the circuity level at 11:30 am of 348 neighborhoods in İzmir (Figure 5.7). This cluster map shows the statistically significant clusters at α=0.05 level with FDR correction.

The four categories were represented. The neighborhoods represented with light blue and light red show the clustered patterns with Low-Low and High-High clusters respectively. It is observed that the Low-Low clusters were mostly concentrated in areas close to the seashore among the İzmir Gulf. The High-High clusters located away from the seashore clustered in the North-South and East direction for the circuity index at 11:30 am. The neighborhoods represented with dark red and dark blue show the locations with High-Low and Low-High spatial outliers respectively.

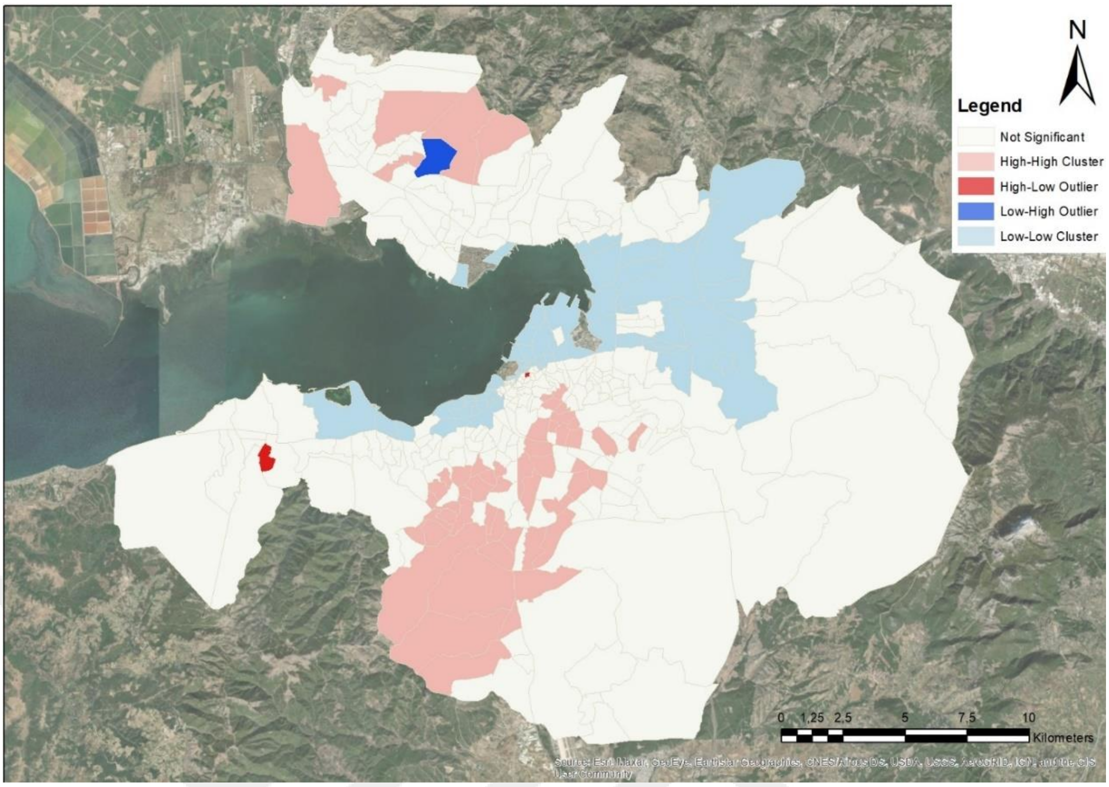


Figure 5.8 Anselin Local Moran’s I clusters and outliers, circuity index at 07:00 pm as the input

The results of the Anselin Local Moran’s *I* Analysis show where the clustered patterns are obtained for the circuity level at 07:00 pm of 348 neighborhoods in İzmir (Figure 5.8). This cluster map shows the statistically significant clusters at α=0.05 level with FDR correction.

The four categories were represented. The neighborhoods represented with light blue and light red show the clustered patterns with Low-Low and High-High clusters respectively. It is observed that the Low-Low clusters were mostly concentrated in areas close to the seashore among the İzmir Gulf with a spread towards the East direction. The High-High clusters located away from the seashore clustered in the North-South direction for the circuity index at 07:00 pm. High-High cluster shows a spread towards the North to the city center. The neighborhoods represented with dark red and dark blue show the locations with High-Low and Low-High spatial outliers respectively.

According to the four different time-of-day analyzes of Local Moran's *I*, it can be concluded that Low-Low clusters mainly concentrated along the seashore of İzmir which indicates greater public transportation efficiency obtained in those areas. On the other hand, High-High clusters located at the edge of the study area that presents lower efficiency levels of public transportation services. The High-Low and Low-High outliers were differentiated in four analyzes, they must be considered in detail due to these areas shows different efficiency levels from its surroundings.

5.1.2.1 Summative Assessment of Univariate Local Spatial Autocorrelation Analyzes

The local spatial associations were detected by Local Moran's *I* Statistic. Four different analyzes were performed for four time-of-day circuity index variations. The results and spatial distributions of clusters and outliers were obtained from the Anselin Local Moran's *I* analyzes were presented in a summary Table 5.2 below:

Table 5.2 Summary table of Anselin Local Moran's I statistics for circuity index

	HH Cluster	**LL Cluster**	**HL Outlier**	**LH Outlier**	**p-value**	**Not Significant**	**Total Neighborhoods**
Circuity Index at 06:00 AM	41	71	5	1	0,05	230	348
Circuity Index at 09:00 AM	41	68	2	1	0,05	236	
Circuity Index at 11:30 AM	46	65	4	1	0,05	232	
Circuity Index at 07:00 PM	55	66	2	1	0,05	224	

As it was represented above in Table 5.2 all of the spatial associations were statistically significant at α=0.05 level. Clustered patterns such as High-High and Low-Low and the outliers such as High-Low and Low-High were located similarly for four time-of-day circuity indexes. Especially the Low-Low and High-High clusters were spatially distributed alike in all four analyzes. Low-Low clusters mainly and dominantly were concentrated in areas close to the seashore among the İzmir Gulf where the High-High clusters located away from the seashore. High-High clusters present the neighborhoods with high circuity levels surrounding by high circuity levels while Low-Low clusters present the neighborhoods with low circuity levels surrounding by low circuity levels.

If we interpret these results in a different perspective, the areas labeled as Low-Low clusters have more efficient public transportation service levels while the areas labeled as High-High clusters getting less efficient public transportation service levels in İzmir.

5.2 Spatial Bivariate Analysis

This research is predominantly focused on the socio-economic variables: population density and per capita income. It is the main concern if there is a statistically significant relationship between the circuity values and the socio-economic variables spatially. The Bivariate Spatial Analysis was used to determine if there is such a relationship. The analyzes were performed for each of the 348 neighborhoods in the metropolitan area of İzmir with four different time-of-day circuity index values. In this research, Spatial Bivariate analyses were performed in the GeoDa 1.18.0.0 software.

5.2.1 Circuity and Per Capita Income

In the literature review section of this research, the relationship between per capita income and public transportation systems has been examined in detail. Many studies investigated the relationship between public transportation usage and per capita income (Brueckner & Rosenthal, 2009; Dong, 2017; California Department of Transportation, 2001; Glaeser et al., 2008). Since this research used the circuity index to assess the efficiency of public transportation services, the per capita income and circuity levels of the neighborhoods were investigated. Bivariate spatial autocorrelation techniques such as Bivariate Global Moran’s *I* and Bivariate Local

Moran's I were used to analyze the spatial autocorrelation between the above-mentioned variables.

5.2.1.1 Bivariate Global Moran's I for Per Capita Income and the Circuity

The idea behind the Bivariate Moran Scatterplot is to reveal whether two variables are in the same location at the same time. Bivariate spatial correlation identifies if there is a relation and which degree between the investigated variable and a different variable at the surrounding neighbors of it (Anselin, 2019). The significance obtained by the approach of permutations, for the α=0,05 level was applied, z-score is also given in the randomization stage. In this case, the hypotheses for the Bivariate Global Moran's I analysis are:

H_0: There is no spatial correlation between the circuity level and per capita income.
H_A: There is a spatial correlation between the circuity level and per capita income.

As an output, the Bivariate Moran Scatter Plot consisted of the x-axis and y-axis as its spatial lag in this case the circuity values.

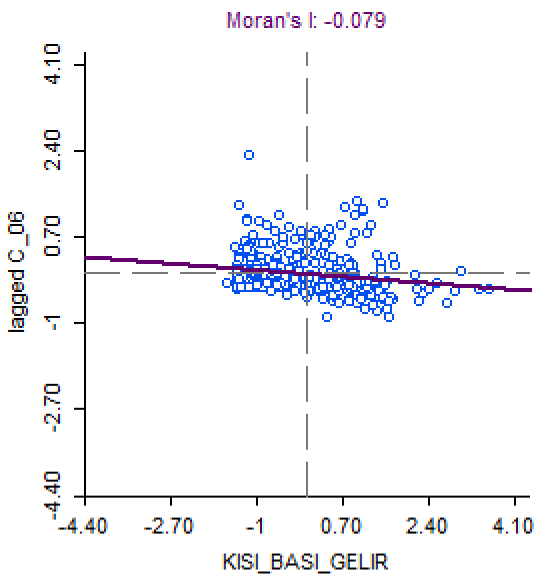


Figure 5.9 Bivariate Global Moran's *I* scatter plot, per capita income and circuity index at 06:00 am

The Bivariate Moran’s *I* index can be obtained from the output Moran Scatter Plot. In this case, Bivariate Moran’s *I* index calculated as -0.0790. Due to the sign of the Bivariate Moran's I index is negative, it indicates a negative correlation (Figure 5.9). But it does not provide information about the significance of the test. The randomization was performed over the Bivariate Moran Scatter Plot with permutations approach corresponding to the α=0.05 level:

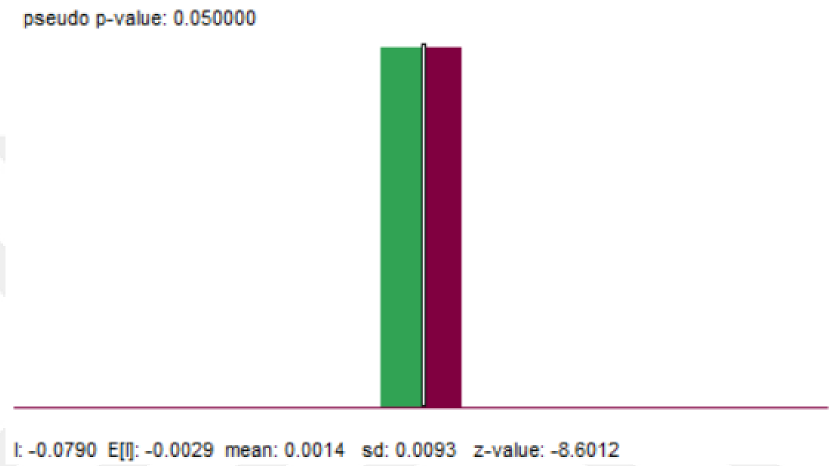


Figure 5.10 Bivariate Global Moran’s *I* randomization, per capita income and circuity index at 06:00 am

The z-score of the analysis was calculated as -8.6012. Observed Moran’s *I* index, and Expected Moran’s *I* index were calculated as -0.0790 and -0.0029 respectively (Figure 5.10). According to the randomization approach, this finding is statistically significant at α=0.05 level. The results of the Bivariate Global Moran’s *I* Analysis revealed that the circuity level at 06:00 am and the per capita income has a negative spatial correlation. As the per capita income increases, the circuity value decreases. More clearly, in the wealthier urban areas, the circuity values are lower than the urban areas with lower per capita income levels according to the findings.

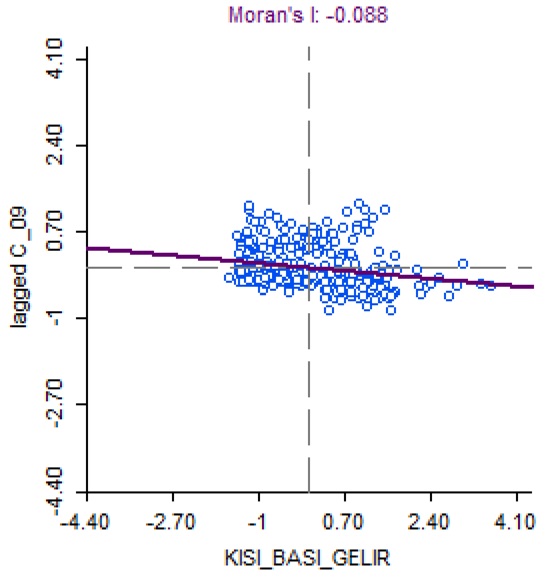


Figure 5.11 Bivariate Global Moran's *I* scatter plot, per capita income and circuity index at 09:00 am

The Bivariate Moran's *I* index can be obtained from the output Moran Scatter Plot. In this case, Bivariate Moran's I index calculated as -0.088. Due to the sign of the Bivariate Moran's *I* index is negative, it indicates a negative correlation (Figure 5.11). But it does not provide information about the significance of the test. The randomization was performed over the Bivariate Moran Scatter Plot with permutations approach corresponding to the α=0.05 level:

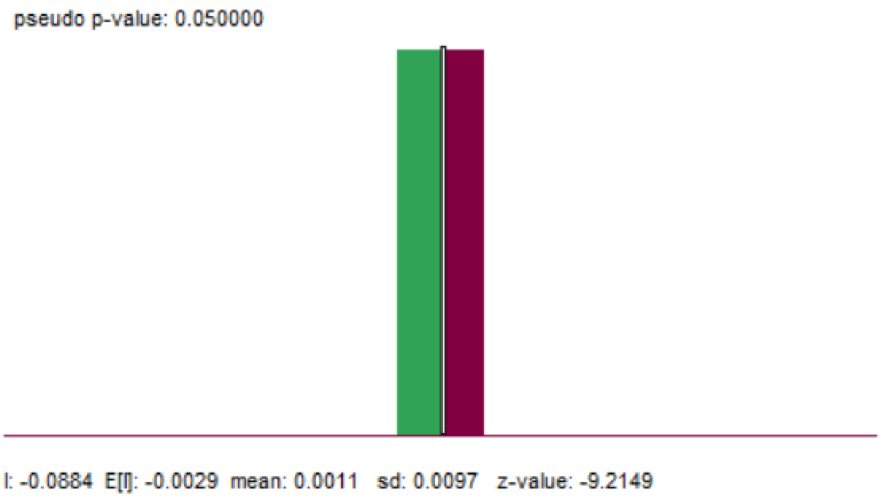


Figure 5.12 Bivariate Global Moran's *I* randomization, per capita income and circuity index at 09:00 am

The z-score of the analysis was calculated as -9.2149. Observed Moran's I index, and Expected Moran's I index were calculated as -0.0884 and -0.0029 respectively (Figure 5.12). According to the randomization approach, this finding is statistically significant at α=0.05 level. The results of the Bivariate Global Moran's I Analysis revealed that the circuity level at 09:00 am and the per capita income has a negative spatial correlation. As the per capita income increases, the circuity value decreases. More clearly, in the wealthier urban areas, the circuity values are lower than the urban areas with lower per capita income levels according to the findings. This finding coincides with the previous result.

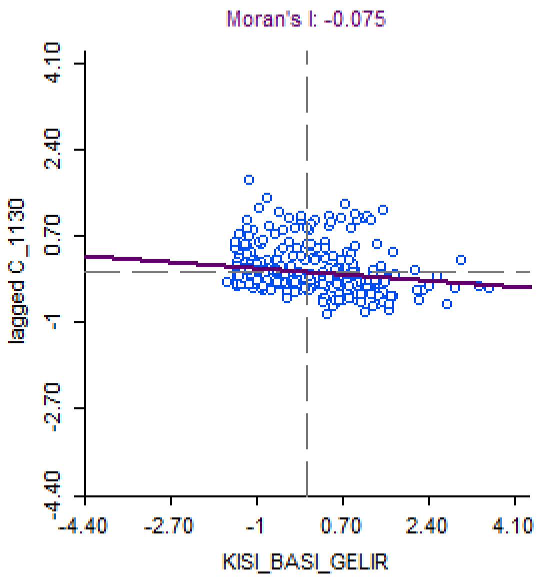


Figure 5.13 Bivariate Global Moran's *I* scatter plot, per capita income and circuity index at 11:30 am

The Bivariate Moran's *I* index can be obtained from the output Moran Scatter Plot. In this case, Bivariate Moran's *I* index calculated as -0.075. Due to the sign of the Bivariate Moran's *I* index is negative, it indicates a negative correlation (Figure 5.13). But it does not provide information about the significance of the test. The randomization was performed over the Bivariate Moran Scatter Plot with permutations approach corresponding to the α=0.05 level:

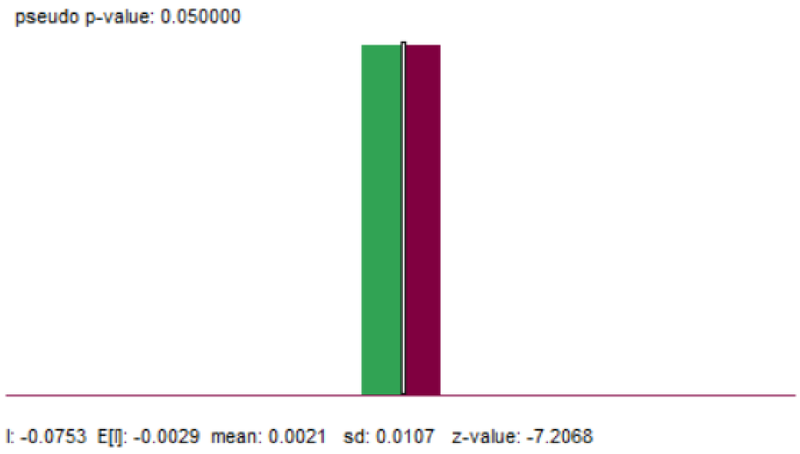


Figure 5.14 Bivariate Global Moran's *I* randomization, per capita income and circuity index at 11:30 am

The z-score of the analysis was calculated as -7.2068. Observed Moran's *I* index, and Expected Moran's *I* index were calculated as -0.0753 and -0.0029 respectively (Figure 5.14). According to the randomization approach, this finding is statistically significant at α=0.05 level. The results of the Bivariate Global Moran's *I* Analysis revealed that the circuity level at 11:30 am and the per capita income has a negative spatial correlation. As the per capita income increases, the circuity value decreases. More clearly, in the wealthier urban areas, the circuity values are lower than the urban areas with lower per capita income levels according to the findings. This finding coincides with the previous results.

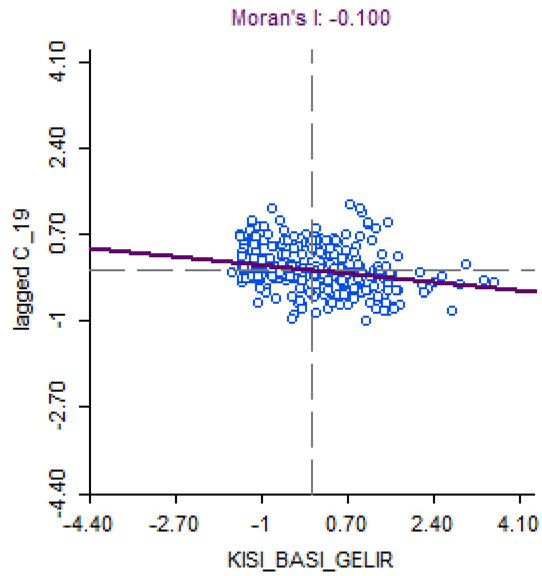


Figure 5.15 Bivariate Global Moran’s *I* scatter plot, per capita income and circuity index at 19:00 am

The Bivariate Moran’s *I* index can be obtained from the output Moran Scatter Plot. In this case, Bivariate Moran’s *I* index calculated as -0.100. Due to the sign of the Bivariate Moran's *I* index is negative, it indicates a negative correlation (Figure 5.15). But it does not provide information about the significance of the test. The randomization was performed over the Bivariate Moran Scatter Plot with permutations approach corresponding to the α=0.05 level:

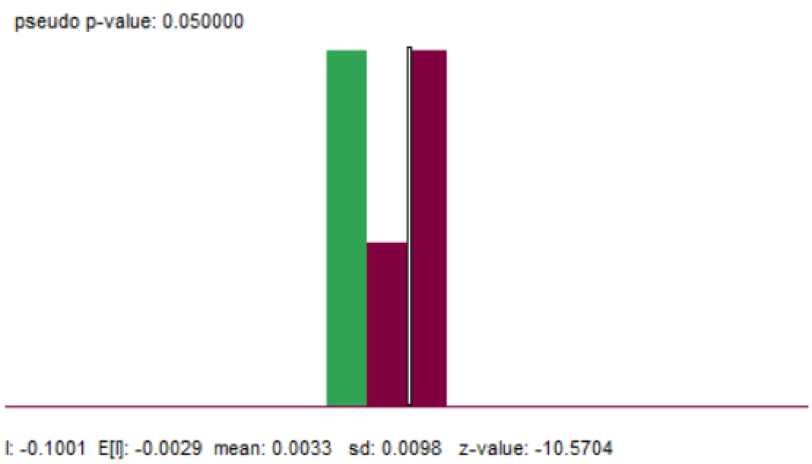


Figure 5.16 Bivariate Global Moran’s *I* randomization, per capita income and circuity index at 19:00 am

The z-score of the analysis was calculated as -10.5704. Observed Moran's *I* index, and Expected Moran's *I* index were calculated as -0.1001 and -0.0029 respectively (Figure 5.16). According to the randomization approach, this finding is statistically significant at α=0.05 level. The results of the Bivariate Global Moran's I Analysis revealed that the circuity level at 19:00 am and the per capita income has a negative spatial correlation. As the per capita income increases, the circuity value decreases. More clearly, in the wealthier urban areas, the circuity values are lower than the urban areas with lower per capita income levels according to the findings. This finding coincides with the previous results.

5.2.1.2 Bivariate Local Moran's I for Per Capita Income and the Circuity

The idea behind the Bivariate Local Moran Analysis is to assess the bivariate spatial correlation at the local level. Bivariate Local Moran's *I* statistic measures the linear association between an *x* value at the location *i* and the average of different variables as the neighboring locations of *x* it is *y* (Anselin et al, 2002). As in the Moran Scatter Plot has quadrants and the interpretation of the Local Moran's I offer the spatial clusters (High-High or Low-Low) or the spatial outliers (High-Low or Low-High) (Anselin, 1995); there is a Bivariate Local Moran's Scatter Plot statistic presenting the if there are spatial clusters and/or spatial outliers. The significance obtained by the approach of permutations, for the α=0.05 level. z-score is also given in the randomization stage. In this perspective, the hypotheses are:

H_0: There is no local spatial association between the circuity level and per capita income.
H_A: There is a local spatial association between the circuity level and per capita income.

In this case, the Bivariate Local Moran's *I* analysis was measured the linear association between per capita income value for each neighborhood and the average of its neighboring circuity levels of the investigated neighborhood. As mentioned above in the Moran Scatter Plot has quadrants and the interpretation of the Local Moran’s I offer the spatial clusters (High-High or Low-Low) or the spatial outliers (High-Low or Low-High). High-High clusters present the neighborhoods with high per capita income surrounding by high circuity levels. To recap, high circuity values indicate lower public transportation efficiency. Low-Low clusters present the neighborhoods with low per capita income surrounding by low circuity levels. To recap, low circuity values indicate higher public transportation efficiency. High-Low outliers present the neighborhoods with high per capita income surrounding by low circuity levels. To recap, low circuity values indicate higher public transportation efficiency. Low-High outliers present the neighborhoods with low per capita income surrounding by high circuity levels. To recap, high circuity values indicate lower public transportation efficiency.

A Bivariate Significance Map, a Bivariate LISA Cluster Map, and a Bivariate Moran Scatter Plot consisted of x-axis and y-axis as its spatial lag, in this case, were presented between the four time-of-day circuity levels and per capita income.

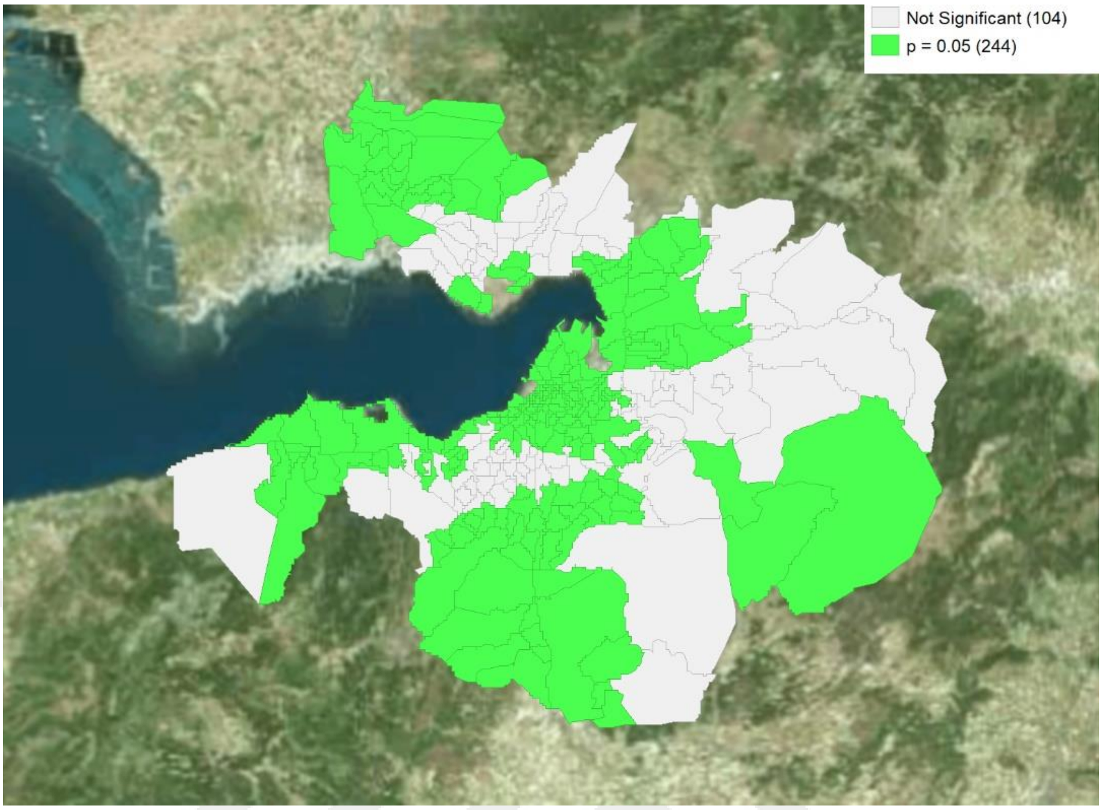


Figure 5.17 Bivariate Local Moran significancy map, per capita income and circuity index at 06:00 am as the input

The results of the Bivariate Local Moran Significancy Map show where the statistically significant clusters at α=0.05 level are obtained for the circuity level at 06:00 am of 348 neighborhoods in İzmir (Figure 5.17).

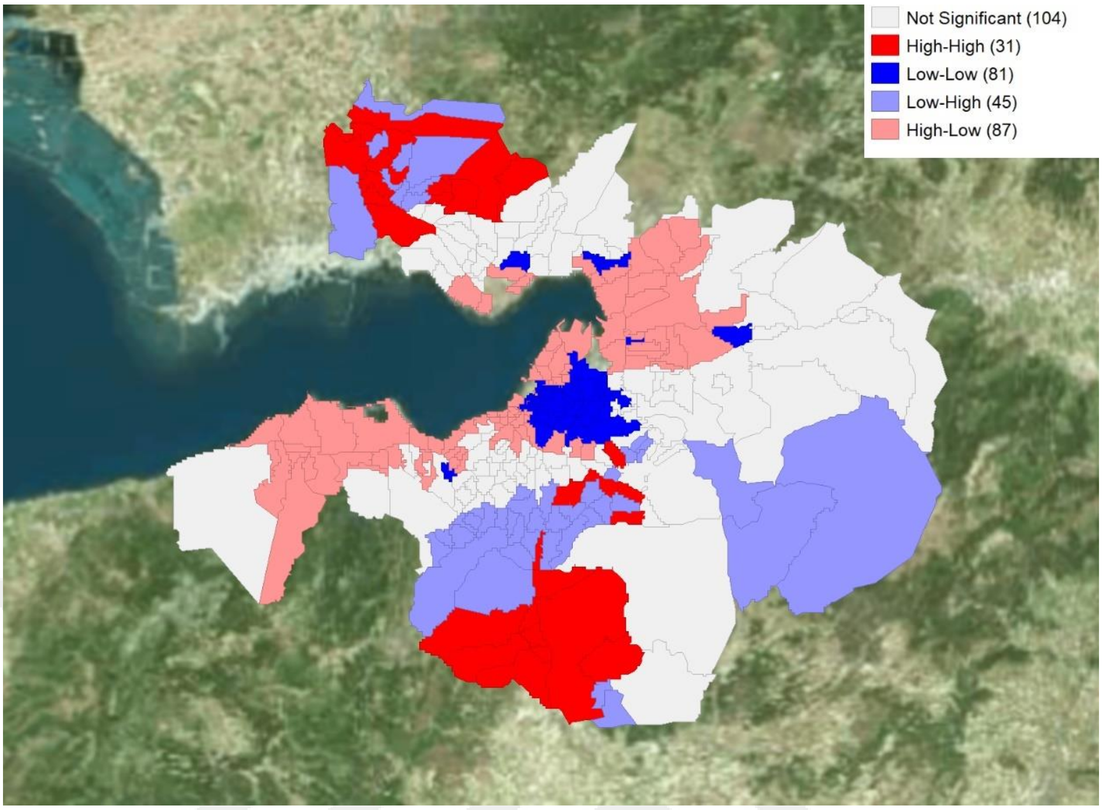


Figure 5.18 Bivariate Local Moran cluster map, per capita income and circuity index at 06:00 am as the input

The four categories were represented. The neighborhoods represented with dark blue and dark red show the clustered patterns with Low-Low and High-High clusters respectively (Figure 5.18). It is observed that the Low-Low clusters were mostly concentrated in the areas close to the traditional city center of İzmir. The High-High clusters located away from the seashore clustered in the North and South of the study area for the circuity index at 06:00 am.

The neighborhoods represented with light red and light blue show the locations with High-Low and Low-High spatial outliers respectively. The High-Low outliers were mostly concentrated in areas close to the seashore among the İzmir Gulf. More clearly, it represents that the neighborhoods with high per capita income levels have lower circuity values in these areas. The Low-High outliers are the neighborhoods with lower income levels and higher circuity values, and it is seen that they were located away from the city center.

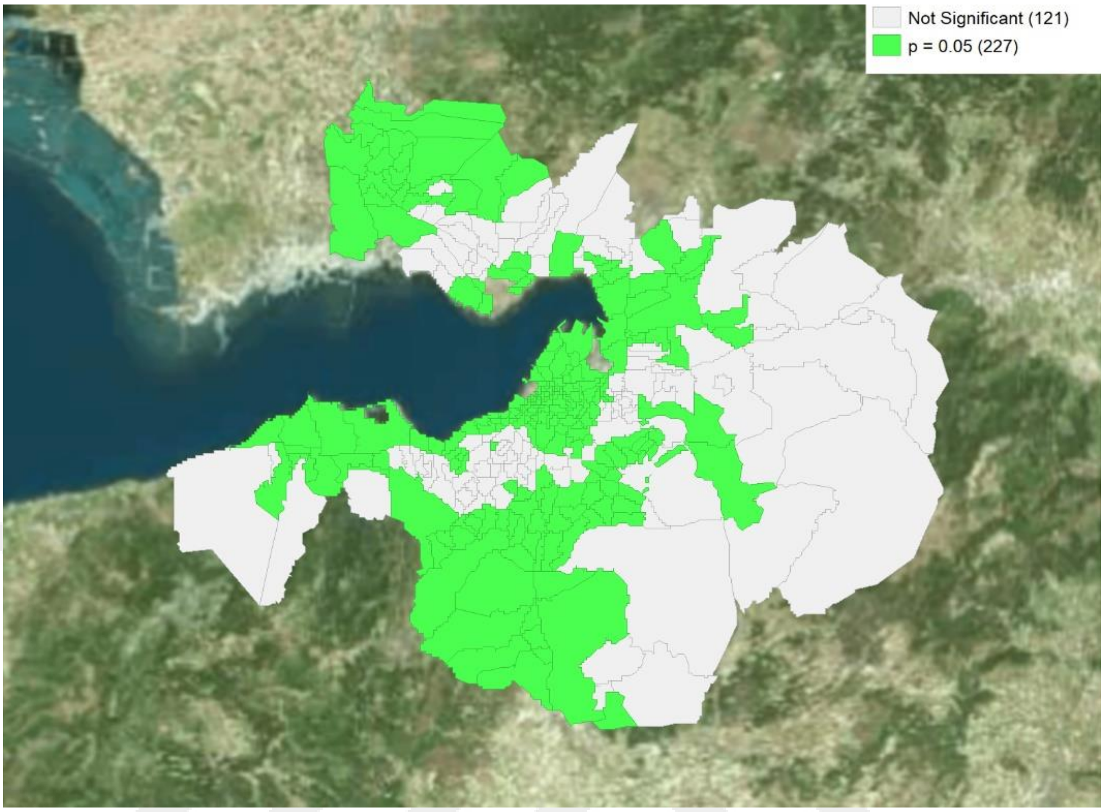


Figure 5.19 Bivariate Local Moran significancy map, per capita income and circuity index at 09:00 am as the input

The results of the Bivariate Local Moran Significancy Map show where the statistically significant clusters at α=0.05 level are obtained for the circuity level at 09:00 am of 348 neighborhoods in İzmir (Figure 5.19).

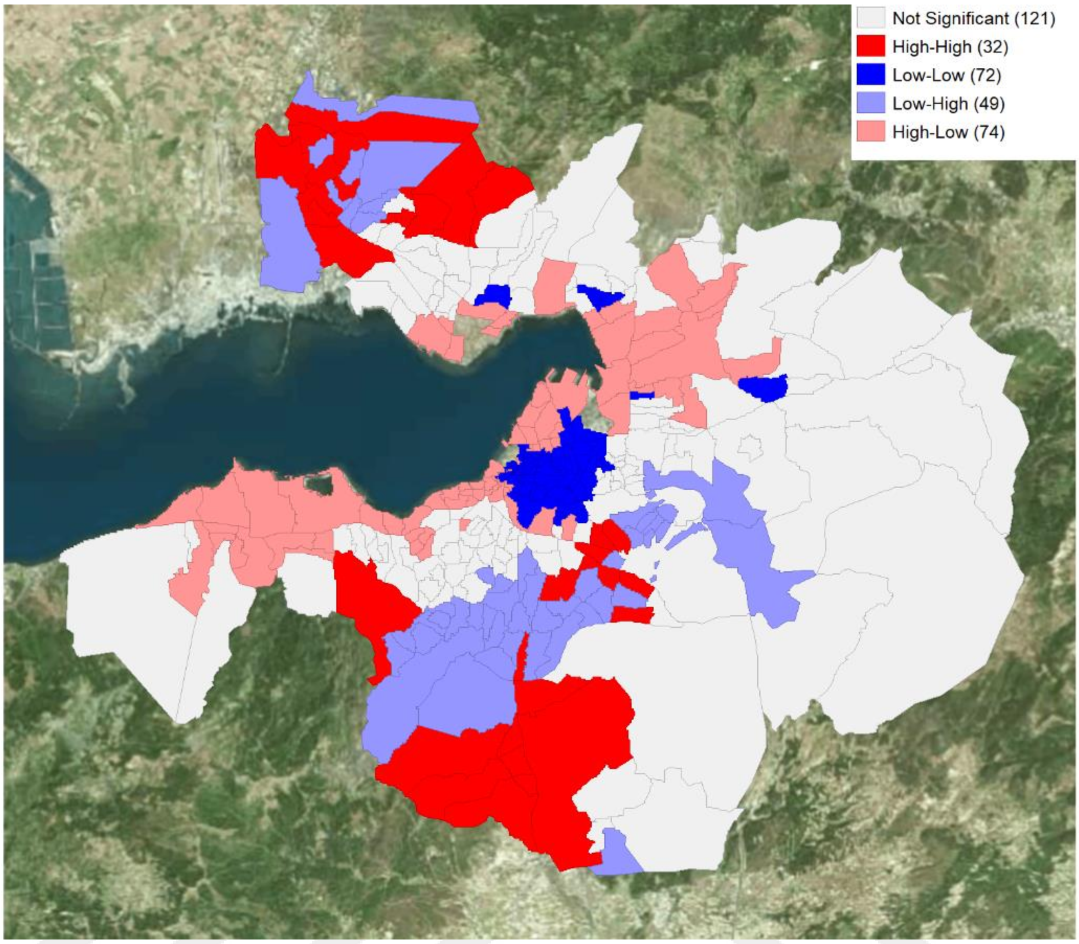


Figure 5.20 Bivariate Local Moran cluster map, per capita income and circuity index at 09:00 am as the input

The four categories were represented. The neighborhoods represented with dark blue and dark red show the clustered patterns with Low-Low and High-High clusters, respectively (Figure 5.20). It is observed that the Low-Low clusters were mostly concentrated in the areas close to the traditional city center of İzmir. The High-High clusters located away from the seashore clustered in the North and South of the study area for the circuity index at 09:00 am.

The neighborhoods represented with light red and light blue show the locations with High-Low and Low-High spatial outliers, respectively. The High-Low outliers were mostly concentrated in areas close to the seashore among the İzmir Gulf. More clearly, the neighborhoods with high per capita income levels have lower circuity values in these areas. The Low-High outliers are the neighborhoods with lower income levels and higher circuity values and they were located away from the city center with a shift from East towards the city center.

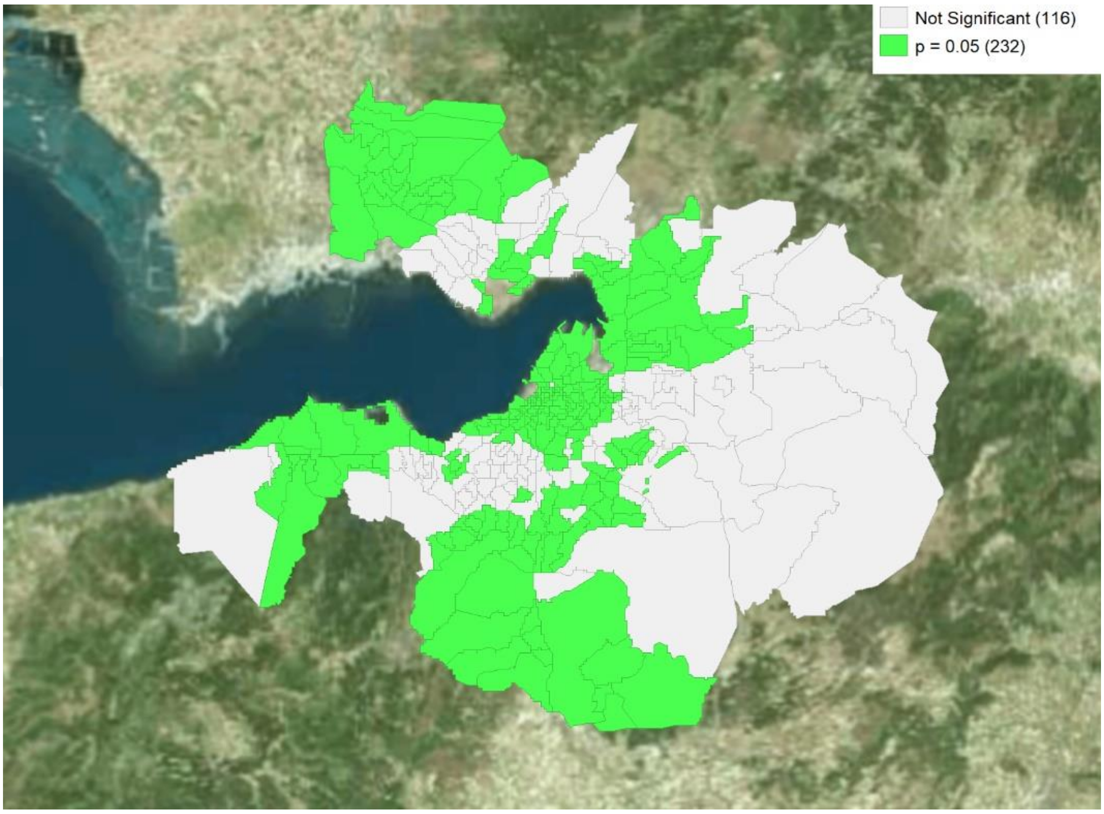


Figure 5.21 Bivariate Local Moran significancy map, per capita income and circuity index at 11:30 am as the input

The results of the Bivariate Local Moran Significancy Map show where the statistically significant clusters at α=0.05 level are obtained for the circuity level at 11:30 am of 348 neighborhoods in İzmir (Figure 5.21).

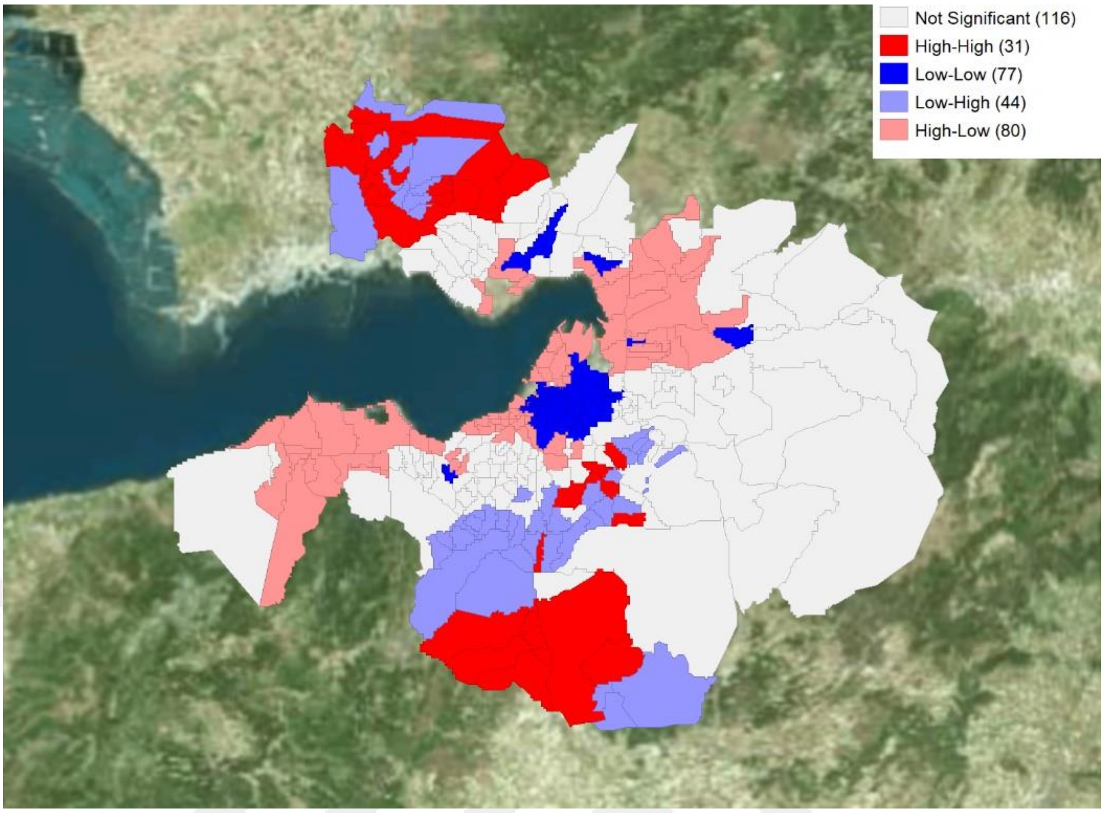


Figure 5.22 Bivariate Local Moran cluster map, per capita income and circuity index at 11:30 am as the input

The four categories were represented. The neighborhoods represented with dark blue and dark red show the clustered patterns with Low-Low and High-High clusters, respectively (Figure 5.22). It is observed that the Low-Low clusters were mostly concentrated in the areas close to the traditional city center of İzmir. The High-High clusters located away from the seashore clustered in the North and South of the study area for the circuity index at 11:30 am.

The neighborhoods represented with light red and light blue show the locations with High-Low and Low-High spatial outliers, respectively. The High-Low outliers were mostly concentrated in areas close to the seashore among the İzmir Gulf concurrent with the previous findings. More clearly, the neighborhoods with high per capita income levels have lower circuity values in these areas. The Low-High outliers are the neighborhoods with lower income levels and higher circuity values, and they were located away from the city center mainly in North to East directions of the study area.

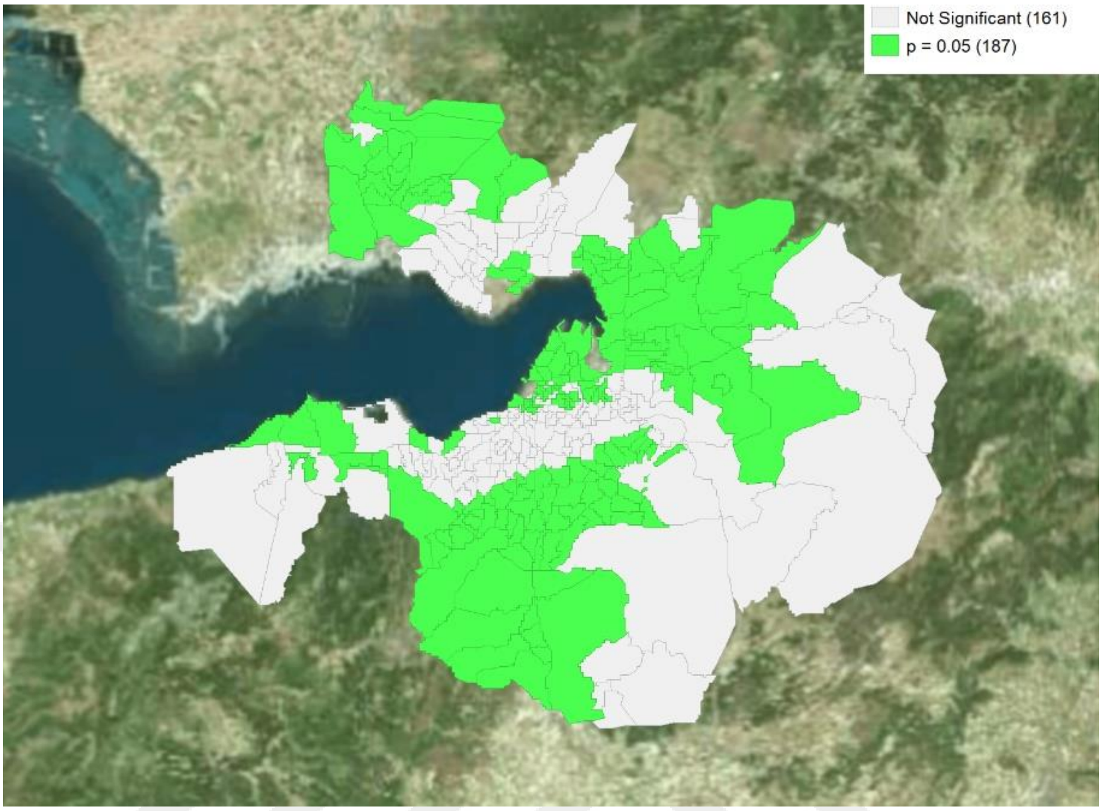


Figure 5.23 Bivariate Local Moran significancy map, per capita income and circuity index at 07:00 pm as the input

The results of the Bivariate Local Moran Significancy Map show where the statistically significant clusters at α=0.05 level are obtained for the circuity level at 07:00 pm of 348 neighborhoods in İzmir (Figure 5.23).

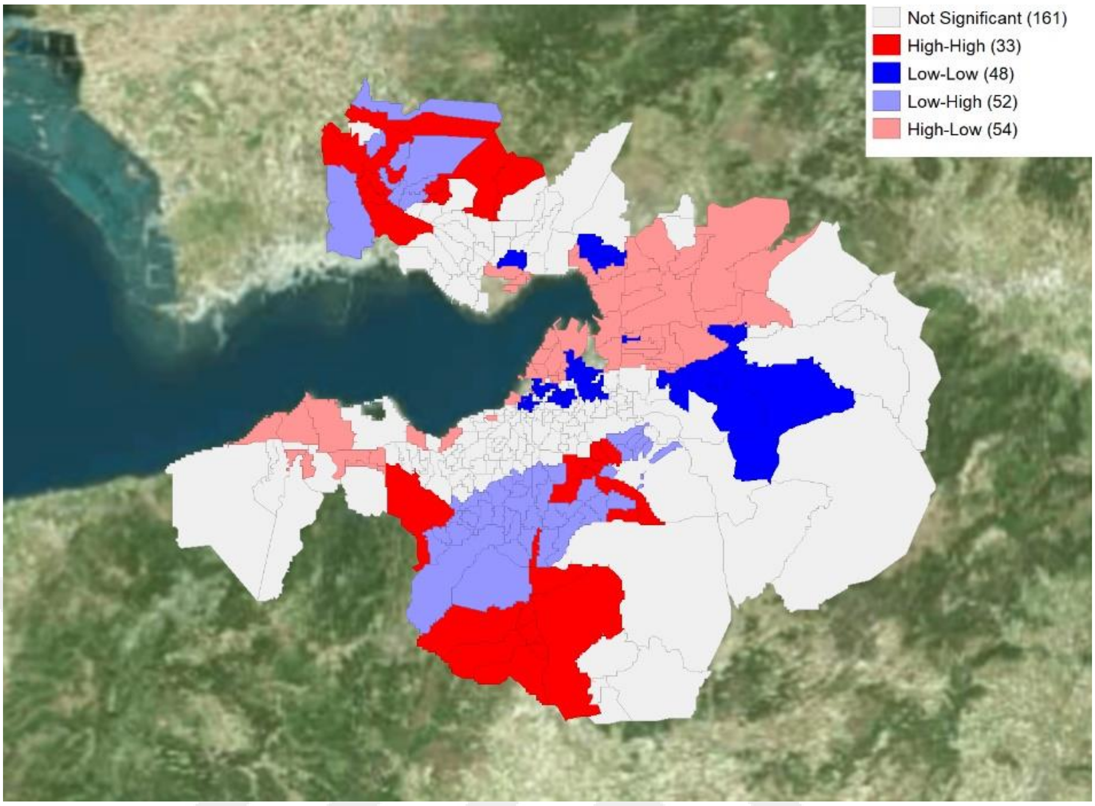


Figure 5.24 Bivariate Local Moran cluster map, per capita income and circuity index at 07:00 pm as the input

The four categories were represented. The neighborhoods represented with dark blue and dark red show the clustered patterns with Low-Low and High-High clusters, respectively (Figure 5.24). It is observed that the Low-Low clusters were mostly concentrated in the areas close to the traditional city center of İzmir but a spread to the East direction was obtained. The High-High clusters located away from the seashore clustered in the North and South of the study area for the circuity index at 07:00 pm as the previous findings.

The neighborhoods represented with light red and light blue show the locations with High-Low and Low-High spatial outliers, respectively. The High-Low outliers were mostly concentrated in a few neighborhoods close to the seashore among the İzmir Gulf concurrent with the previous findings. More clearly, the neighborhoods with high per capita income levels have lower circuity values in these areas. The Low-High outliers are the neighborhoods with lower income levels and higher circuity values, and they were located away from the city center mainly in the North to East directions of the study area.

5.2.1.3 Summative Assessment of Bivariate Spatial Autocorrelation Analyzes of Circuity and Per Capita Income

The results from the two bivariate spatial analyzes such as Global Moran's I and Local Moran's I statistic for Circuity and Per Capita Income were explained in detail earlier. The overall spatial correlation between the circuity level and the per capita income level was investigated by Bivariate Global Moran’s *I* Statistic and Bivariate Local Moran’s I Statistic. Four different analyzes were performed for four time-of-day circuity index variations. The results and spatial distribution patterns obtained from the Bivariate Global Moran’s I analyzes were presented in a summary Table 5.3 below:

Table 5.3 Summary table of Bivariate Global Moran’s *I* statistics for circuity index and per capita income

	Moran's I Index	**Expected Index**	**z-score**	**p-value**
Circuity Index at 06:00 AM and Per Capita Income	-0.079	-0.003	-8.601	0.05
Circuity Index at 09:00 AM and Per Capita Income	-0.088	-0.003	-9.215	0.05
Circuity Index at 11:30 AM and Per Capita Income	-0.075	-0.003	-7.207	0.05
Circuity Index at 07:00 PM and Per Capita Income	-0.100	-0.003	-10.570	0.05

As it was represented above in Table 5.3 circuity and the per capita income are negatively spatially correlated for the four analyzes. All the four analyzes were statistically significant at $\alpha=0.05$ level. This finding revealed that the neighborhoods with lower per capita income levels have higher circuity values than the other urban areas. To recap, high circuity values indicate lower public transportation efficiency. In other words, in the wealthier urban areas, the circuity values are lower than the lower income urban areas to the findings.

The bivariate local spatial correlations were detected by Bivariate Local Moran's *I* Statistic for Circuity and Per Capita Income. In this case, the Bivariate Local Moran's I analysis was measured the linear association between per capita income value for each neighborhood and the average of its neighboring circuity levels of the investigated neighborhood. Four different analyzes were performed for four time-of-day circuity index variations. The results and spatial distributions of clusters and outliers were obtained from the Bivariate Local Moran's *I* analyzes were presented in a summary Table 5.4 below:

Table 5.4 Summary table of Bivariate Local Moran's *I* statistics for circuity index and per capita income

	HH Cluster	**LL Cluster**	**HL Outlier**	**LH Outlier**	**p-value**	**Not Significant**	**Total Neighborhoods**
Circuity Index at 06:00 AM and Per Capita Income	31	81	87	45	0.05	104	348
Circuity Index at 09:00 AM and Per Capita Income	32	72	74	49	0.05	121	
Circuity Index at 11:30 AM and Per Capita Income	31	77	80	44	0.05	116	
Circuity Index at 07:00 PM and Per Capita Income	33	48	54	52	0.05	161	

As it was represented above in Table 5.4 all of the spatial analyzes were statistically significant at α=0,05 level. Clustered patterns such as High-High and Low-Low and the outliers such as High-Low and Low-High were located similarly for four time-of-day circuity indexes. Especially the Low-High and High-Low outliers; and High-High clusters were spatially distributed alike in all four analyzes. High-Low clusters mainly and dominantly were concentrated in areas close to the seashore among the İzmir Gulf.

The High-High clusters and Low-High outliers located away from the seashore. High-Low outliers present the neighborhoods with high per capita income levels surrounding by low circuity levels while Low-High outliers present the neighborhoods with low per capita income levels surrounding by high circuity levels.

If we interpret these results in a different perspective, the areas labeled as High-Low clusters have more efficient public transportation service levels while the areas labeled as Low-High clusters getting less efficient public transportation service levels in İzmir.

5.2.2 Circuity and Population Density

In the literature review section of this research, the relationship between population density and public transportation systems has been examined in detail. Many studies investigated and found a positive relationship between public transportation usage and population density (Ewing and Cervero, 2001; Frank and Pivo, 1994; Kitamura, 1997; Zhang, 2004). Since this research used the circuity index to assess the efficiency of public transportation services, the population density and circuity levels of the neighborhoods were investigated. Bivariate spatial autocorrelation techniques such as Bivariate Global Moran's I and Bivariate Local Moran's *I* were used to analyze the spatial autocorrelation between the above-mentioned variables.

5.2.2.1 Bivariate Global Moran's I for Population Density and the Circuity

The idea behind the Bivariate Moran Scatterplot is that whether two variables are in the same location at the same time. Bivariate spatial correlation identifies if there is a relation and which degree between the investigated variable and a different variable at the surrounding neighbors of it (Anselin, 2019). The significance obtained by the approach of permutations, for the α=0,05 level was applied, z-score is also given in the randomization stage. In this perspective, the hypotheses are:

H_0: There is no spatial correlation between the circuity level and population density.
H_A: There is a spatial correlation between the circuity level and population density.

As an output, the Bivariate Moran Scatter Plot consisted of the x-axis and y-axis as its spatial lag in this case the circuity values.

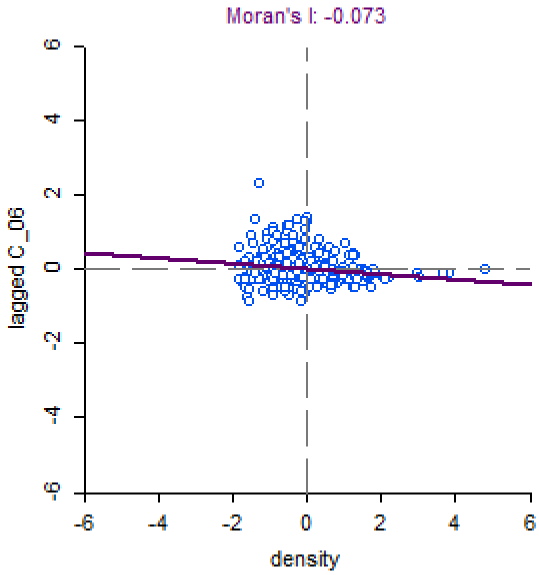


Figure 5.25 Bivariate Global Moran's *I* scatter Plot, Population Density and Circuity index at 06:00 am

The Bivariate Moran's *I* index can be obtained from the output Moran Scatter Plot. In this case, Bivariate Moran's *I* index calculated as -0.073. Due to the sign of the Bivariate Moran's *I* index is negative, it indicates a negative correlation between the circuity level at 06:00 am and the population density (Figure 5.25). But it does not provide information about the significance of the test. The randomization was performed over the Bivariate Moran Scatter Plot with permutation approach corresponding to the α=0.05 level:

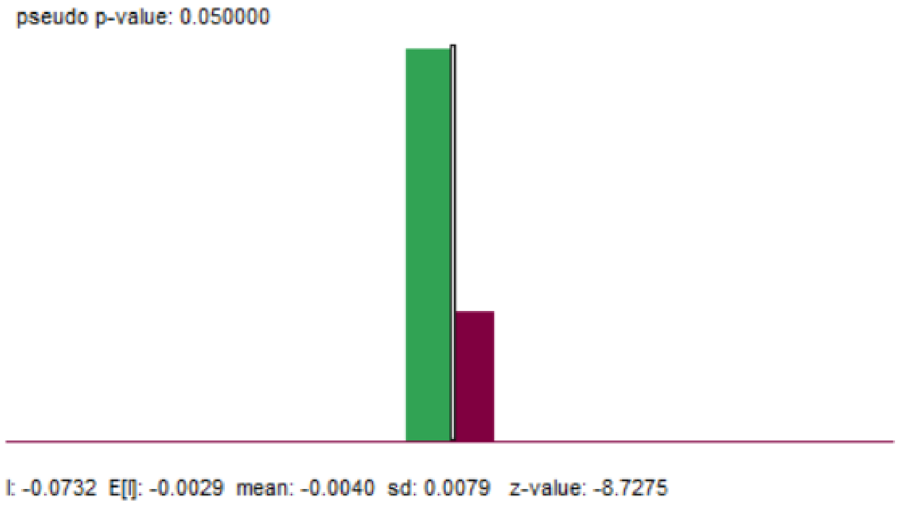


Figure 5.26 Bivariate Global Moran's *I* Randomization, Population Density and Circuity index at 06:00 am

The z-score of the analysis was calculated as -8.7275. Observed Moran's *I* index, and Expected Moran's *I* index were calculated as -0.0732 and -0.0029 respectively (Figure 5.26). According to the randomization approach, this finding is statistically significant at α=0.05 level. The results of the Bivariate Global Moran's *I* Analysis revealed that the circuity level at 06:00 am and the population density has a negative spatial correlation. As the population density increases, the circuity value decreases. More clearly, in the less dense urban areas, the circuity values are lower than the urban areas with high population density levels according to the findings.

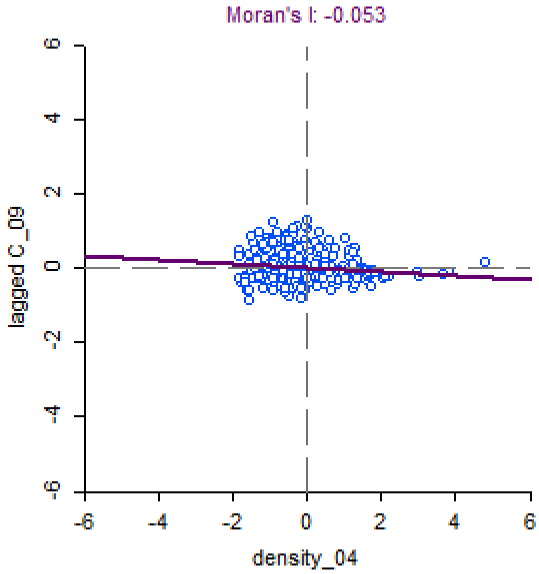


Figure 5.27 Bivariate Global Moran’s *I* Scatter Plot, Population Density and Circuity index at 09:00 am

The Bivariate Moran’s I index can be obtained from the output Moran Scatter Plot. In this case, Bivariate Moran’s I index calculated as -0.053. Due to the sign of the Bivariate Moran's *I* index is negative, it indicates a negative correlation between the circuity level at 09:00 am and the population density (Figure 5.27). But it does not provide information about the significance of the test. The randomization was performed over the Bivariate Moran Scatter Plot with permutation approach corresponding to the α=0.05 level:

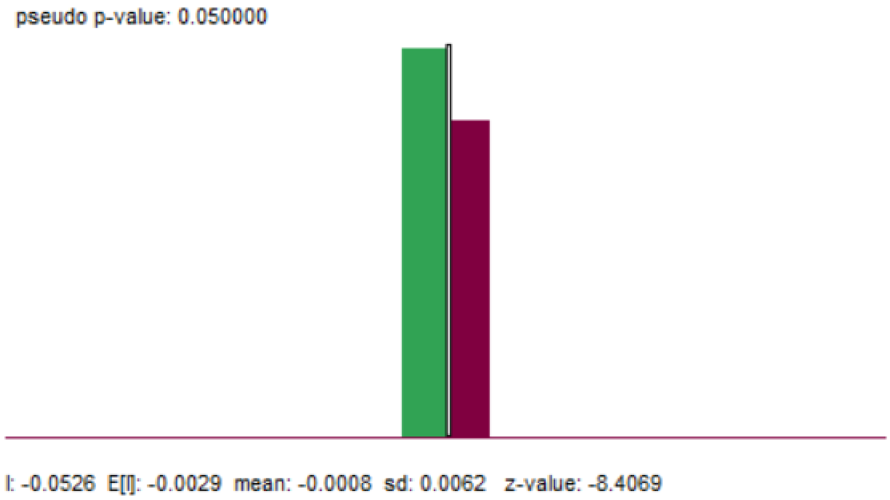


Figure 5.28 Bivariate Global Moran's *I* Randomization, Population Density and Circuity index at 09:00 am

The z-score of the analysis was calculated as -8.4069. Observed Moran's *I* index, and Expected Moran's I index were calculated as -0.0526 and -0.0029 respectively (Figure 5.28). According to the randomization approach, this finding is statistically significant at α=0.05 level. The results of the Bivariate Global Moran's *I* Analysis revealed that the circuity level at 09:00 am and the population density has a negative spatial correlation. As the population density increases, the circuity value decreases. More clearly, in the less dense urban areas, the circuity values are lower than the urban areas with high population density levels coincide with the previous result.

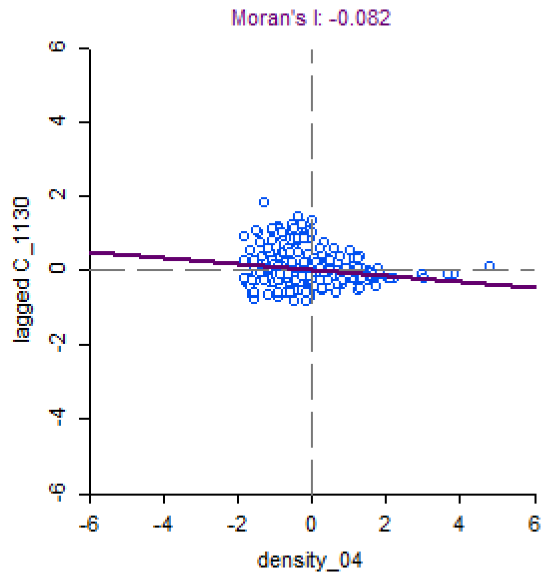


Figure 5.29 Bivariate Global Moran’s *I* Scatter Plot, Population Density and Circuity index at 11:30 am

The Bivariate Moran’s *I* index can be obtained from the output Moran Scatter Plot. In this case, Bivariate Moran’s *I* index calculated as -0.082. Due to the sign of the Bivariate Moran's *I* index is negative, it indicates a negative correlation between the circuity level at 11:30 am and the population density (Figure 5.29). But it does not provide information about the significance of the test. The randomization was performed over the Bivariate Moran Scatter Plot with permutation approach corresponding to the α=0.05 level:

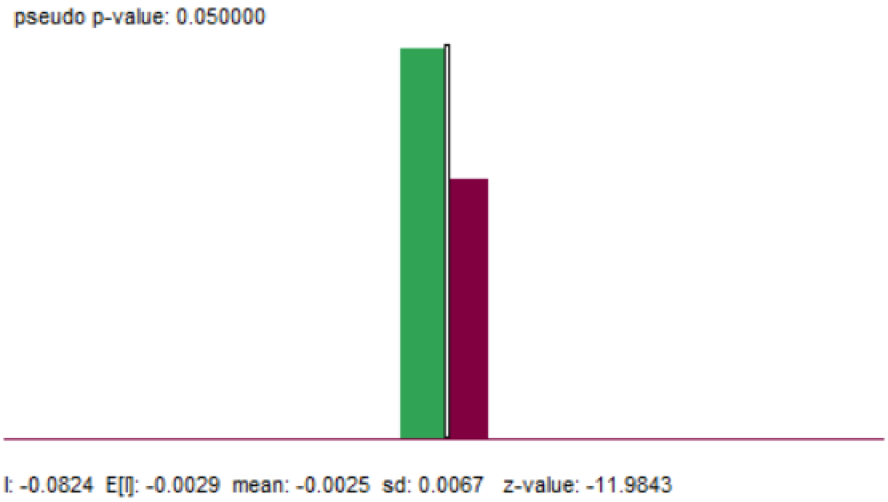


Figure 5.30 Bivariate Global Moran's *I* Randomization, Population Density and Circuity index at 11:30 am

The z-score of the analysis was calculated as -11.9843. Observed Moran's *I* index, and Expected Moran's *I* index were calculated as -0.0824 and -0.0029 respectively (Figure 5.30). According to the randomization approach, this finding is statistically significant at α=0.05 level.

The results of the Bivariate Global Moran's *I* Analysis revealed that the circuity level at 11:30 am and the population density has a negative spatial correlation. As the population density increases, the circuity value decreases. More clearly, in the less dense urban areas, the circuity values are lower than the urban areas with high population density levels coincide with the previous results.

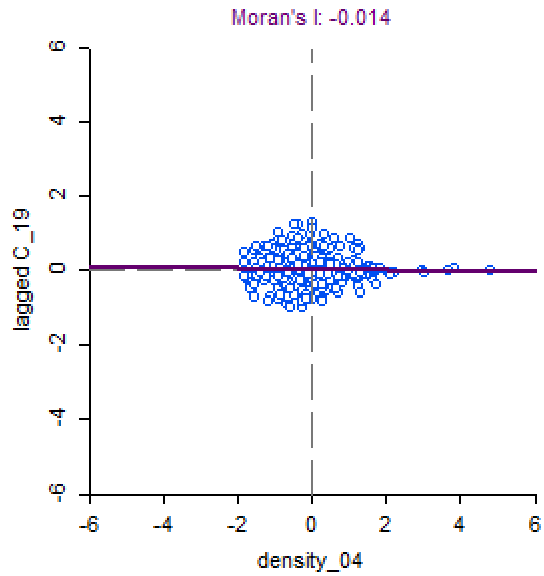


Figure 5.31 Bivariate Global Moran’s *I* Scatter Plot, Population Density and Circuity index at 07:00 pm

The Bivariate Moran’s *I* index can be obtained from the output Moran Scatter Plot. In this case, Bivariate Moran’s I index calculated as -0.014. Due to the sign of the Bivariate Moran's *I* index is negative, it indicates a negative correlation between the circuity level at 07:00 pm and the population density (Figure 5.31). But it does not provide information about the significance of the test. The randomization was performed over the Bivariate Moran Scatter Plot with permutation approach corresponding to the α=0.05 level:

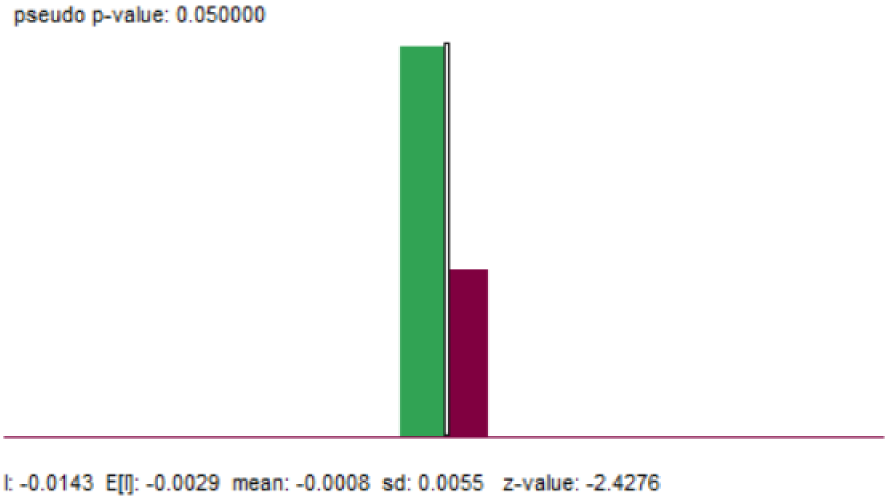


Figure 5.32 Bivariate Global Moran's *I* Randomization, Population Density and Circuity index at 07:00 pm

The z-score of the analysis was calculated as -2.4276. Observed Moran's *I* index, and Expected Moran's *I* index were calculated as -0.0143 and -0.0029 respectively (Figure 5.32). According to the randomization approach, this finding is statistically significant at α=0.05 level. The results of the Bivariate Global Moran's *I* Analysis revealed that the circuity level at 07:00 pm and the population density has a negative spatial correlation. As the population density increases, the circuity value decreases. More clearly, in the less dense urban areas, the circuity values are lower than the urban areas with high population density levels coincide with the previous results.

5.2.2.2 Bivariate Local Moran's I for Population Density and the Circuity

The idea behind the Bivariate Local Moran Analysis is to assess the bivariate spatial correlation at the local level. Bivariate Local Moran's *I* statistic measures the linear association between an *x* value at the location *i* and the average of different variable as the neighboring locations of *x* it is *y* (Anselin et al, 2002). As in the Moran Scatter Plot has quadrants and the interpretation of the Local Moran's I offer the spatial clusters (High-High or Low-Low) or the spatial outliers (High-Low or Low-High) (Anselin, 1995); there is a Bivariate Local Moran's Scatter Plot statistic presenting the if there are spatial clusters and/or spatial outliers.

The significance obtained by the approach of permutations, for the α=0.05 level. Z-score is also given in the randomization stage. In this perspective, the hypotheses are:

H_0: There is no local spatial association between the circuity level and population density.
H_A: There is a local spatial association between the circuity level and population density.

In this case, the Bivariate Local Moran's I analysis was measured the linear association between population density value for each neighborhood and the average of its neighboring circuity levels of the investigated neighborhood. As mentioned above in the Moran Scatter Plot has quadrants and the interpretation of the Local Moran's I offer the spatial clusters (High-High or Low-Low) or the spatial outliers (High-Low or Low-High).

High-High clusters present the neighborhoods with high population density surrounding by high circuity levels. To recap, high circuity values indicate lower public transportation efficiency. Low-Low clusters present the neighborhoods with low population density surrounding by low circuity levels. To recap, low circuity values indicate higher public transportation efficiency. High-Low outliers present the neighborhoods with high population density surrounding by low circuity levels. To recap, low circuity values indicate higher public transportation efficiency. Low-High outliers present the neighborhoods with low population density surrounding by high circuity levels. To recap, high circuity values indicate lower public transportation efficiency.

A Bivariate Significance Map, a Bivariate LISA Cluster Map, and a Bivariate Moran Scatter Plot consisted of x-axis and y-axis as its spatial lag, in this case, were presented between the four time-of-day circuity levels and population density.

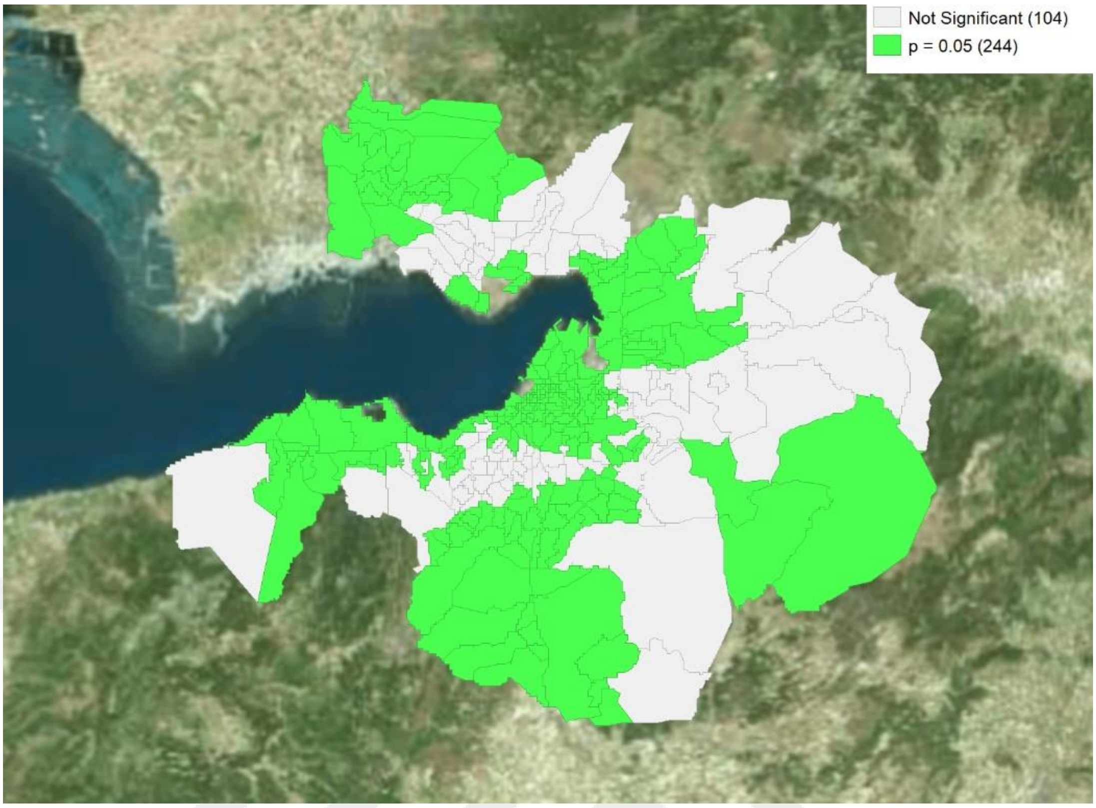


Figure 5.33 Bivariate Local Moran Significancy Map, Population Density and Circuity index at 06:00 am as the input

The results of the Bivariate Local Moran Significancy Map show where the statistically significant clusters at α=0.05 level are obtained for the circuity level at 06:00 am of 348 neighborhoods in İzmir (Figure 5.33).

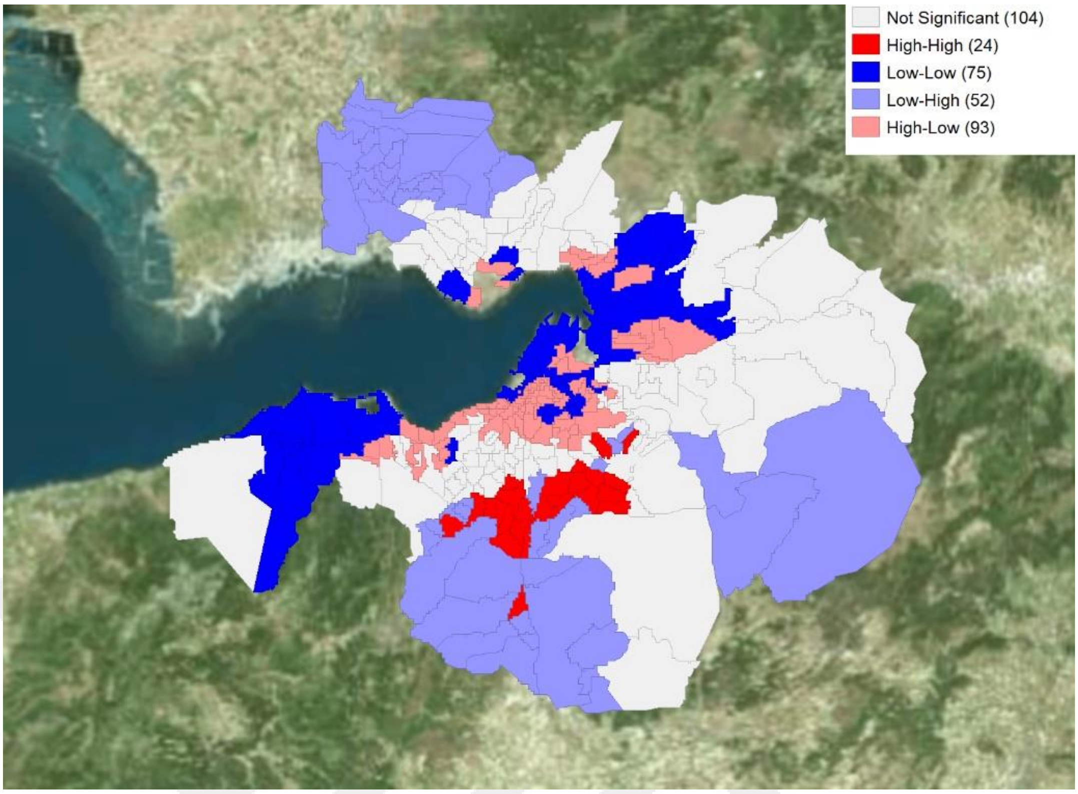


Figure 5.34 Bivariate Local Moran Cluster Map, Population Density and Circuity index at 06:00 am as the input

The four categories were represented. The neighborhoods represented with dark blue and dark red show the clustered patterns with Low-Low and High-High clusters respectively (Figure 5.34). It is observed that the Low-Low clusters were mostly concentrated in areas close to the seashore among the İzmir Gulf. The High-High clusters located away from the city center clustered in the South of the study area for the circuity index at 06:00 am.

The neighborhoods represented with light red and light blue show the locations with High-Low and Low-High spatial outliers respectively. The High-Low outliers were mostly concentrated in the areas close to the traditional city center of İzmir. More clearly, it represents that the neighborhoods with high population density levels and lower circuity values in these areas. The Low-High outliers are the neighborhoods with lower population density levels and higher circuity values, and they located at the North, East, and the South of the study area away from the city center.

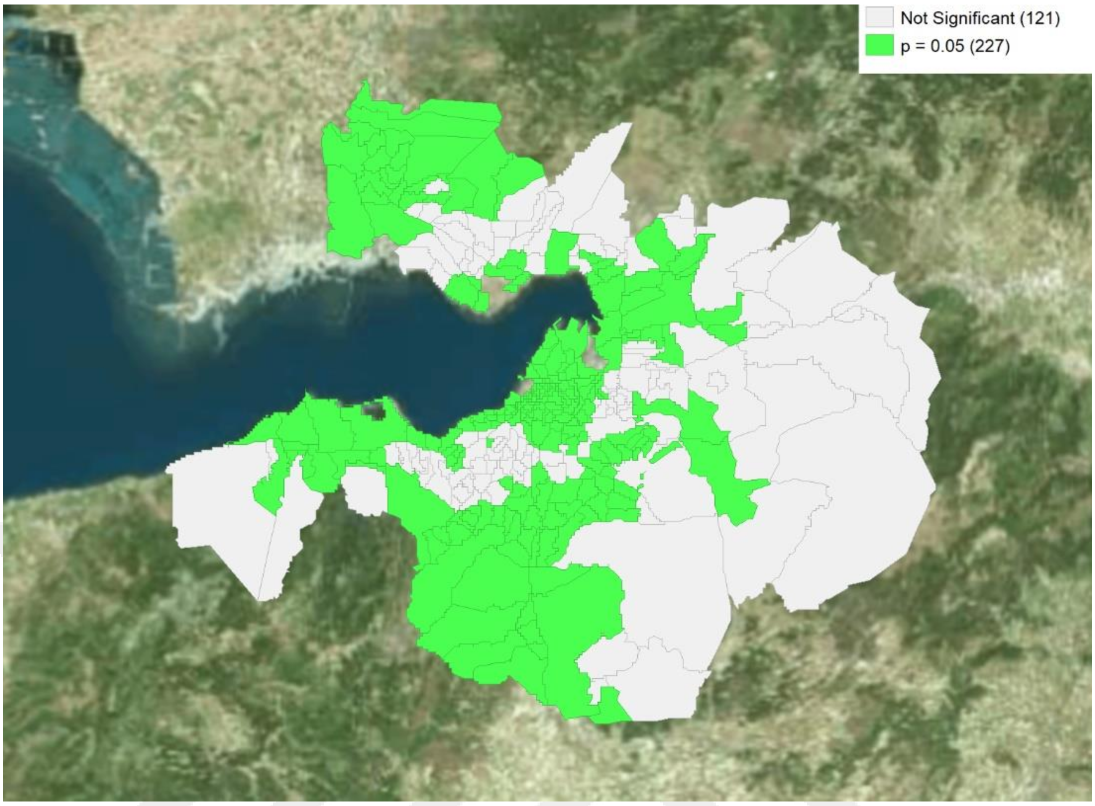


Figure 5.35 Bivariate Local Moran Significancy Map, Population Density and Circuity index at 09:00 am as the input

The results of the Bivariate Local Moran Significancy Map shows where the statistically significant clusters at α=0.05 level are obtained for the circuity level at 09:00 am of 348 neighborhoods in İzmir (Figure 5.35).

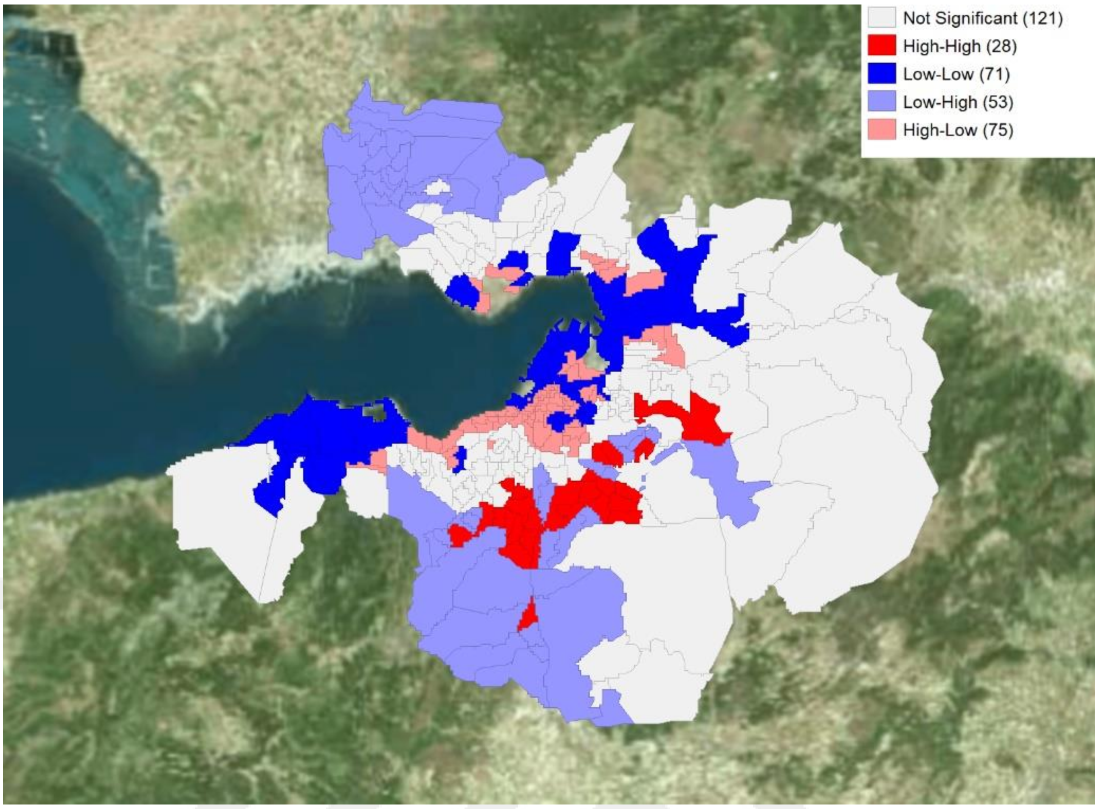


Figure 5.36 Bivariate Local Moran Cluster Map, Population Density and Circuity index at 09:00 am as the input

The four categories were represented. The neighborhoods represented with dark blue and dark red show the clustered patterns with Low-Low and High-High clusters respectively (Figure 5.36). It is observed that the Low-Low clusters were mostly concentrated in areas close to the seashore among the İzmir Gulf. The High-High clusters located away from the city center for the circuity index at 09:00 am.

The neighborhoods represented with light red and light blue show the locations with High-Low and Low-High spatial outliers respectively. The High-Low outliers were mostly concentrated in the areas close to the traditional city center of İzmir. More clearly, it represents that the neighborhoods with high population density levels and lower circuity values in these areas. The Low-High outliers are the neighborhoods with lower population density levels and higher circuity values, and they located at the North and the East of the study area away from the city center.

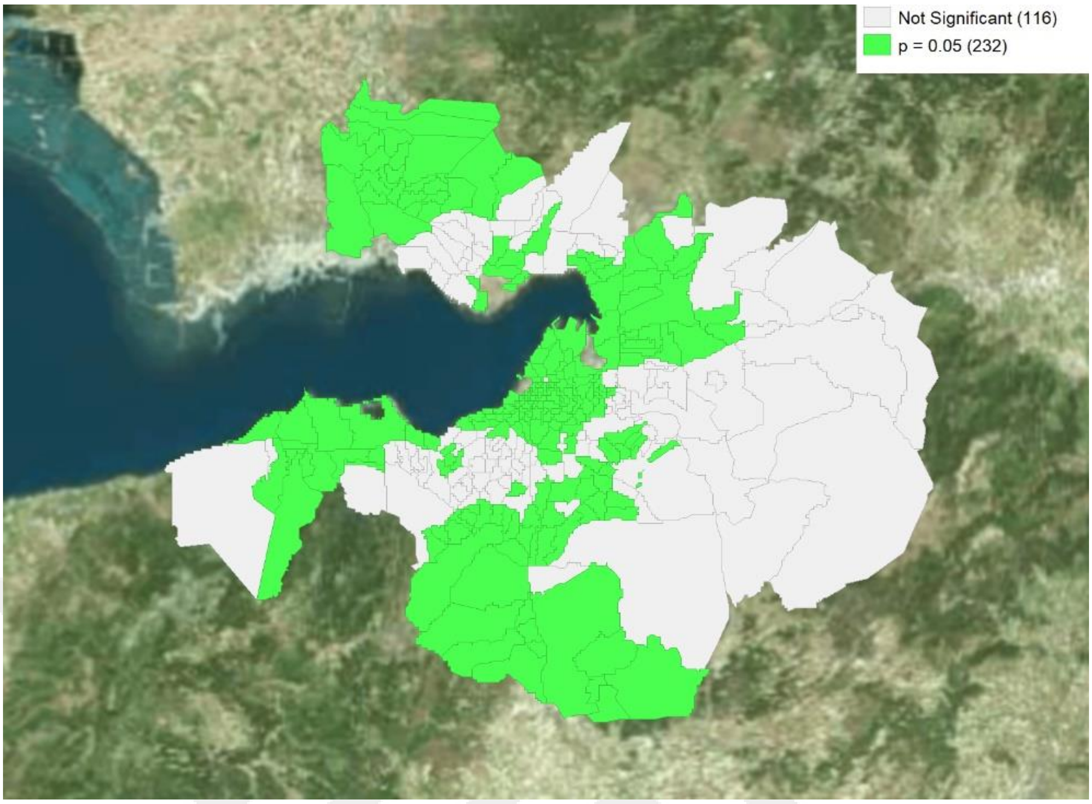


Figure 5.37 Bivariate Local Moran Significancy Map, Population Density and Circuity index at 11:30 am as the input

The results of the Bivariate Local Moran Significancy Map show where the statistically significant clusters at α=0.05 level are obtained for the circuity level at 11:30 am of 348 neighborhoods in İzmir (Figure 5.37).

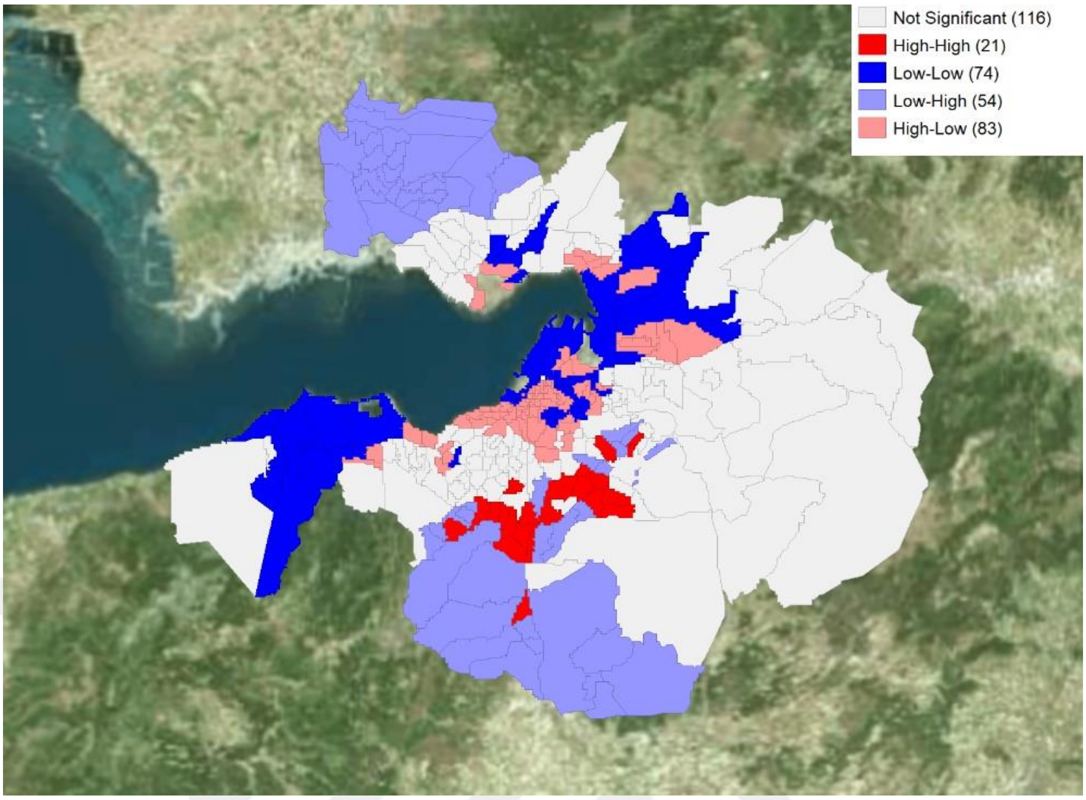


Figure 5.38 Bivariate Local Moran Cluster Map, Population Density and Circuity index at 11:30 am as the input

The four categories were represented. The neighborhoods represented with dark blue and dark red show the clustered patterns with Low-Low and High-High clusters respectively (Figure 5.38). It is observed that the Low-Low clusters were mostly concentrated in areas close to the seashore among the İzmir Gulf. The High-High clusters located South away from the city center for the circuity index at 11:30 am.

The neighborhoods represented with light red and light blue show the locations with High-Low and Low-High spatial outliers respectively. The High-Low outliers were mostly concentrated in the areas close to the traditional city center of İzmir. More clearly, it represents that the neighborhoods with high population density levels and lower circuity values in these areas. The Low-High outliers are the neighborhoods with lower population density levels and higher circuity values, and they located at the North and the East of the study area away from the city center.

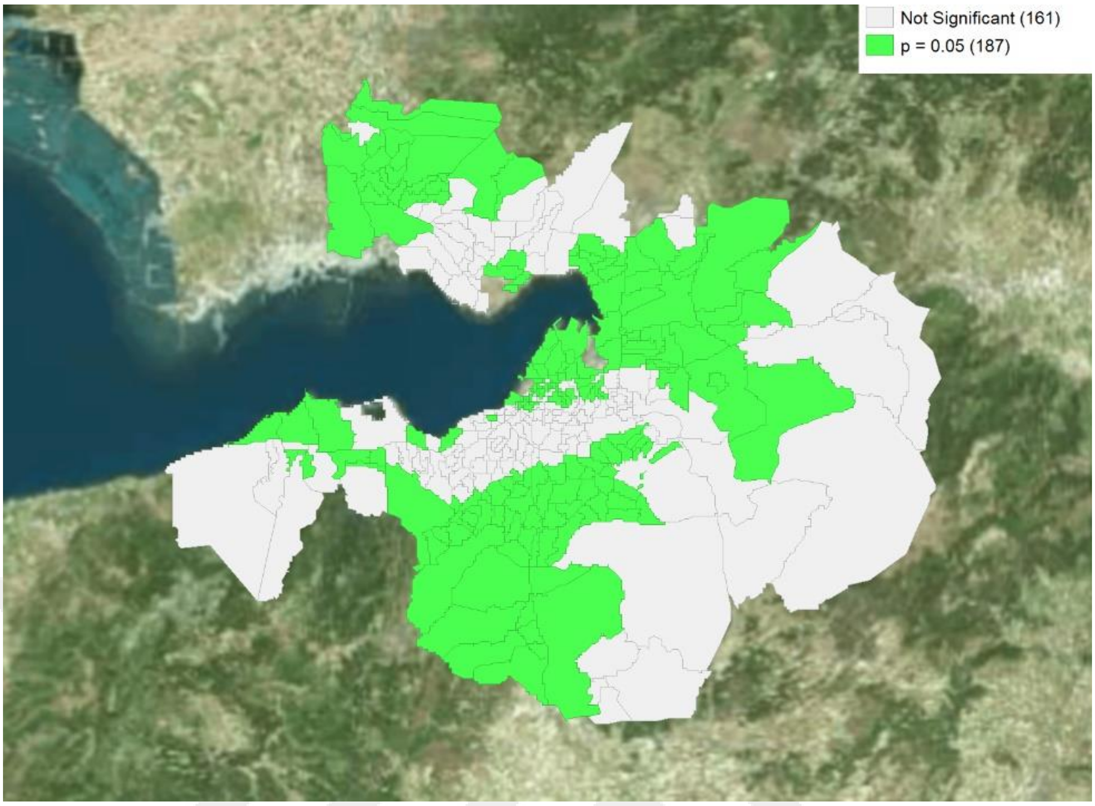


Figure 5.39 Bivariate Local Moran Significancy Map, Population Density and Circuity index at 07:00 pm as the input

The results of the Bivariate Local Moran Significancy Map show where the statistically significant clusters at $\alpha=0.05$ level are obtained for the circuity level at 07:00 pm of 348 neighborhoods in İzmir (Figure 5.39).

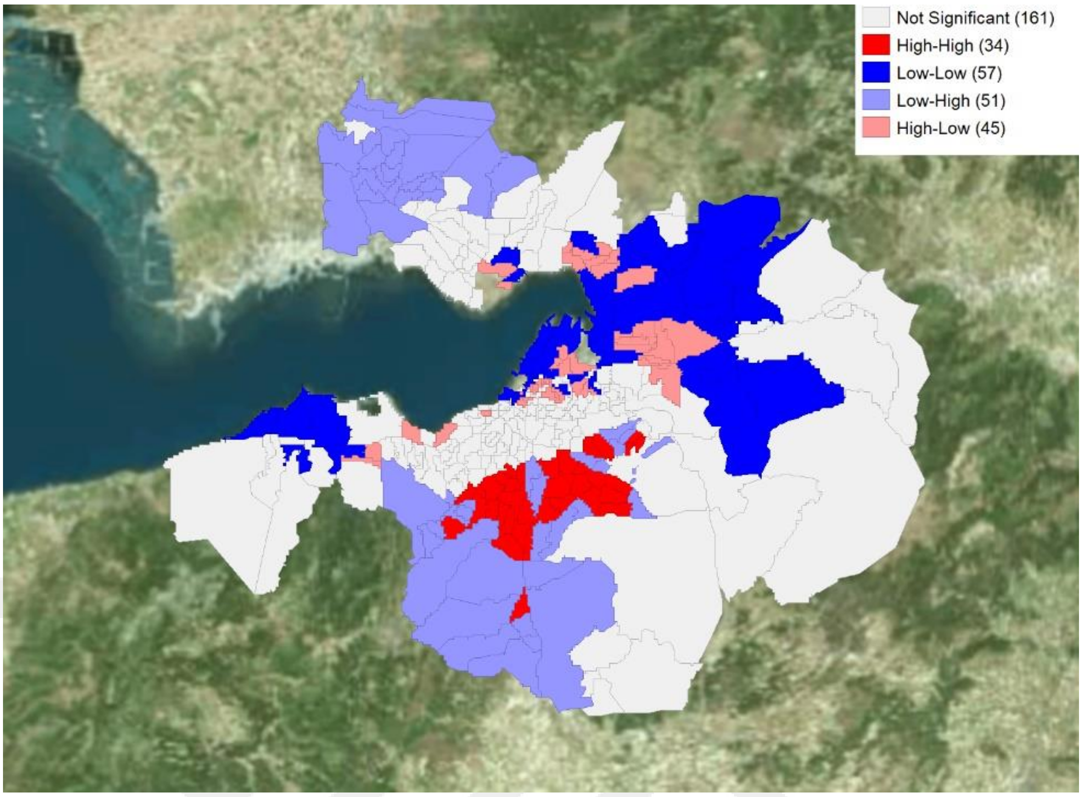


Figure 5.40 Bivariate Local Moran Cluster Map, Population Density and Circuity index at 07:00 pm as the input

The four categories were represented. The neighborhoods represented with dark blue and dark red show the clustered patterns with Low-Low and High-High clusters respectively (Figure 5.40). It is observed that the Low-Low clusters were mostly concentrated in areas close to the seashore among the İzmir Gulf with a spread to the East. The High-High clusters located in the South, away from the city center for the circuity index at 07:00 pm.

The neighborhoods represented with light red and light blue show the locations with High-Low and Low-High spatial outliers respectively. The High-Low outliers were mostly located in the areas close to the traditional city center and near the transfer hub of İzmir. More clearly, it represents that the neighborhoods with high population density levels and lower circuity values in these areas. The Low-High outliers are the neighborhoods with lower population density levels and higher circuity values, and they located at the North and the East of the study area away from the city center.

5.2.2.3 Summative Assessment of Bivariate Spatial Autocorrelation Analyzes of Circuity and Population Density

The results from the two bivariate spatial analyzes such as Global Moran's *I* and Local Moran's *I* statistic for Circuity and Population Density was explained in detail earlier.

The overall spatial correlation between the circuity level and the population density level was investigated by Bivariate Global Moran’s *I* Statistic and Bivariate Local Moran’s *I* statistic. Four different analyzes were performed for four time-of-day circuity index variations. The results and spatial distribution patterns obtained from the Bivariate Global Moran’s I analyzes were presented in a summary Table 5.5 below:

Table 5.5 Summary table of Bivariate Global Moran’s *I* Statistics for circuity index and population density

	Moran's I Index	**Expected Index**	**z-score**	**p-value**
Circuity Index at 06:00 AM and Population Density	-0.073	-0.003	-8.728	0.05
Circuity Index at 09:00 AM and Population Density	-0.053	-0.003	-8.407	0.05
Circuity Index at 11:30 AM and Population Density	-0.082	-0.003	-11.984	0.05
Circuity Index at 07:00 PM and Population Density	-0.014	-0.003	-2.428	0.05

As it was represented above in Table 5.5 circuity and the population density are negatively spatially correlated for the four analyzes. All the four analyzes were statistically significant at $\alpha=0.05$ level. This finding revealed that the neighborhoods with lower population density levels have higher circuity values than the other urban areas. To recap, high circuity values indicate lower public transportation efficiency. In other words, less dense urban areas have more efficient public transportation services.

The bivariate local spatial correlations were detected by Bivariate Local Moran’s *I* Statistic for Circuity and Population Density. In this case, the Bivariate Local

Moran's I analysis was measured the linear association between population density value for each neighborhood and the average of its neighboring circuity levels of the investigated neighborhood. Four different analyzes were performed for four time-of-day circuity index variations. The results and spatial distributions of clusters and outliers were obtained from the Bivariate Local Moran's *I* analyzes were presented in a summary Table 5.6 below:

Table 5.6 Summary table of Bivariate Local Moran's *I* Statistics for circuity index and population density

	HH Cluster	**LL Cluster**	**HL Outlier**	**LH Outlier**	**p-value**	**Not Significant**	**Total Neighborhoods**
Circuity Index at 06:00 AM and Population Density	24	75	93	52	0.05	104	348
Circuity Index at 09:00 AM and Population Density	28	71	75	53	0.05	121	
Circuity Index at 11:30 AM and Population Density	21	74	83	54	0.05	116	
Circuity Index at 07:00 PM and Population Density	34	57	45	51	0.05	161	

As it was represented above in Table 5.6 all of the spatial analyzes were statistically significant at α=0.05 level. Clustered patterns such as High-High and Low-Low and the outliers such as High-Low and Low-High were located similarly for four time-of-day circuity indexes. Especially the Low-High outliers; and High-High and Low-Low clusters were spatially distributed alike in all four analyzes. Low-Low clusters mainly and dominantly were concentrated in areas close to the seashore among the İzmir Gulf.

The High-High clusters and Low-High outliers located away from the seashore. High-Low outliers present the neighborhoods with high population density levels surrounding by low circuity levels while Low-High outliers present the neighborhoods with low population density levels surrounding by high circuity levels.

If we interpret these results in a different perspective, the areas labeled as High-Low outlier and Low-Low cluster have more efficient public transportation service levels while the areas labeled as Low-High and High-High cluster getting less efficient public transportation service levels in İzmir.

CHAPTER 6
DISCUSSION AND CONCLUSIONS

This study mainly aims to reveal the efficiency of the urban public transportation systems and their relationship with the socio-economic variables at the neighborhood level in İzmir. The assessment of the efficiency is the main concentration of the study: the degree of circuity. Circuity index is basically the ratio of the network to Euclidean distance. The circuity values of the neighborhoods were examined with the per capita income and population density variables. The spatial autocorrelation analysis such as Univariate Global Moran's *I* statistics, Univariate Local Moran's *I* statistics, Bivariate Global Moran's *I* statistics, Bivariate Local Moran's *I* statistics gave the final results of the research.

6.1 Discussion

The first part of the analyzes involved the univariate spatial autocorrelation analyzes of the circuity degree at the neighborhood level in İzmir, Turkey. According to the results of the univariate spatial autocorrelation analyzes, it can be estimated that circuity indexes that explain the efficiency of the public transportation systems have a significant distribution pattern at $\alpha=0.05$ level. The results of the four different time-of-day Global Univariate Moran's *I* analyses had a clustered distribution pattern in circuity levels. This can be explained as the neighborhoods with similar circuity indexes tend to be located in the urban areas close to each other. To recap, high circuity values indicate lower public transportation efficiency, while low circuity values indicate higher public transportation efficiency. Regarding these results, it can be said that public transportation service efficiencies and deficiencies are being clustered and concentrated in some urban areas in İzmir. As Çubukcu (2020) found that circuity degrees vary in the city related to the network distance traveled, and lower circuity values can be observed from the city center to the outwards, these findings of the global Moran's I analyzes can be explained from this point of view. The Global Moran's *I* analysis does not give any spatial information about the data. The local spatial associations of the circuity levels of neighborhoods were detected by Local Moran's I Statistic.

Univariate Local Moran's *I* statistics reveal the clusters and the outliers in spatial extent. Considering the results of the univariate Global Moran's *I* statistic it was expected to see clustered patterns in terms of circuity levels. In this case, the spatial clustering and the outliers were revealed in İzmir city with four different analyzes were performed for four time-of-day circuity index variations with a significance at $\alpha=0.05$ level. It was seen that clustered patterns such as High-High and Low-Low and the outliers such as High-Low and Low-High were located similarly. Low-Low clusters mainly and dominantly were concentrated in areas close to the seashore among the İzmir Gulf where the High-High clusters located away from the seashore. To recap, high circuity values indicate lower public transportation efficiency, while low circuity values indicate higher public transportation efficiency. As an explanation, higher public transportation efficiency was observed in areas close to the seashore and the traditional city center of İzmir while lower public transportation efficiency located away from the seashore.

Some urban researchers in previous studies stated that public transportation is more concentrated and easier to access in the city center (Brueckner & Rosenthal, 2009; Erwing & Cervero, 2001, 2010; Kawabata, 2003; Levinson et al, 1963; Schouten, 2019). Kawabata (2003) remarked that old and compact urban metropolitan areas have more enhanced public transportation systems. It was found that the findings coincide with the literature.

The first part of the analyzes involved the bivariate spatial autocorrelation analyzes of the circuity degree with socio-economic variables at the neighborhood level in İzmir, Turkey. The main concern is that if there is a statistically significant relationship between the circuity values and the socio-economic variables spatially. This research is predominantly focused on the socio-economic variables: population density and per capita income. The bivariate spatial autocorrelation analyzes performed at the neighborhood level in İzmir.

Many studies investigated the relationship between public transportation usage and per capita income (Brueckner & Rosenthal, 2009; Dong, 2017; California Department of Transportation, 2001; Glaeser et al., 2008). In this research, Bivariate Global Moran's I Statistics and Bivariate Local Moran's I Statistic for circuity and per capita income were performed to reveal if there is a relationship. Bivariate Global Moran's *I* Statistics between per capita income and circuity index revealed that the neighborhoods with lower per capita income levels have higher circuity values than the other urban areas. To recap, high circuity values indicate lower public transportation efficiency. In other words, according to the findings, in the wealthier urban areas, the efficiency of the public transportation systems better than the urban areas with lower income levels. It was relatable with Galster (1995), who stated that higher-income households are more advantaged in giving adequate public services. Since their mobility, resources, and abilities are limited, lower-income groups tend to make shorter and fewer trips per day rather than high-income households (California Department of Transportation, 2001; Guiliano, 2005; Krizek, 2003; Pucher & Renne, 2003). Although it was obtained that a significant relationship between circuity and per capita income, the Global Moran's I analysis does not give any spatial information about the data.

Bivariate Local Moran's *I* statistics between circuity and per capita income revealed the clusters and the outliers in spatial extent. In this case, the spatial clustering and the outliers were revealed in İzmir city with four different analyzes were performed for four time-of-day circuity index variations with a significance at α=0.05 level. It is observed that the Low-Low clusters were mostly concentrated in the areas close to the traditional city center of İzmir. Low-Low clusters present the neighborhoods with low per capita income surrounding by low circuity levels. To recap, low circuity values indicate higher public transportation efficiency. As stated earlier, the lower-income groups tend to locate near CBD in order to use public transportation and have easier access to amenities and jobs in the city center (Brueckner & Rosenthal, 2009). Concurrently, Rosenblatt and DeLuca (2012) reported that public transportation existence is a significant factor for households, especially those living in low-income urban neighborhoods. Pathak et al. (2017) concurred with the findings of Glaeser et al. (2008) and Brueckner & Rosenthal (2009) and further stated that public bus transportation access is an important indicator for those households with lower-income level. Among these conclusions, the results of this analysis are compatible with the previous literature. The High-High clusters located at the edge of the study area. High-High clusters present the neighborhoods with high per capita income surrounding by high circuity levels. To recap, high circuity values indicate lower public transportation efficiency. These areas are wealthier neighborhoods and possibly car-dependent areas with high car ownership levels.

The High-Low outliers were mostly concentrated in areas close to the seashore among the İzmir Gulf concurrent with the previous findings. High-Low outliers present the neighborhoods with high per capita income surrounding by low circuity levels. To recap, low circuity values indicate higher public transportation efficiency. The results are as was expected, and concurred with Galster (1995), as they stated that higher-income households are more advantaged in giving adequate public services. The seashore neighborhoods in İzmir consist of high-income level households, and since car owner has a relationship with income level, it can be said that the public transportation needs are lower than the lower-income parts of the city. As it interrelated with the mode choice, mobility which is “a function of resources” is related to the travel behavior of households (California Department of Transportation, 2001).

The Low-High outliers are the neighborhoods with lower income levels and higher circuity values, and they were located away from the city center mainly in North to East directions at the edge of the study area. Low-High outliers present the neighborhoods with low per capita income surrounding by high circuity levels. To recap, high circuity values indicate lower public transportation efficiency. These areas are the areas where the public transportations deficiency exists with lower income levels. The results are as was expected and concurred with the statements of Pucher (1987). They suggested that neighborhoods with lower income have been giving insufficient public transportation service with high fares contradiction to the unqualified and crowded travel supply. When these neighborhoods examined in detail it was seen that there are two reasons that caused these results: one of them is the long network distance to the destination locations, another one is mostly the public transportation services provided only by bus. These neighborhoods need special attention with more efficient and enhanced public transportation services. Low-income households commonly do not own a car and abstain to relocate due to their dependence on public transportation (Rosenblatt and DeLuca, 2012). Since the lower-income neighborhoods are more dependent on the existence of an adequate public transportation system for their daily needs and mobility, the installment of such systems must be enhanced in the disadvantaged urban areas primarily. There must be a primary concern in those areas with high public transportation demands.

In this research, Bivariate Global Moran's *I* Statistics and Bivariate Local Moran's *I* Statistic for circuity and population density were performed to reveal if there is a relationship. Bivariate Global Moran's *I* Statistics between population density and circuity index revealed that the neighborhoods with higher population density have lower circuity values than the other urban areas. To recap, low circuity values indicate higher public transportation efficiency. In other words, according to the findings, in densely populated urban areas, the efficiency of the public transportation systems better than the urban areas with lower population density.

Many studies found a positive relationship between public transportation usage and population density (Ewing & Cervero, 2001; Frank & Pivo, 1994; Kitamura, 1997; Zhang, 2004). Levinson et al. (1963) stated that there is a strong positive correlation between public transportation system occupancy and high-density. Concurrently, Schouten (2019) argued that in an urban metropolitan area, mixed-use highly dense urban residential neighborhoods are higher levels of public transportation accessibility besides other parts of the city. The findings are compatible with the literature but although it was obtained that a significant relationship between circuity and population density, the Global Moran's I analysis does not give any spatial information about the data.

Bivariate Local Moran's *I* statistics between circuity and population density revealed the clusters and the outliers in spatial extent. In this case, the spatial clustering and the outliers were revealed in İzmir city with four different analyzes were performed for four time-of-day circuity index variations with a significance at $\alpha=0.05$ level.

It is observed that the Low-Low clusters were separately clustered but generally observed in the gulf and its periphery and among the shoreline to the West. Low-Low clusters present the neighborhoods with low population density surrounding by low circuity levels. In these neighborhoods, higher public transportation efficiency is seen according to results. As stated earlier high-density urban areas generally have a high demand for transportation services. California Department of Transportation (2001) stated that households that has a dependency on public transportation presumed to reside in high-density neighborhoods rather than low-density suburbs. Low-density urban areas generally associated with higher-income levels, in such areas car ownership levels are higher and public transportation demand is lower than the highly dense urban areas. Kenworthy & Laube (1999) stated that the higher costs are applied to the public transportation fares especially in low-density, highly private car-dependent areas because they have low occupancy rates. In addition, Giuliano (2005) stated that many studies in the past showed that it is more effective to offer low fares in the public transportation system and install them in the areas where the continuous service could be sustained, would increase the usage. High-High clusters present the neighborhoods with high population density surrounding by high circuity levels that indicate lower public transportation efficiency. As California Department of Transportation (2001) stated that households that has a dependency on public transportation. Although they have high-density rates these neighborhoods have serious service deficiencies and must be examined in detail.

The High-Low outliers were mostly concentrated in areas close to the seashore and traditional city center. High-Low outliers present the neighborhoods with high population density surrounding by low circuity levels. To recap, low circuity values indicate higher public transportation efficiency. The results are as were expected, and concurred with Levinson et al. (1963) stated that employment and commercial activities are located in the high-density urban central areas due to the availability of public transportation system with less dependency on private cars. These neighborhoods the areas where daily commercial activity and business centers are intense. Highly dense urban areas with mixed-uses have high accessibility with shorter travel times (Steiner, 1994; Ewing & Cervero, 2001, 2010). Schouten (2019) argued that in an urban metropolitan area, mixed-use highly dense urban residential neighborhoods are higher levels of public transportation accessibility besides other parts of the city.

The Low-High outliers are the neighborhoods with lower population density and higher circuity values, and they were located away from the city center mainly in North to East directions at the edge of the study area. Low-High outliers present the neighborhoods with a low population density that have public transportation deficiency. The circuity values are very high in these areas it can be due to the network distance to the destination locations is long. The literature has studied with low-population density relating to high-income and suburban settlements (Anderson & Egeland, 1961; Kitamura et al., 1997). In the literature, low-density residential areas such as suburban settlements are generally associated with high-income households with private car access. Schouten (2019) argued that there is low public transportation access in the outlying rural areas that sparsely populated. It is crucial that the demographics and the characteristics must be examined in detail in such areas. In public transportation systems installment, it must be considered that the low-income households living outside the high-density inner cities (Giuliano, 2005).

6.2 Conclusion

This study was conducted to shed light on the relationship between socioeconomic variables such as population density and per capita income, and the efficiency of the public transportation systems at the neighborhood level. According to the results of this research, the efficiency of public transportation service of neighborhoods is significantly differentiated with their socio-economic structure. A comprehensive study can be conducted with detailed examinations.

The results are consistent with the relevant literature. The neighborhoods with better socio-economic structures are getting more efficient public transportation services than other parts of the city. This study revealed the relationship between population density and per capita income with the efficiency in public transportation. Levinson et al. (1963) noted that transportation needs must be evaluated by taking the density into the account while Kawabata (2003) offered that it would be an overall advantage for all to develop more efficient and connected public transportation systems, not only for the low-income, low-skilled, and those with dependence on public transit.

Accessing and participating the urban mobility which shapes the lives of the inhabitants is the basic right for everybody. The process of making policies in transportation planning and development plans should focus on the interest of all the citizens and even more qualified public transportation services should be provided for the ones unable to access these services.

Since the data was unavailable to reach various socio-economic variables could not be applied to the study. It could have helped to define the different reasons for the differentiation among the neighborhoods, in terms of giving adequate public transportation services. Travel time data acquisition for public transportation systems from Moovit online services might have been caused errors in the analysis stage due to these services presented the data using timetables. Besides these, if the circuity data is collected in periods within a year, it would be possible to present more reliable results. The methods used in this study would address different outcomes if the data collection and analysis were performed during a year. So, it can be possible to reveal the seasonal changes in public transportation efficiencies in a spatial context.

The presence of ferry services has a share and advantage in the general public transportation system in the city of Izmir. But methodologically, there has been a situation of immeasurability for these systems. For this reason, the effects of ferry systems have been ignored due to this thesis configuration. Neighborhood sizes and populations were used directly and as they were, and the overall study was conducted at the neighborhood level. Nevertheless, at this point, it should be noted that since the sizes and populations of neighboring neighborhoods differ, this might have caused errors in the analysis phase or presented different results.

Despite these shortcomings, these findings were revealed important inefficiencies in the public transportation services to a spatial extent. This study is unique in that it measures the efficiency of public transport systems at the neighborhood level using the degree of circuity. Nevertheless, the series of methods used in this research can provide a practical and theoretical basis in urban comparative studies.

This research is valuable in terms of services supplied for the public interest. Public policymaking and actions for public transportation purposes would be more reliable and accurate with applying such analyzes and interpretations used in this research. These methods and the outcomes if applied in a comprehensive spatial context may use from a bigger scale such as decision-making processes of transportation master plans to a smaller scale such as the installment of a new public transportation system in the city.

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