ASSESSMENT OF SPATIAL PATTERN AND INFLUENCING FACTORS OF WATER CONSUMPTION: THE CASE OF İZMİR (TÜRKİYE)

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ABSTRACT

ASSESSMENT OF SPATIAL PATTERN AND INFLUENCING FACTORS OF WATER CONSUMPTION: THE CASE OF İZMİR (TÜRKİYE)

The increasing demand for water resources worldwide brings to the fore water demand management that requires examining factors affecting water consumption patterns. This study focuses on per capita water consumption at the neighborhood level and broadly categorizes its driving factors as demographic, socioeconomic, and urban environments. This study aims to aid water demand management and urban planning by providing a comprehensive overview of per capita water consumption, spatial patterns, and underlying determinants through rigorous analysis and empirical findings. To achieve its aim, this study has two objectives. The first objective is to examine per capita water consumption and neighborhood characteristics. To examine the per capita water consumption and its spatial pattern, with the aim of understanding local variations, the study utilized cluster analysis and spatial autocorrelation techniques. The second objective of this study is to identify factors that influence per capita water consumption by analyzing various factors affecting water consumption. Correlation analysis revealed the link between per capita water consumption and demographic, socioeconomic, and urban environment characteristics, providing a comprehensive understanding of their relationship. The application of multiple linear regression analysis yielded a prediction model that elucidated the collective impact of several factors influencing per capita water consumption. The study shows that socioeconomic status and impervious surfaces substantially impact water consumption, offering valuable insights for city planners and policymakers to improve water demand management. The research emphasizes the importance of holistic approaches to understanding patterns and trends in water consumption and the quantity of water consumed.

ÖZET

SU TÜKETİMİNİN MEKANSAL DESENİ VE ETKİLEYEN FAKTÖRLERİNİN İNCELENMESİ: İZMİR ÖRNEĞİ (TÜRKİYE)

Dünya çapında su kaynaklarına olan talebin artması, su tüketim kalıplarını etkileyen faktörlerin incelenmesini gerektiren su talep yönetimini ön plana çıkarmaktadır. Bu çalışma mahalle düzeyinde kişi başına su tüketimine odaklanmakta ve bu tüketimin itici faktörlerini geniş anlamda demografik, sosyoekonomik ve kentsel ortamlar olarak sınıflandırmaktadır. Bu çalışma, titiz analizler ve ampirik bulgular yoluyla kişi başına su tüketimi, mekansal modeller ve altta yatan belirleyiciler hakkında kapsamlı bir genel bakış sunarak su talep yönetimi ve kentsel planlamaya yardımcı olmayı amaçlamaktadır. Amacına ulaşmak için bu çalışmanın iki hedefi vardır. İlk hedef kişi başına su tüketimini ve mahalle özelliklerini incelemektir. Yerel farklılıkları anlamak amacıyla kişi başına su tüketimini ve mekansal yapısını incelemek için çalışmada kümeleme analizi ve mekansal otokorelasyon teknikleri kullanılmıştır. Bu çalışmanın ikinci hedefi, su tüketimini etkileyen çeşitli faktörleri analiz ederek kişi başına su tüketimini etkileyen faktörleri belirlemektir. Korelasyon analizi, kişi başına su tüketimi ile demografik, sosyoekonomik ve kentsel çevre özellikleri arasındaki bağlantıyı ortaya çıkararak, aralarındaki ilişkinin kapsamlı bir şekilde anlaşılmasını sağladı. Çoklu doğrusal regresyon analizinin uygulanması, kişi başına su tüketimini etkileyen çeşitli faktörlerin kolektif etkisini aydınlatan bir tahmin modeli ortaya çıkardı. Çalışma, sosyoekonomik durumun ve geçirimsiz yüzeylerin su tüketimini önemli ölçüde etkilediğini, şehir plancılarına ve politika yapıcılara su talep yönetimini iyileştirme konusunda değerli bilgiler sunduğunu göstermektedir. Araştırma, su tüketimindeki kalıpları ve eğilimleri ve tüketilen su miktarını anlamak için bütünsel yaklaşımların önemini vurgulamaktadır.

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CHAPTER 1

INTRODUCTION

The presence of water is of utmost importance in ensuring the preservation of the overall well-being and sustainability of life on Earth. The global utilization of water resources has witnessed significant growth, raising concerns regarding the effectiveness of supply-side measures. The demand for water resources is experiencing a constant increase because of considerable population growth, technological advancements, and economic development. Water scarcity and crises in urban areas are significant and delicate issues due to ongoing urbanization and the rising water demand[1]. Water consumption has increased by approximately 1% each year over the last 40 years. This rate is expected to increase at a similar pace by 2050 owing to socioeconomic development, population growth, and changing consumption patterns, and by 50% of increase is attributed to population growth, socioeconomic development, and changing consumption patterns. This increase is expected to intensify, especially in low- and middle-income countries[2]. The Falkenmark Index is commonly employed to quantify the extent to which the population's demand for water places strain on available water supplies, hence emphasizing the presence of water stress. Accoring to the "Falkenmark Water Stress Indicator," a country or region is considered to be under "water stress" when the yearly water supply per person falls below 1,700 cubic meters. When water resources fall below 1000 cubic meters per person per year, the country/region is described as subject to "water scarcity"[3]. According to the Turkish State Hydraulic Works[4], the per capita yearly quantity of accessible water in Turkey is approximately 1.652 m^3. Turkey falls among the nations that are now grappling with water scarcity. According to the World Resources Institute (WRI) Aqueducts Water Risk Atlas, Turkey ranks 39th among countries experiencing high water stress. According to 2040 projections, Turkey is predicted to rank 27th among countries experiencing high water stress[5].

The issue of increasing water demand is complex and involves multiple elements contributing to its escalation. Population growth, urbanization, economic development, and climate fluctuations affect water demand. The balance between supply and demand may be disrupted due to rapid urbanization. The risk of water scarcity may increase globally[6,7]. İzmir is known for its seasonal/annual water scarcity. The issue of water scarcity is a significant challenge for İzmir, and its impact is projected to intensify in the future due to population expansion, excessive and unregulated water consumption in sectors such as agriculture and industry, and contamination from many sources. Due to the effects of climate change, it is anticipated that there will be a decrease in the availability of water resources. İzmir is an area characterized by water scarcity, with an annual available water supply of 639 m^3 per person. This situation shows that İzmir is among the water poor regions[8]. Due to the impact of global climate change, the air temperature in İzmir exceeded the average by 3 degrees Celsius compared to prior years. İzmir substantially declined the frequency of rainy days and the volume of rainfall per square meter. Based on statistics from the İzmir Water and Sewerage Administration General Directorate (İZSU), the Tahtalı Dam, which is the primary source of drinking water for the city, had an occupancy rate of 54.33% during the same period last year. Still, it has now decreased to 39.95%[9]. In İzmir, which has been facing the problem of water scarcity from the past to the present, a project for managing existing resources was carried out in 2001. In the project called "İzmir İli Metropolitan Alanı Dahilinde Yerleşime Açılmış ya da Açılmakta Olan Kentsel Mekanların, Su Kaynaklarını Kullanımına Yönelik Mevcut Durumlarının ve Olası Yönlenmelerinin Saptanması" carried out in İzmir in 2001, it was stated that urban settlements had high demands in the use of natural resources and that the supply should be provided continuously[10]. Intercalarily, population density, household size, income levels, climate conditions, and residential water consumption are key determinants of water consumption. High-income households consume more water due to luxuries, while climate conditions impact resource demand. Housing typology, water pricing, and residential practices influence water consumption. In literature, the factors that affect water consumption are studied using different analysis techniques to understand the water consumption pattern and manage water demand. The subsequent sections thoroughly analyzed the impact of these factors on water consumption.

According to İzmir Development Agency data, examining the factors affecting water consumption for İzmir province, which is among the water-poor regions, is essential. The study uses 286 neighborhoods from 11 districts in the old metropolitan area of İzmir. This study evaluated per capita water consumption using several factors. Per capita water consumption is considered a dependent variable for the assessments, where the independent variables are demographic variables such as population density, 0-14 population ratio, rate of 15-64 population ratio, 65+ population ratio, average household size; Socioeconomic variables such as primary school graduate population, higher education graduate population, child-woman ratio, square meter sales price; urban variables such as Normalized Difference Impervious Surface Index (NDISI), Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-Up Index (NDBI), Land Surface Temperature (LST). ArcMap and SPSS software were used in the study. In the study, the study area was characterized through cluster analysis. The spatial dependence of water consumption was examined by spatial autocorrelation analysis. The water consumption model was analyzed using local spatial autocorrelation. Correlation analysis and multiple linear regression analysis determined the relationship between the amount of per capita water consumption and other variables.

1.1. Problem Definition

According to statistics from the World Resources Institute (WRI) Aqueduct Water Risk Atlas, 25 countries, home to a quarter of the world's population, face increasing water stress yearly. In addition, at least half of the world's population faces high water stress for at least one month a year. Turkey is among the countries experiencing high levels of water stress. In İzmir, extremely high-water stress is observed[5]. The water risk maps created by the World Resources Institute are displayed above. Consequently, it is evident that a significant portion of Turkey, now experiencing high water stress, will face even more severe water stress conditions in 2030, 2050, and 2080, as per the optimistic projection.

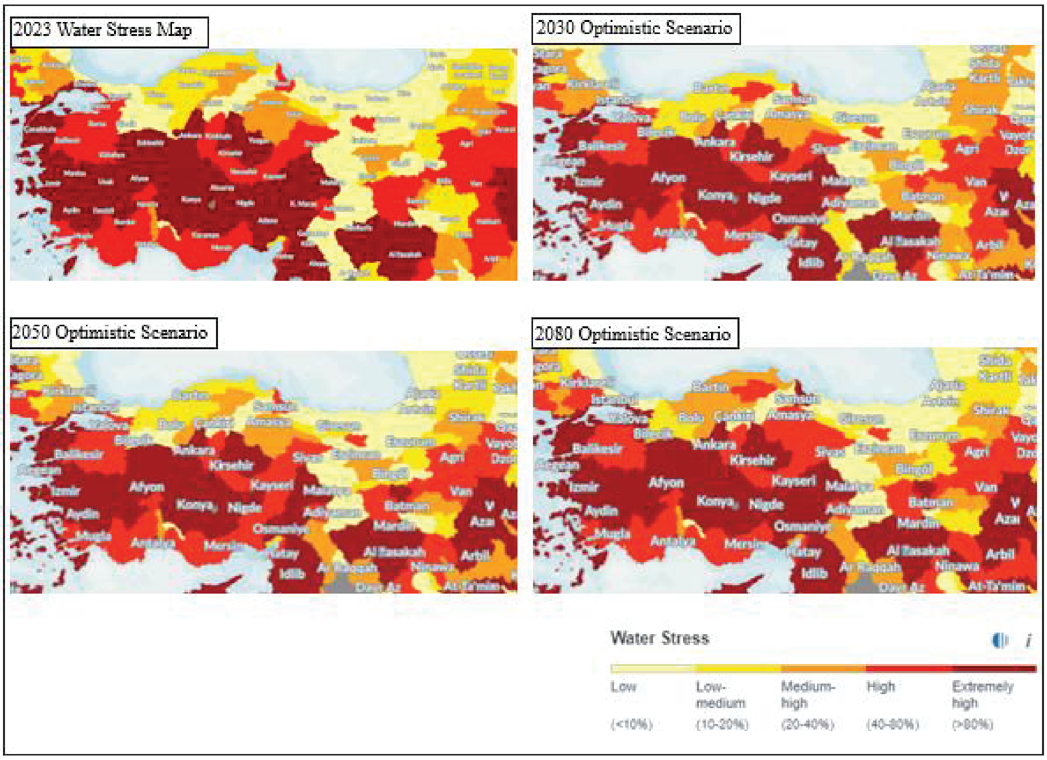


Figure 1. Water Stress Map

(Source: Aqueduct[5])

The city of İzmir in Turkey also has heightened strain on its water resource infrastructure due to escalating urban water consumption. The prevalence of water scarcity is progressively escalating annually, therefore underscoring the significance of accurately forecasting water consumption and consumption statistics to address societal demands adequately. İzmir is under the influence of the Mediterranean climate. Although high temperatures and lack of rainfall characterize the summers, the winters are characterized by mild temperatures and abundant precipitation. The maximum temperature reaches 22.7 °C, while the average annual rainfall amounts to 709.9 mm[11]. In addition to this situation, the pollution problem also comes to the fore in basins where urbanization, industry, and agriculture are intense, for example, in Büyük Menderes and Ergene Basins. As a result, water quality decreases and brings water stress to the agenda[12]. İzmir holds significant coastal prominence and is renowned for its noteworthy contributions to industry, commerce, and culture. Nevertheless, the urban area's water supplies face substantial challenges due to the escalating population, evolving socioeconomic dynamics, and the impacts of climate change.

1.2. Aim and Scope of the Study

This study aims to aid sustainable water resources management and urban planning by providing a comprehensive overview of per capita water consumption and its underlying determinants through rigorous analysis and empirical findings. There are two main objectives of this study. The first objective is to obtain a spatially comprehensive picture of per capita water consumption. This study shed light on the spatial water consumption pattern across the study area. Depicting the regions with higher or lower water consumption patterns provides valuable information on spatial variability of water consumption. The second objective is to investigate the factors determining per capita water consumption.

The geographical scope of this study consists of the neighborhoods of 11 districts in the İzmir Metropolitan Region. The criteria for participation in the study were limited to communities categorized as built-up urban areas that possessed a complete collection of indicators and factors that influence water consumption. Data from 2019 were used in the study. The dependent variable in the study is per capita water consumption. The study's quantity of per capita water consumption was determined by using residential water consumption as the basis for the calculation. Independent variables were determined as a result of the literature review. Independent variables include population density, average household size, and age group rates as demographic variables; education levels, child-woman ratio, and square meter sales price as socioeconomic variables; Normalized Difference Impervious Surface, Normalized Difference Vegetation Index, Normalized Difference Built-up Index, and Land Surface Temperature as urban variables. In methodological terms, the study employs specific methodologies, including cluster analysis, spatial autocorrelation analysis, local spatial autocorrelation analysis, correlation analysis, and multiple linear regression, to investigate patterns and relationships in water consumption. As a result, this study aims to provide information that can shed light on policies and strategies for sustainable water consumption.

1.3. Research Questions

This study investigates the spatial pattern of water consumption and examines the factors affecting water consumption.

In this regard, this study intends to find answers to the following research questions:

1. Does the water consumption show a spatial variation across the urban space, and if so, how is the spatial pattern characterized?

2. What drivers influence per capita water consumption within the study area, and to what degree do these factors affect water consumption?

1.4. Methodology

The methodology used in this study is based on a comprehensive and multi-faceted approach to investigating per capita water consumption in the context of the İzmir Metropolitan Area at the neighborhood level. Data from several sources, including the Turkish Statistical Institute, "sahibinden.com/endeksa.com", RsLab, and "earthexplorer.usgs.gov", were meticulously gathered for a comprehensive and multidimensional dataset. These sources were carefully chosen to include various data types, including socioeconomic statistics and geospatial data. A vital phase of data preprocessing was carried out to improve data quality and assure compatibility. The data obtained was prepared in Excel to provide sufficient input for subsequent analyses. This phase was critical in resolving data inconsistencies and preparing them for further research.

One of the study's crucial aspects is conducting geographical analyses to reveal the spatial characteristics of per capita water consumption trends. The first objective of this study was to obtain a comprehensive picture of per capita water consumption. Cluster analysis was performed for independent variables with the Statistical Package for Social Sciences (SPSS). Thus, the characteristics of the study area were extracted as clusters (statistical classes). Spatial autocorrelation analysis was then performed to examine the spatial dependence of the dependent variable. Local spatial autocorrelation was performed to investigate the water consumption pattern in the study area with its reliance on urban space. Arcgis was used for Global Moran’s I and Local Moran’s I. Global Moran's I comprehensively assesses spatial autocorrelation throughout the whole research region, whereas Local Moran's I provides more specific information about local patterns. These measures are essential tools for analyzing the spatial distribution of variables. As a result, regions with high and low water consumption were depicted, and the characteristic features of these regions were evaluated.

The second objective of this thesis was to investigate the factors that determine per capita water consumption. For this purpose, correlation analysis was performed to examine the relationship between variables and the direction of this relationship. Secondly, multiple linear regression analysis was used to determine the explanatory effect of independent variables on dependent variables. Analyses were carried out via SPSS.

1.5. Structure of Thesis

This thesis is structured under six headings.

In the first part, a short introduction is given along with information about the problem definition, the aim and scope of the study, the research questions, and the study's methodology.

The second part includes the literature review. First, concepts such as water stress, water crisis, water scarcity, and water demand were examined. Then, the factors affecting water consumption and the methodological approaches used to investigate the factors were included. Information on water demand management was included in this section.

The third section contains the study area. In this section, the description of the study area is included.

The fourth chapter consists of method and material. This section includes the method of understanding the water consumption model in İzmir and determining the factors affecting water consumption. Additionally, this section introduced the data set used in the study.

The fifth part of the study contains the results. The spatial pattern of water consumption and the driving factors affecting consumption are discussed in this section.

The last chapter includes the conclusion, where the study is evaluated holistically. Additionally, the future studies explained in this section.

CHAPTER 2

LITERATURE REVIEW

2.1. Water Consumption and Related Concepts

Water is an indisputably essential resource for the Earth, comprising around two-thirds of its surface area. Freshwater is the sole accessible resource for various activities, including drinking, industrial processes, agriculture, and other functions. Approximately 70% of the Earth's total area is enveloped by water, with a mere 3% being freshwater suitable for human utilization[13]. Nevertheless, due to the disparate allocation of these water resources, only a minor proportion of the overall supply can be efficiently utilized. Water is an essential resource for both human people and diverse types of natural life. It sustains urban environments, meets physiological requirements, and offers habitats for numerous organisms. Urban settlements significantly impact water consumption due to various functions, such as providing drinking water, sanitation, preservation of ecosystems, agricultural irrigation, industrial activities, tourism, and fishing operations. The increasing need for water can be ascribed to various variables, encompassing population expansion, climate change, industrial progress, and evolving societal norms[14]. In this context, the concepts of water demand, water consumption, water scarcity, and water stress should be explained.

The term "**water demand**," as specified by the Food and Agriculture Organization (FAO) in 2012**,** refers to users' economic capacity and desire to pay for water and the associated services it offers. In this context, the need for water has distinct characteristics compared to water as a fundamental human necessity, necessitating a sufficient quantity of secure provision. Within the water scarcity framework, water demand refers to quantifying the necessary or desired amount of water, considering the associated costs concerning a specific level of water supply service[15].

In conversations about water usage, "demand" is frequently synonymously with "requirement." Demand is a fundamental notion in economics that refers to the inclination of customers or users to buy products, services, or inputs for production. This inclination is influenced by the price of the item being purchased.

Previous research has mainly focused on water usage or demand by industrial facilities, farms, and families. However, other specialized aspects of water demand have not been well studied. In summary, there are six dimensions[16]:

1. The quantity of water drawn at the point of entry for a specific process (withdrawals);

2. The overall water consumption, including recirculation (gross water applied);

3 The quantity of water lost through evaporation, incorporation into the product, or other means before discharge (consumptive use);

4. The quantity of water released into the environment (discharge);

5. The caliber of the released water (request for wastewater disposal services); and

6. Trends in each of the abovementioned variables over time.

Different variables affect water demand. These variables are generally divided into seasonal and socioeconomic variables. While seasonal variables investigate short-term effects on water demand, socioeconomic variables examine long-term effects[17].

Water demand and water consumption are concepts that refer to different aspects of water use but are interrelated. Many studies in the literature use the two concepts interchangeably. However, according to World Resources Institute, "water consumption" refers to the water used and not returned to the source. Water is consumed when it evaporates into the air or is used up by a product or plant and cannot be recovered for further use. It is important to include water consumption while studying water shortage and the effects of human activities on water availability[18].

While water scarcity refers to an area's inability to get enough water to satisfy its needs, water stress encompasses both quantity and quality concerns, emphasizing the strain on water resources as a result of demand outstripping supply. It is possible to see water stress as an early warning indicator of impending water scarcity, indicating that water supplies are already experiencing strain and will require vigilant management to prevent further scarcity. In a general sense, water scarcity refers to the condition in which water availability or quality is compromised to such an extent that the demand from various sectors cannot be adequately fulfilled. The concept of water scarcity is subjective and can manifest at many levels of both supply and demand. The concept of scarcity can be understood as a social construct that is influenced by factors such as money, societal expectations, and conventional habits. Additionally, scarcity can arise from shifts in supply patterns, such as those caused by climate change[19].

As stated in the 2012 report by the FAO the term "water shortage" denotes a condition wherein the water demand surpasses the existing supply. Scarcity is manifested by unfulfilled demand, disputes among users, competition for water resources, excessive exploitation of groundwater, and insufficient allocation to the natural environment. The issue of water scarcity is multifaceted and influenced by temporal variations resulting from natural hydrological variability[15].

Nevertheless, the primary factors that shape water availability are predominantly impacted by prevailing economic policies, strategic planning, management approaches, and the capacity of societies to anticipate and address fluctuations in water supply and demand[15]. In addition, socioeconomic, demographic, and technological characteristics also have a significant impact on water demand.

According to the chosen definition, there is a wide range of potential reasons for scarcity, each of which calls for a unique reaction. The Comprehensive Assessment of Water Management in Agriculture found that a lack of available water poses a significant barrier to effective agricultural methods in many parts of the world[20]. According to the results of an earlier study by Seckler et al. (1998), there are two basic types of water scarcity: physical and economic.

Physical water scarcity is a frequently used term to describe a condition where the existing water resources are inadequate to meet the diverse range of demands, including human necessities and environmental prerequisites like sustaining natural flows. The physical water scarcity is evident through significant ecological damage, depletion of groundwater reserves, and the implementation of water allocations that favor specific populations while disregarding others.

Economic water scarcity is a state that emerges as a result of inadequate investment in water resources or a shortfall in human capacity to fulfill the water demand. The symptoms associated with economic water scarcity include the constrained development of infrastructure, which affects both small and large-scale contexts. This ultimately leads to insufficient availability to water for agricultural and domestic needs.

Furthermore, it is plausible for the distribution of water supplies to exhibit disparities in fairness, even in situations where the requisite infrastructure is established. A dearth of economic resources characterizes a considerable proportion of the sub-Saharan African region, thus rendering supplementary water development activities potentially imperative in mitigating poverty levels[21].

The Falkenmark Indicator, which hydrologist Falkenmark formulated, is a widely acknowledged measure utilized to evaluate water stress and the prospective strain on freshwater supplies. The main focus of the indicator revolves around the correlation between the overall availability of water and its utilization. This situation involves classifying different regions into three categories: absolute water scarcity, chronic water shortage, and those experiencing regular water stress. These classifications are based on the measurement of renewable water resources per capita, as proposed by Falkenmark and Widstrand[3].

Table 1. Water Stress Index Proposed by Falkenmark, 1989

(Source: Falkenmark[22])

Falkenmark Indicator (m^3/capita/year)	Level of Water Stress
<500	Absolute water scarcity
500-1000	Scarcity
1000-1700	Stress
>1700	No stress

According to the European Environment Agency, **water stress** is a condition that arises when the water demand surpasses the available supply within a specific timeframe or when the utilization of water is limited due to its poor quality. Water stress leads to the degradation of freshwater resources in quantity, such as aquifer over-exploitation and dry rivers, and quality, including eutrophication, organic matter contamination, and saline intrusion[23].

Water stress is a condition that is distinguished by constraints on the utilization of water, disputes among individuals or groups about its consumption, rivalry for resources, reduced reliability and quality of water services, instances of crop failures, and apprehensions regarding the security of food supply[15]. However, water scarcity develops when insufficient water is available to meet the necessary quality standards. Many factors, including weather, infrastructure constraints, and water availability, play a role.

New Water Risk Atlas data shows that a quarter of the world's population has been under extremely high-water stress. Studies show that 60% of the world's population will be exposed to water stress by 2050[18].

The exacerbation of the global water problem can be attributed to various reasons, such as urbanization, population expansion, and increased expectations for improved livelihoods[24]. Water scarcity and crises in urban areas are significant and delicate issues due to ongoing urbanization and the rising water demand[1]. According to the United Nations [25], it is estimated that by the year 2050, the urbanization rate will rise to 66.4%, resulting in a population of 9.8 billion individuals residing in urban areas. Urban centers in emerging African and Asian economies are experiencing significant and rapid expansion. City water supplies are especially at risk due to rising urbanization and high population densities. Due to climate change, an extra 10% reduction in freshwater availability is projected for 685 million people residing in more than 570 cities by the year 2050. Freshwater availability can decrease by 30–49% in some places, including Amman, Cape Town, and Melbourne, and more than 50% in Santiago [26]. Turkey is one of the countries under extremely high-water stress. The annual amount of usable water per capita in Turkey is expected to decrease to 1,200 cubic meters in 2030, 1,116 cubic meters in 2040, and 1,069 cubic meters in 2050, with the increasing population[12]. This table reveals that Turkey is one of the countries suffering from water shortage. Briefly, only nine of Turkey's 25 main river basins do not experience water stress. In addition, it has been determined that four river basins are at risk of definite famine (Marmara, Küçük Menderes, Burdur and Akarçay), water levels are at famine level in five basins (Susurluk, Northern Aegean, Gediz, Sakarya and Asi famine), and water stress is in question in seven basins (Meriç-Ergene, Büyük Menderes, Yeşilırmak, Kızılırmak, Konya Closed, Seyhan and Van Lake). Especially with the increase in the population benefiting from basins, the water shortage problem has been encountered[12]. In addition to climate change and population growth, increased consumption at the household level increases water stress. The degree of water consumption in each household is influenced by the socioeconomic features of households[27].

In conclusion, population growth, climate change, and socioeconomic trends are just a few factors contributing to water scarcity and its many repercussions. To effectively manage and mitigate the effects of water scarcity on ecosystems and human societies, it is crucial to have a thorough understanding of these factors.

2.2. Factors Affecting Water Consumption

Urban areas are human settlements that have a high demand for water resources. There exist multiple reasons for this phenomenon. The demand for urban water consumption is impacted by many interconnected factors that collectively contribute to the complicated dynamics of this essential resource. The study of population dynamics is crucial in understanding the water requirements for domestic, industrial, and commercial purposes in urban settings. This includes factors such as population size, population density, and the rate at which urbanization occurs.

Moreover, it is crucial to consider the impact of socioeconomic variables, such as income levels and living standards, on water consumption patterns. Demographic factors such as population density, average household size, and age groups are crucial in determining urban water usage. Hence, urban water consumption is multifaceted and requires a thorough comprehension of the intricate interrelationships among different elements. Comprehending this concept is crucial for creating effective strategies that advance sustainable water management in metropolitan areas.

In studies in the literature, factors affecting water consumption are generally classified as water price, demographic characteristics, socioeconomic characteristics, and urban characteristics. The dependent variable considered as water consumption varies such as per capita water consumption[27,28], total water consumption (daily, monthly, annual)[29], and per residence water consumption[30,31].In addition, water price is a significant explanatory variable in water consumption studies, affecting private and public water resource management. Estimating price elasticity helps forecast the revenue impact of price increases and is crucial for developing effective water-saving programs[29].

In this section, the effects of relevant variables on water consumption were examined under subheadings.

2.2.1. Climatic Characteristics

A group of variables that are used to explain water consumption in the literature is climatic features. Climatic factors such as rainfall, humidity, and temperature can affect individuals' water consumption. Generally, studies have found that total water consumption increases with increasing temperature. This situation has been associated with increased outdoor use with temperature[32–34]. Furthermore, researchers have shown that areas with abundant rainfall and high humidity have elevated per capita water consumption levels. Elevated humidity levels and frequent precipitation have been seen to correlate with a heightened occurrence of personal hygiene habits, such as bathing and changing clothes. As a result, this causes an increase in water consumption and the frequency of water consumption in households[27]. There are studies in the literature that find that climatic variables are not necessary[35]. Studies using climatic features are generally studies involving different regions and years.

2.2.2. Socioeconomic Characteristics

The water demand, similar to the needs of different consumer goods, tends to increase in parallel with the wealth of households. In the context of scholarly investigation, variable income is typically defined as the total amount of money earned by people or families within a specific period after deducting expenses and taxes[36,37]. The concept of income elasticity of demand, frequently used in water demand and water consumption studies, measures how sensitive the demand for a specific commodity or service is to changes in income, assuming that all other factors remain the same. The concept pertains to the degree of responsiveness exhibited by customer demand for a particular item about alterations in consumer income levels[38]. At present, the allocation of financial resources towards household budgets represents a negligible proportion of the total expenditures on water. Therefore, it is crucial to understand the true extent of the relationship between wealth and per capita water consumption[36,39]. Previous studies have repeatedly emphasized a positive correlation between income elasticity. The responsiveness of higher-income families to changes in water pricing is lower than lower income households, indicating a drop in the elasticity of demand for water as family income grows. This phenomenon can be attributed to the fact that water constitutes a small fraction of their overall expenses[40–42]. Worthington and Hoffman[43] argue that the lack of income elasticity can be attributed to two main factors: specification error and a limited representation of socioeconomic variety within the families included in the sample. Based on the findings of Flörke and Alcamo[44] about various scenarios in Europe, it is suggested that developing countries may exhibit a higher income elasticity than developed nations. The authors propose the presence of a positive link between the mean consumption levels of households and their corresponding mean income levels. In the final analysis, it is envisioned that a point of income achievement exists, beyond which the level of consumption remains unchanged despite the accumulation of substantial wealth after a time of stabilization. The relationship between income level and per capita water consumption can be hypothesized, indicating the impact of customers' financial capability and willingness[45].

Researchers established that increased income levels were associated with higher levels of per capita water consumption[28,29].

In addition to income, educational attainment is another indicator of socioeconomic position. The studies classified the education factor according to the completed education level. Numerous inquiries have examined the perceptions regarding water conservation, considering the interconnectedness of income and educational achievement, resulting in observable beneficial outcomes. Flack and Greenberg[46] documented an increasing propensity for water conservation as educational attainment levels rise. It has been revealed that individuals with a higher education level are more conscious about saving water than individuals with a high school degree[47].

De Oliver[48] found that those with higher levels of education showed a significant lack of knowledge about water conservation. Per capita water consumption positively correlates with higher education levels, as Fan et al. (2017) stated. The study showed that persons with higher levels of education inhabited regions with higher per capita water consumption[27]. Households with higher education levels may have more financial resources, thus allowing them to allocate a more significant portion of their income to water consumption for domestic purposes. However, researchers claim that education level alone has no significant influence on water consumption.

Child-woman raito is defined as the number of children under the age of five per 1000 women of reproductive age (15-49 years) in a population in a given year and is considered one measure of socioeconomic growth. It has been found to correlate with income level negatively[49]. It can be used as a parameter to examine the socioeconomic effects of water consumption.

2.2.3. Demographic Characteristics

Demographic characteristics of urban populations can significantly impact water consumption: household size, population density, and age group distribution influence per capita water consumption.

Studies that study demographic factors affecting per capita water consumption examine the impact of different age groups on water consumption. Arbues et al.[50] explored the relationship between the two age groups, the young population and the elderly population, and per capita water consumption. The population is young people under 20 and older people aged 60 or over. The results show that young people consume more water than older people. Researchers explain this to the fact that older individuals have fewer baths and lower incomes than younger ones. Koegst et al.[31] found no meaningful relationship between age groups and per capita water consumption. This situation can be explained by different dynamics in the regions where the study was conducted.

Another factor examined in the demographic characteristics is the size of the household. Höglund[40] stated that per capita water consumption and household size may have an inverse relationship. According to Höglund (1999), per capita water consumption can be expected to be less in larger households. Arbués et al. (2010) found that per capita water consumption decreases as household size increases. When researchers examined per capita water consumption trends, they concluded that small households consume more water than larger ones[50]. Wentz and Gober[51] concluded that household size had no significant effect on water consumption. It is indicated that the rise in overall water use is smaller than the growth in household size, showing a negative correlation between average household size and per capita water consumption.

Another factor that researchers are looking at within demographic variables is population density. In their study in Italy, Mazzanti and Montini[52] found that population density had a weak positive correlation with per capita water consumption. Öztürk et al.[53] found that population density reduces per capita water consumption increases.

2.2.4. Physical Characteristics

It is known that urbanization has a direct and indirect impact on water consumption. However, most studies in the literature primarily focus on examining the relationship between the physical characteristics of individual households and water consumption. Characteristics such as the age, size, number of bathrooms, and value of residential units have been studied with water consumption in urban areas. Studies have indicated that properties with pools and gardens have higher water consumption rates[54,55]. Some studies investigate the impact of different housing typologies on water consumption. These studies often classify housing typologies as semi-detached, detached, and apartment units[54,56]. However, the results of these studies have generally not found significant differences in water consumption among different housing typologies. In contrast to these studies, Domene and Sauri[24] found that housing type influences per capita water consumption in Barcelona, Spain. It has been determined that high per capita water consumption in low-density housing type (detached house) is related to housing characteristics such as the size of the house, the number of installations, the size of the garden, and the garden water need[24]. In short, different housing types and especially garden size are important factors affecting water consumption. In addition to examining housing typologies, studies show that cities' sprawl and growth also affect water consumption. While urban sprawl describes the low-density urban development model, the high-density model describes urban areas that include commercial, residential, and other uses. The sprawl model may lead to a high-water consumption trend with increased outdoor use[57]. Allen[58] compared two areas and discovered that a low-density growth neighborhood consumed more water per capita than a high-density neighborhood. Per capita water consumption is higher in low-density urban areas than in high-density urban areas. This density is explained by using landscaping and the presence of a pool by supporting other studies[59].

Öztürk et al.[53] estimated that houses with large green areas may cause more water consumption. At the same time, it is estimated that urban sprawl, which causes an increase in landscape elements, including greenery and trees, will lead to higher per capita water consumption. It is also stated that impervious surfaces may increase the per capita water consumption due to increased built-up area in regions with high-density development. It may negatively affect the urban water cycle[60].

In a study that examined the relationship between urban variables, e.g., the NDVI, a spectral index derived from remote sensing imagery that is used to assess the health and quantity of vegetation in a given area, had a strong positive relationship with water consumption[61]. It demonstrates that areas with elevated NDVI values, indicating healthier plants, typically have increased water demand levels. This finding emphasizes the intricate relationship between urban expansion, ecological infrastructure, and water usage in urban settings.

2.3. Methods Used in Water Consumption Assessment

In this part of the study, the standard methods that are used to examine the factors influencing water consumption are examined. The literature review aims to identify and discuss the commonly used ways under subheadings.

While traditional methods such as correlation analysis and regression analysis are widely used in studies aimed at modeling and estimating water consumption, Advanced methods such as fuzzy logic and artificial neural networks are also used[62,63]. Artificial intelligence algorithms are utilized with regression analysis to investigate the variables influencing water consumption. These algorithms are particularly employed for future prediction and analysis of large-scale data sets. Furthermore, investigations are being conducted on geographical analysis and clustering methodologies[64–66]. This section includes traditional methods and spatial analyses used when examining the factors affecting water consumption.

This section includes three subheadings: correlation and regression analysis, classification technique, and spatial autocorrelation.

2.3.1. Correlation and Regression Analysis

Correlation analysis and regression analysis, which are statistical analysis methods, are among the types of analyses that examine the relationship and causality between variables. In studies investigating the factors affecting water consumption, correlation and regression analysis are frequently used to explore the relationship and cause between variables.

According to O'Brien and Scoot [67], correlation analysis is used to examine whether there is a relationship between two variables. The correlation coefficient in correlation analysis quantifies the extent of the association between two variables[68]. The correlation coefficient ranges from -1 to +1.

Table 2. Meaning of Correlation Coefficient

(Source: Tekin[69])

Correlation Coefficent	Description
0,90-1,00	Very Strong Correlation
0,70-0,90	Strong Correlation
0,40-0,70	Normal Correlation
0,20-0,40	Weak Correlation
0,00-0,20	Very Weak Correlaiton

Correlation is a statistical measure used to examine the strength and direction of the relationship between two variables under investigation. The correlation coefficient is a statistical measure used to evaluate the degree of association between variables. Two correlation coefficients are commonly employed in various applications: Pearson's Product Moment Correlation Coefficient (for normally distributed data) and Spearman's Rank Correlation Coefficient (for non-normally distributed data). Karl Pearson initially established and investigated the correlation coefficient in 1896. Hauke and Kossowski[70] assert that Pearson's Product Moment Correlation Coefficient (R or r) is a metric used to quantify the magnitude of a linear relationship between variables. When examining the degree of linear relationship between variables, it is crucial to investigate interval or ratio variables. However, it is necessary to ensure that the variables being studied adhere to a normal distribution.

Pearson's mathematical framework for quantifying the degree of relationship (r) between variables X and Y can be expressed as follows: eq. (1):

$$r = \frac{n(\sum XY) - (\sum X).(\sum Y)}{\sqrt{n(\sum X^2) - (\sum X)^2}\sqrt{n(\sum Y^2) - (\sum Y)^2}} \tag{1}$$

Where n represents the number of observations; X represents the measurements of Variable 1; Y represents the measurements of Variable 2; the expression ΣXY represents the sum of the products of the different measurements of the variables; the symbol ΣX represents the sum of the measurements of a variable 1; the symbol ΣY represents the summation of the measurements of a variable 2; the expression ΣX^2 represents the sum of the squared values of the measurements of a variable 1; the expression ΣY^2 represents the sum of the squared values of the measurements of Variable 2. The degree of correlation can be classified into three categories: positive correlation, zero correlation, and negative correlation, based on the given direction. Observing a correlation coefficient of exactly zero between variables is uncommon in most applications. Consequently, positive and negative correlations are often treated as equivalent categories in statistical analysis[71]. The coefficient of correlation, denoted as r, exhibits a range of values from -1 to +1, namely $-1 \leq r \leq +1$.

However, correlation analysis cannot model casual relationships and estimate causality between variables. Regression analysis is used to examine causality between variables. In regression analysis, two groups of variables exist: the dependent and independent variables. The impact of the independent variable on the dependent variable is quantified through regression analysis, and F statistic and T-tests are utilized to assess the significance of the overall regression model and the individual coefficients of the independent variables. F-statistic is used when testing the significance of the general model in regression analysis; a T-test is used to test the significance of the coefficients of the independent variables[67]. However, Brentan et al. (2017) argue that correlation analysis helps understand variables' dependencies. Researchers have stated that using correlation analysis can lead to a better understanding of variables and result in constructing a healthier model[34]. Since regression analysis allows modeling with understandable assumptions, researchers commonly use it in their studies; linear regression can be divided into two groups: simple linear regression and multiple linear regression.

In simple linear regression, there is one independent variable. The equation is expressed as follows: eq. (2):

$$Y=\alpha+\beta X+e \quad (2)$$

where Y denotes the dependent variable, the constant quantity is represented by α. The coefficient is indicated by β. The independent variable is defined by X. The error term is implied by e.

In multiple linear regression, there are numerous independent variables. The effect of each variable on the dependent variable is examined. Unlike the simple linear regression equation, multiple independent variables are included[67].

The degree of correlation is between multiple independent variables and a single dependent variable. The dependent variable's value is at a specific value of the independent variables[72].

The multiple linear regression formula is given as eq. (3):

$$y= \beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n + \epsilon \quad (3)$$

where y represents the anticipated value of the dependent variable. The symbol β_0 represents the y-intercept, which is the value y when all other parameters are set to 0. The term "$\beta_1 X_1$" represents the regression coefficient (β_1) associated with the first independent variable (X_1). The symbol $\beta_n X_n$ represents the regression coefficient of the last independent variable. ϵ represents the model error, which refers to the amount of fluctuation in our estimate of a certain variable.

Multiple linear regression relies on several assumptions. The assumptions underlying regression analysis play a critical role in ensuring the reliability and validity of the findings derived from the model. These assumptions are the basis for creating precise deductions and forecasts using regression models. The main assumptions encompass the concepts of linearity, independence, homoscedasticity, normality of residuals, and lack of multicollinearity[73]:

1) **A linear relationship between the dependent and independent variables:**

The initial assumption of multiple linear regression pertains to a linear association between the dependent variable and each independent variable.

2) **The independent variables have a low degree of correlation among themselves:**

The presence of multicollinearity, which refers to a strong correlation between independent variables (variables that explain the outcome), should not be observed in the data. When there is multicollinearity among independent variables, it becomes difficult to determine the specific impact of each variable on the observed variation in the dependent variable. The most optimal strategy for evaluating the assumption is to use the Variance Inflation Factor (VIF) technique.

3) **The variance of the residuals is constant:**

The multiple linear regression model is based on the assumption of constant residual variability across all points in the linear model. The term typically used to describe this occurrence is homoscedasticity. The analyst should generate a scatter plot of the standardized residuals concerning the predicted values when analyzing data. This enables the evaluation of the dispersion of points among all independent variables.

4) **Independence of observation:**

The model assumes that the observed data points are mutually independent. The model assumes that the residuals possess independence in their values. To evaluate this hypothesis, we should use the Durbin-Watson statistic.

5) **Normality:**

Multivariate normality is observed when the residuals have a normal distribution. Checking the distribution of residual values is an essential step in evaluating the assumption of normality.

6) **Outliers cases:**

Similar to the context of simple linear regression, it is crucial to identify instances that may exert a disproportionate influence on the regression model.

To test the assumptions in multiple linear regression analysis, VIF value for multicollinearity, Durbin-Watson coefficient for the independence of observation, scatter plot for homoscedasticity, histogram plot, and Normal P-P Plot of Residual for normality, Casewise Diagnostics table and Residual Statistics table for outliers cases were used.

In addition to the assumptions of multiple linear regression analysis, it is important to test spatial dependence. In multiple linear regression analysis, spatial dependence testing entails evaluating whether the residuals (errors) of the regression model have spatial autocorrelation. Spatial autocorrelation in residuals suggests the presence of a discernible arrangement or organization in the unaccounted fluctuation of the dependent variable, which is linked to the geographical positions of the observations. The Lagrange Multiplier (LM) test is an econometric diagnostic tool that evaluates the validity of a given model by analyzing the residuals for particular forms of non-randomness[74].

A regression model is generally built for water consumption concerns so that the response (dependent) variable, which may otherwise be difficult to collect, may be estimated from more readily available information. Researchers have examined the relationship between water consumption and many independent variables, including socioeconomic, demographic, physical characteristics, and climatic variables, to investigate the factors affecting water consumption. For example, Cochran and Cotton [35] examined factors like average monthly rainfall, income, water price, and household size through multiple regression. Correlation and regression analysis are frequently used in studies investigating factors affecting water consumption. Multiple linear regression analysis is widely preferred in studies where more than one variable will be analyzed, such as seasonal, demographic, socioeconomic, and physical variables.

2.3.2. Classification Technique

Classification strategies in data mining involve categorizing data into distinct classes or categories, relying on certain qualities or properties. These methodologies employ algorithms to scrutinize extensive information and discern patterns that can be utilized to forecast forthcoming trends or behaviors. Classification aims to allocate new data points to the appropriate class by leveraging the patterns discovered in the training dataset. Classification approaches encompass decision trees, neural networks, support vector machines, and k-nearest neighbors. Data mining encompasses two primary categorization methodologies: supervised and unsupervised[75]. In short, while supervised learning aims to predict new data results, unsupervised learning aims to classify new data. In supervised learning, there is a training set and a test set. Training models are time-consuming and require expertise[76].

2.3.2.1. Supervised Learning

Supervised learning in classification techniques refers to a form of machine learning in which the algorithm is trained using a dataset that has been labeled, indicating that the input data is associated with specific output labels. Supervised learning aims to acquire a mapping function that can predict or classify fresh, unseen data by mapping input variables to output labels. Classification involves training the algorithm to categorize incoming data into predetermined groups or categories. Throughout the training phase, the algorithm acquires knowledge of the connections and patterns in the labeled data, fine-tuning its parameters to reduce the disparity between expected and actual labels. Popular supervised learning methods for categorization encompass logistic regression, decision trees, support vector machines, and neural networks. The crucial factor is that the algorithm acquires knowledge from a dataset that has been labeled, enabling it to provide predictions on fresh, unlabeled data by using the patterns it has learned throughout the training process[75].

The core concept underlying supervised learning is allowing the algorithm to extrapolate patterns from the labeled training data to generate precise predictions on novel, unseen data. The paradigm is highly potent and may be applied to solve real-world problems in various fields[66].

2.3.2.2. Unsupervised Learning

Unsupervised learning is a branch of machine learning that involves algorithms analyzing unlabeled data to discover concealed patterns, structures, or connections within the dataset without explicit instructions. In contrast to supervised learning, unsupervised learning does not rely on predetermined output labels and instead focuses on exploring the intrinsic structure of the data. In the simplest definition, clustering is the unsupervised classification of existing data/observations into groups. K-means clustering is a prevalent technique that involves dividing data into separate groups. An alternative method is hierarchical clustering, which arranges data in a hierarchical structure like a tree. Clustering is a fundamental approach in unsupervised learning, wherein an algorithm categorizes data points with comparable properties or commonalities into groups. Cluster analysis entails grouping data points that have similarities to create clusters or segments without prior knowledge of predetermined classifications. This approach is precious for examining the inherent organization of data and discerning commonalities or differences across observations. Dimensionality reduction is a frequently encountered job in unsupervised learning, intending to simplify complex datasets. Principal Component Analysis (PCA) is widely used in this scenario. Unsupervised learning is beneficial when the objective is to uncover inherent patterns or connections without explicit instruction, making it especially relevant in exploratory data analysis and feature extraction. It is utilized in several applications, such as consumer segmentation, anomaly detection, and topic modeling[75].

2.3.3. Spatial Autocorrelation

Spatial analysis is an effective way to make accurate decisions and acquire new information. Many institutions and organizations like companies, governments, businesses, and universities use spatial analysis. Spatial analysis enables the production of new results by using data from different sources[77].

There are spatial analyses in which Moran's I value is calculated to examine the spatial dependence of water consumption[62]. Moran's I is a value that quantifies spatial dependence of the phenomenon of interest, where the index value ranges between -1 and +1. A score close to +1 implies positive autocorrelation, whereas a value close to -1 suggests negative autocorrelation. A value of 0 signifies the presence of randomness[78].

In its broadest interpretation, spatial autocorrelation pertains to the extent to which things or activities in a particular geographic location exhibit similarities with other objects or activities close. The concept of its existence is encapsulated in the notion coined by Tobler[79] as the "first law of geography," which posits that all elements are interconnected, with closer entities exhibiting stronger relationships compared to those that are farther apart. Spatial autocorrelation can be conceptualized as a descriptive metric that captures the spatial arrangement of phenomena. Simultaneously, it can also be regarded as a causal mechanism that quantifies the extent of impact exerted by a particular entity on its neighboring entities. The Moran's I statistic is a long-standing measure of spatial autocorrelation that can be employed to examine both global and local spatial autocorrelation within continuous datasets[80]. The Moran's I formula is given as eq. (4):

$$I = \frac{n}{S_0}\frac{\sum_i^n \sum_j^n w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i^n (x_i - \bar{x})^2} \tag{4}$$

where $\bar{x}$ represents the average value of the variable x. x_i represents the value of variable x at a specific position i. x_j represents the value of variable x at a specific location j. w_{ij} represents the spatial weight between feature i and j. n represents the total number of observations.

S_0: is the sum of the elements of the weight matrix:

$$S_0 = \sum_i^n \sum_j^n w_{ij} \tag{5}$$

The p-value is a probability. The P-value indicates whether the observed spatial pattern is random. If the P-value is less than 0.10 at the 90% confidence level, it suggests that the spatial pattern does not occur randomly. The Z value refers to the standard deviation. It is found at the tail points of the chart as very low and very high values. Suppose the p-values are modest and the z-score is notably high or low. In that case, the observed spatial pattern is unlikely to result from the theoretical random pattern represented by the null hypothesis[81].

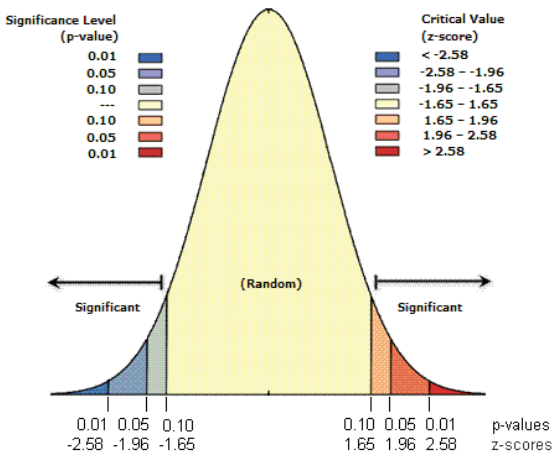


Figure 2. Spatial Autocorrelation Graph

(Source: ESRI[81])

The local indicator of spatial association, sometimes known as the LISA statistic, was introduced by Anselin in 1995. According to Anselin, LISA statistics possess the following two properties: The Local Indicators of Geographical Association (LISA) measure provides insight into the significant geographical clustering of comparable values surrounding each observation. Additionally, the cumulative sum of LISAs across all observations is directly related to a global indicator of spatial association[80]. The primary purpose of utilizing the LISA map was to uncover the spatial variability of the subjects under investigation and assess the spatial distribution of distinct clusters[82]. These clusters were categorized into four types: low values surrounded by low values (L-L) or high values surrounded by high values (H-H), as well as outliers with low values surrounded by high values (L-H) or high values surrounded by low values (H-L).

The Local Moran's I is formulated as in eq. (6):

$$I_i = \frac{x_i - \bar{x}}{S_i^2} \sum_{j=1}^{n} w_{ij}(x_j - \bar{x}) \tag{6}$$

$\bar{x}$ represents the average value of the variable x. x_i represents the value of variable x at a specific position i. x_j represents the value of variable x at a specific location j. w_{ij} represents the spatial weight between feature i and j. n represents the total number of observations, and:

$$S_i^2 = \frac{\sum_{j=1}^{n}(x_j - \bar{x})^2}{n-1} \tag{7}$$

The values assigned to this index often span from -1.0 to +1.0. A score of -1.0 indicates the existence of negative spatial autocorrelation, whereas a value of +1.0 denotes positive spatial autocorrelation.

House-Peters et al. (2010), although water consumption is affected by physical, climatic, and socioeconomic variables, it is also affected by the spatial location and the interaction of locations. Therefore, residences close to each other are expected to have similar water consumption trends. In short, it is expected to see spatial dependence in water consumption[62]. A study conducted in Turkey using spatial autocorrelation analysis determined that provinces with similar water consumption tendencies were located within the same basin. In the study, where different time groups were used, the relationship between the water consumption trends of the provinces and their neighbors over time was examined[83].

2.4. Water Demand Management

Integrated urban water management involves the management of the water cycle in urban areas, with a focus on promoting collaboration between different institutions. The strategy covers groundwater, rainwater, wastewater, and water supply management[84]. Water Demand Management is adopted as a critical Integrated Water Resources Management component focusing on water demand.

A full definition of Water Demand Management should include both the series of actions that transport water from the source to use and the time and spatial dimensions of water usage. Water demand management encompasses several strategies, including technological, economic, administrative, financial, or social approaches, that aim to fulfill one or more of the following five goals[85]:

- ❖ Minimize the quantity or standard of water required to carry out a certain task.
- ❖ Alter the characteristics of the task or its execution in order to do it with a reduced quantity or worse grade of water.

- ❖ Minimize the loss of water, both in terms of quantity and quality, as it moves from its source to its utilization and eventual disposal.
- ❖ Change the schedule of usage from high-demand to low-demand hours.
- ❖ Enhance the resilience of the water system to sustain civilization during periods of water scarcity.

Due to rapid urbanization and population growth, the demand for urban water is also increasing. However, limited and exhaustible water resources and competition from different sectoral uses make access to water difficult. Since traditional water management approaches are supply-oriented, they fail to perceive individuals' water needs as variable demands. For this reason, efforts are being made to maximize water resources to meet the increasing water need. However, the traditional supply-oriented approach has caused faster water resource depletion, increased water supply capital, and pollution. In this respect, it is notable that the traditional water management approach is not sustainable[86–88].

For this reason, "Water Demand Management" is essential. In its broadest definition, Water Demand Management focuses on water demand. This approach emphasizes reducing water demand before making a plan for water supply. Water Demand Management has three main measures: technical, economic, and sociopolitical. In this context, measures such as leakage control, use of alternative resources, pricing of water, laws encouraging water saving, training programs, and awareness-raising projects are included. In this case, the participation of all stakeholders, from consumers to distributors, is essential[88]. At this point, examining the factors affecting water consumption is critical. Water demand is variable for different segments, and examining the factors affecting this variability is an essential step in demand management[89]. The demand analysis component of water demand management examines the trends and factors influencing water use within a specific setting. This examination can aid in identifying options for decreasing water use or enhancing efficiency. Demand analysis may be performed at several levels, ranging from individual families to large cities or regions. The process might encompass gathering data on water use, for instance, using meters or surveys.

Additionally, it entails examining several factors that impact water demand, including population expansion, economic progress, and climatic fluctuations.

Decision-makers can analyze the factors influencing water demand and implement specific measures to decrease or encourage water utilization during non-peak hours. Conducting demand analysis is a crucial aspect of efficient water demand management, as it furnishes the necessary data for devising and executing suitable plans[85].

Mohamed & Savenije (2000) further classify demand management strategies into positive or negative incentives and water-quota rules to aid water managers in evaluating these approaches. Typically, demand management relies on five fundamental principles[90]:

1. Implement measures to ensure water conservation, such as enacting legislation and establishing standards.

2. Promote water conservation by implementing positive incentives, such as tax rebates or voluntary agreements, to encourage responsible and efficient water use.

3. Allocate resources towards water conservation efforts, such as investing in initiatives to reduce water network losses and implement water metering systems.

4. To address the issue, use economic mechanisms such as incentives, disincentives, and water prices.

5. Provide education to water users and enhance their capabilities (e.g., via demonstrating best practices, conducting awareness campaigns, and ensuring access to information and data).

Kampragou et al.[91] found that for developing countries, raising the awareness of politicians and consumers through training is more important than policies such as fines, taxation, and pricing. To effectively control water demand, it is crucial to identify the attributes of consumers with high water consumption and thoroughly analyze the elements contributing to their water consumption.

Water demand management (WDM) and urban water demand management (UWDM) are interconnected ideas that focus on managing water usage and guaranteeing the long-term viability of water resources in urban areas. WDM refers to implementing methods and regulations that focus on the optimal utilization of water resources, minimizing wastage, and encouraging responsible usage. In contrast, UWDM customizes these ideas to address urban areas' distinct problems and dynamics. Urban water management encompasses the meticulous planning and execution of strategies inside cities to meet the growing water needs, considering issues like population increase, infrastructure expansion, and climate change[88]. Urban water demand management prioritizes comprehensive systems integrating urban planning, infrastructure design, and community participation to achieve water efficiency, resilience, and conservation effectively. UWDM enhances the durability of urban water systems and the general welfare of communities by harmonizing water usage with sustainable methods, even in the presence of changing environmental and demographic problems[92].

CHAPTER 3

STUDY AREA

İzmir, the third largest city in Turkey and a coastal city with active development in trade, industry, and agriculture, has a population of 4,462,056 people by 2022[93]. İzmir province has 30 districts and 1296 neighborhoods[93]. The 2014-2023 İzmir Regional Plan, in line with the characteristics of the districts within the territorial borders, includes the Metropolitan Area (Balçova, Bayraklı, Bornova, Buca, Çiğli, Gaziemir, Güzelbahçe, Karabağlar, Karşıyaka, Konak, Narlıdere); industrial focus (Aliağa), tourism focus (Çeşme, Selçuk, Bergama), secondary tourism focus (Foça, Dikili, Karaburun, Seferihisar), regional growth focus (Torbalı, Urla, Kemalpaşa), agricultural focus (Tire, Ödemiş, Bayındır, Menderes, Menemen) and finally secondary agricultural focus (Kınık, Kiraz, Beydağ)[94].

The focus of this study is on 11 districts located within the İzmir Metropolitan Area. Figure 3 takes a detailed look at the neighborhoods within those districts. The criteria for participation in the study were limited to communities categorized as built-up urban areas that possessed a complete collection of indicators and factors that influence water consumption. For this reason, a dataset of 286 out of 386 neighborhoods of 11 districts that satisfied these requirements was generated for analytical purposes. Furthermore, data from the year 2019 were particularly employed to guarantee a reliable evaluation and avoid any potential distortions that may be attributed to the influence that the pandemic of 2020 had on water consumption.

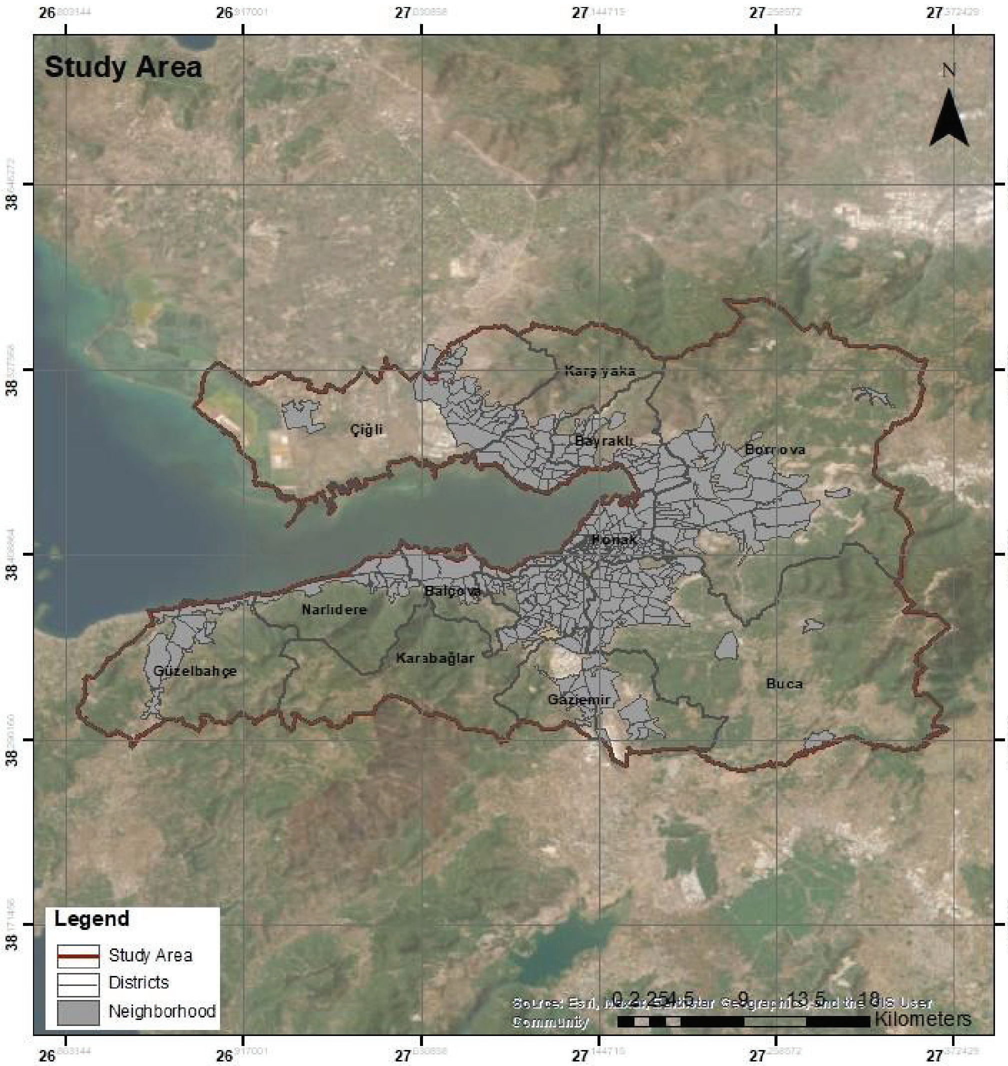


Figure 3. Study Area and Neighborhoods

3.1. Water Resources and Sectoral Water Consumption in İzmir Metropolitan Area

According to the information announced by the General Directorate of İzmir Water and Sewerage Administration, the drinking water distribution system of 11 districts within the İzmir Metropolitan Area has an integrated structure. The resources that meet the drinking water needs are located within the borders of Manisa and İzmir provinces[9]. These resources are Sarıkız wells, Göksu wells, Menemen wells, Halkapınar wells, Pınarbaşı wells, Buca and Sarnıç wells, Tahtalı Dam, Balçova Dam and Gördes Dam (Fig. 4).

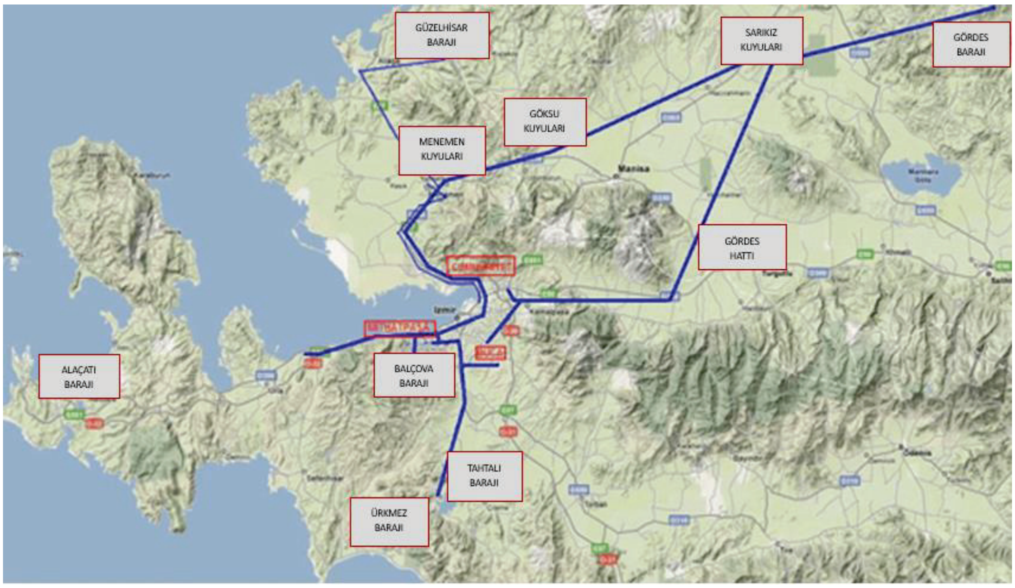


Figure 4. Map of Water Resources

(Source: İZSU[9])

Water production in 2019 and its distribution by resources are given in the chart (Fig. 5). The most essential water source to the districts in the study area is Tahtalı Dam, with 37% water production.

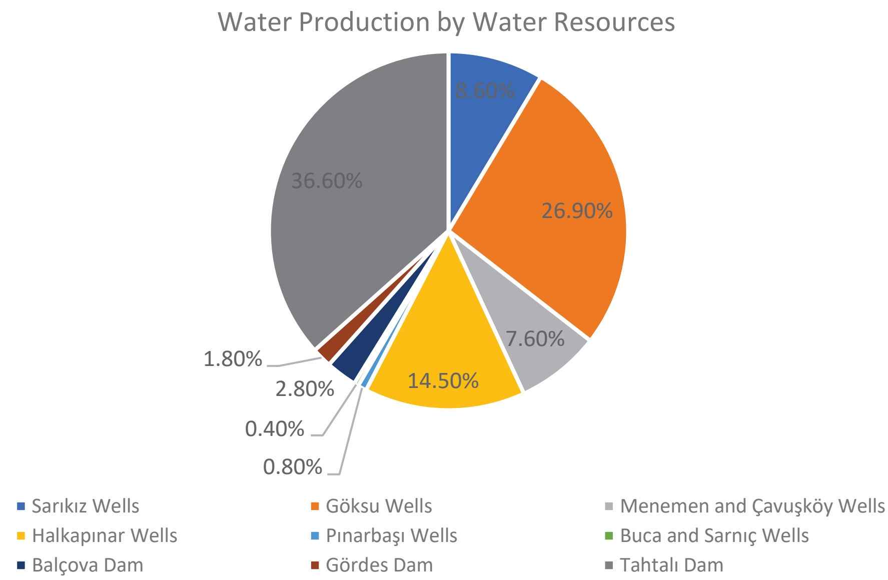


Figure 5. Water Production by Water Resources

(Source: İZSU[9])

Of the total 231,473,030 m³ of water produced in 2019, 136,057,376 m³ was obtained from underground water resources, and 95,415,218 m³ was obtained from surface water resources[9].

According to data received from the İzmir Water and Sewerage Administration, total water consumption in residential, non-residential, industry, irrigation, and agriculture-livestock sectors is given in the chart (Fig. 6). When the sectoral water consumption in the study area is examined; it is seen that the most water consumption belongs to the residential sector with 72%[95].

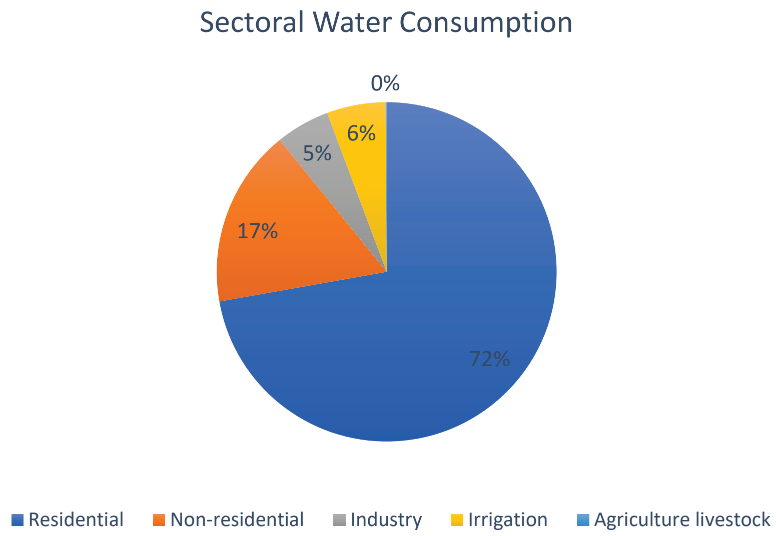


Figure 6. Sectoral Water Consumption (2019)

(Source: Açık Veri Portalı[95])

CHAPTER 4

METHODS & MATERIALS

4.1. Method of Water Consumption Assessment

This study section aims to elucidate the methodologies employed for assessing water consumption. Figure 7 depicts the regional heterogeneity in per capita water consumption across several geographical areas. Per capita water consumption values increase from light blue to dark blue. This thesis examines the regional distribution of per capita water consumption and the factors that influence this consumption pattern. The primary objective of this study is to thoroughly investigate per capita water consumption to gain a deeper understanding of the spatial intricacies of per capita water consumption within the specified research region. In this context, a categorization methodology known as cluster analysis was utilized. Spatial autocorrelation, especially the Global Moran's I statistic, was employed to examine the geographical patterns in per capita water consumption. In addition, the Local Moran's I method was employed to investigate the associations between geographical proximity and per capita water consumption.

This study's second objective is to analyze the factors that impact per capita water consumption. In the present situation, correlation analysis and multiple linear regression analysis methods were selected as the recommended analytical techniques. These analytical methodologies aim to elucidate the complex relationships and determinants that influence the disparities in individual water consumption.

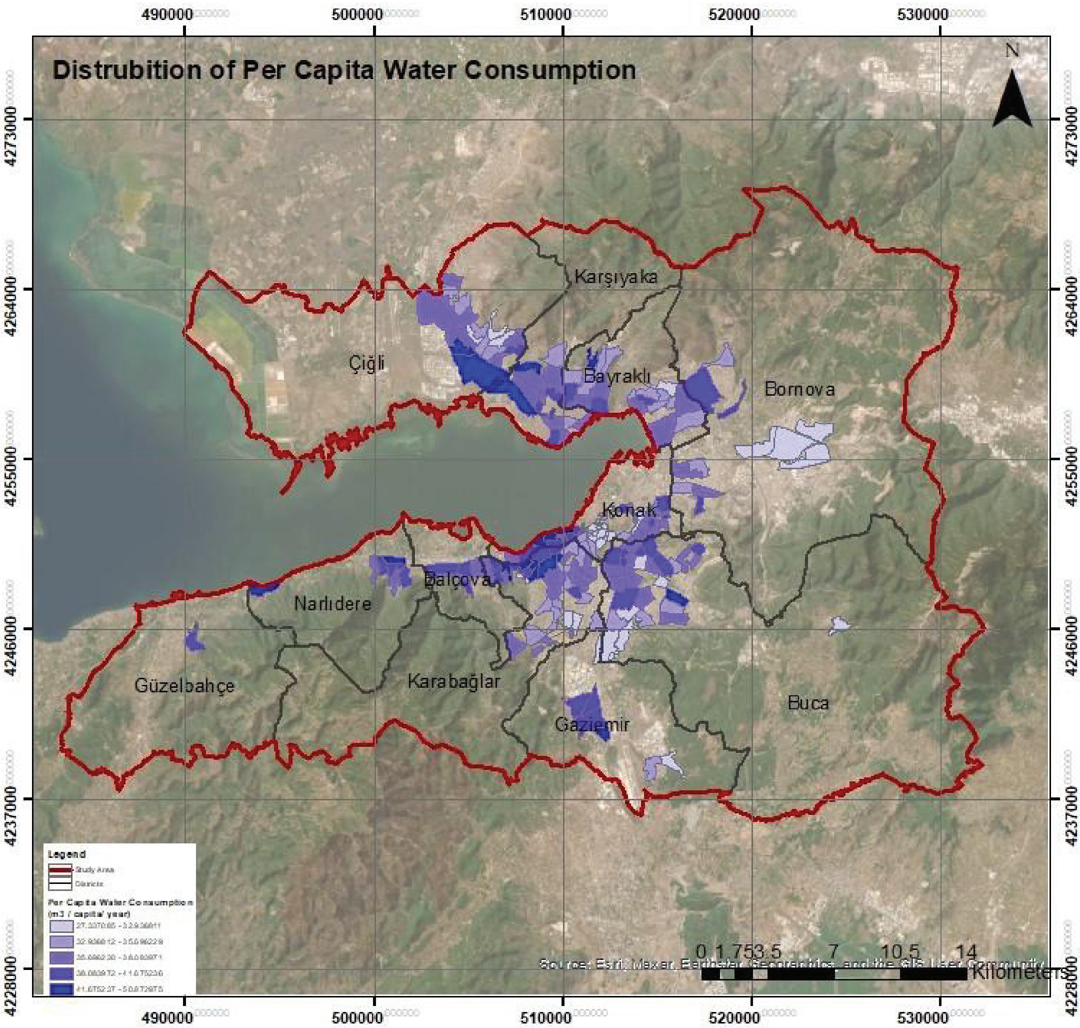


Figure 7. Distribution of Per Capita Water Consumption

The flowchart of employed to examine the spatial distribution of per capita water consumption and analyze the factors influencing consumption is presented in Figure 8.

According to this flowchart, demographic variables such as population density, child population ratio, active population ratio, and elderly population ratio, average household size; socioeconomic variables such as primary school graduate rate, higher education graduate rate, child-woman population ratio, and square meter unit sales price; urban variables as NDISI, NDBI, NDVI, LST, a data set was created for independent variables. The dataset was completed by adding water consumption per capita as a dependent variable. As part of the data preparation procedure, outlier values, which are defined as data points that substantially deviate from the overall trend, were routinely removed from the dataset. By implementing this process, the objective is to improve the robustness and reliability of the succeeding studies by reducing the excessive effect that extreme values have on the statistical results. The elimination of outliers is consistent with the principles that have been established in research methodology. This situation ensures that the dataset utilized for analysis is more indicative of the underlying trends and patterns present within the data, contributing to the validity and accuracy of the study findings.

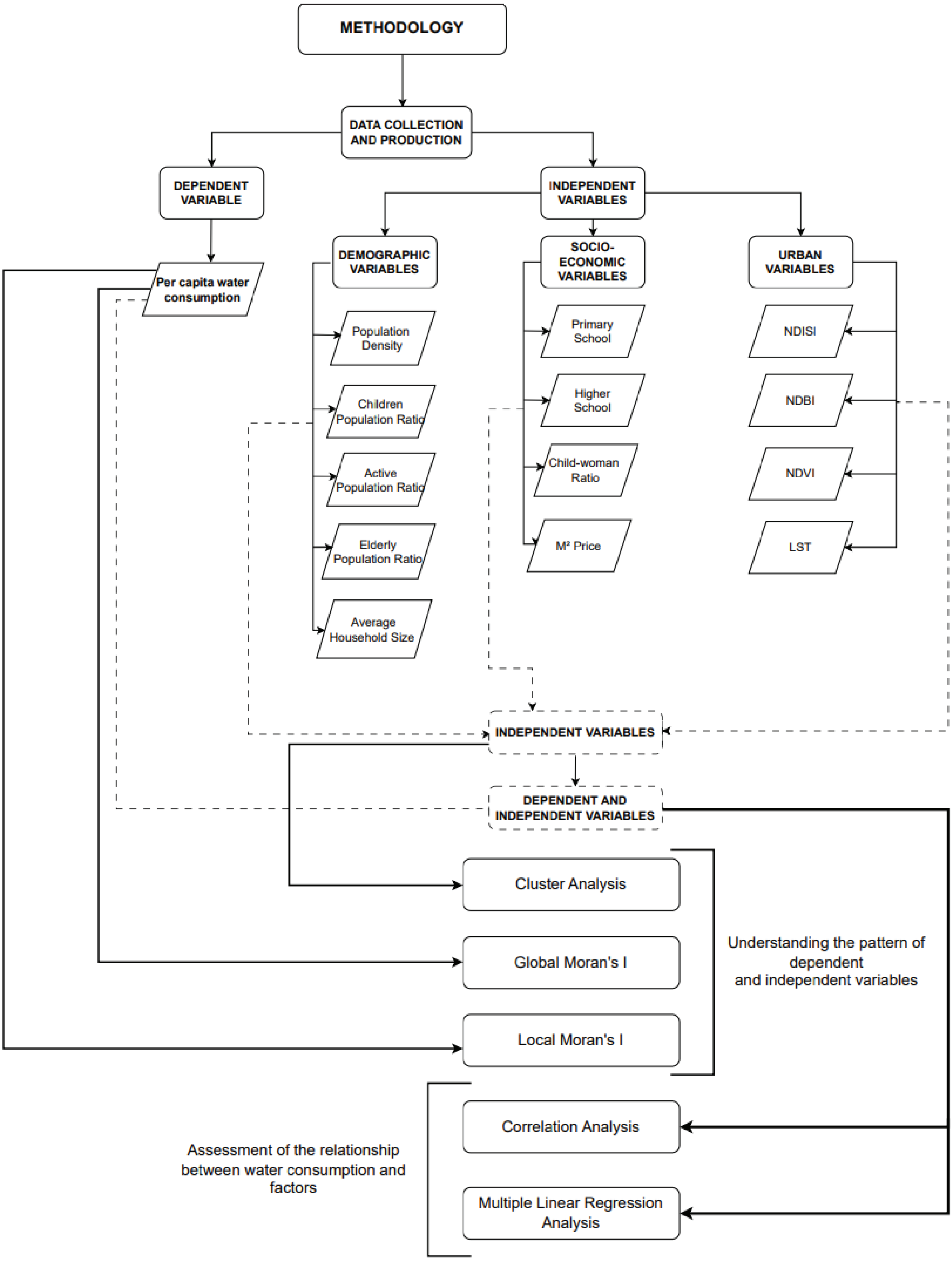


Figure 8. Flowchart of Study

4.1.1. Methods Used to Understand Spatial Pattern

The first stage in comprehending the interaction between dependent and independent variables inside the research domain entailed using methodological strategies. This study first aimed to understand the spatial pattern of dependent and independent variables. The study began by collecting a dataset consisting of independent variables. Subsequently, a thorough cluster analysis was performed to uncover the inherent characteristics of the studied region. Cluster analysis is a methodological tool for classifying neighborhoods into discrete "clusters" according to common attributes, revealing underlying patterns within the data. Cluster analysis is utilized to comprehensively investigate the prevailing characteristic qualities within the designated research region. The categorization of the research area based on its unique characteristics provides a foundation for a comprehensive examination of regions experiencing increased water consumption. The clustering analysis was performed using the SPSS, and the resulting clusters were visually represented using GIS. Utilizing this integrated methodology facilitates a comprehensive comprehension of the geographical and non-spatial factors that affect per capita water consumption patterns.

In this study, the two-step algorithm for cluster analysis was automatically determined. "Direct marketing" tool in SPSS was used to implement Cluster Analysis commands.

In addition, spatial analyses were conducted to examine the spatial dependence and pattern of per capita water consumption using Global Moran's I and Local Moran's I values. The methodology employed for examining per capita water consumption involves the utilization of the Global Moran's I statistic, a robust technique for evaluating spatial autocorrelation. This statistical metric assesses whether the observed per capita water consumption pattern demonstrates clustering, dispersion, or randomization over the entirety of the research region. The Global Moran's I statistic spans a range from -1 to 1, where a value of -1 signifies complete dispersion, 1 signifies complete clustering, and 0 suggests a random spatial pattern. This study utilizes the Global Moran's I analysis to determine the presence of statistically significant geographical clusters or outliers in terms of per capita water consumption, both high and low. The research seeks to reveal possible geographical correlations in water consumption patterns by directing attention to this specific variable. ESRI ArcMap 10.8.2 software extends the analytical functionalities, enabling a thorough investigation of spatial autocorrelation in per capita water consumption within the selected research area. This geospatial data analysis tool facilitates the process of cartography, visualization, and interpretation of the spatial connections within the dataset, enhancing a comprehensive comprehension of the geographic dispersion of water consumption.

Within this research's framework, the Local Moran I statistic is mainly employed to assess the spatial autocorrelation of per capita water consumption. This analysis necessitates thoroughly examining the correlation between water consumption statistics in a specific place and those in adjacent regions. The statistical analysis offers valuable insights into considerable geographical dependency in water consumption patterns within specific locations, suggesting the likelihood of clustering. The Local Moran I analysis is implemented using ESRI ArcMap 10.8.2, a software application. The utilization of this program facilitates the generation of spatial weight matrices, which play a pivotal role in evaluating the interconnections among various geographical areas. In this particular case, the weight matrices serve the purpose of capturing the spatial relationships among neighborhoods. The results of this research lead to the identification of geographical clusters characterized by either high-high or low-low patterns of per capita water consumption. Adopting a localized viewpoint contributes to a deeper comprehension of the reciprocal relationship concerning water consumption between specific regions and their immediate spatial surroundings. Local spatial autocorrelation analysis is vital in unraveling complex geographic variations and patterns in per capita water consumption, which is necessary to guide specific water management plans. ESRI ArcMap 10.8.2 was used to perform the analysis.

4.1.2. Methods Used to Assessment Factors Influencing Water Consumption

The study's second objective is to examine the factors influencing per capita water consumption. Correlation and multiple linear regression analysis were preferred to investigate the factors affecting water consumption. In this way, this study examined the complex factors underlying per capita water consumption. The resulting relationships aim to contribute to water consumption reduction policies. Correlation analysis, a fundamental statistical method, investigated the interrelationships between the dependent variable, per capita water consumption, and the identified independent factors. The present approach facilitated a comprehensive comprehension of the magnitude and orientation of connections, illuminating the discernible trends of impact among the variables. The coefficients of Pearson's correlation were calculated to measure the linear associations, offering valuable information on the magnitude and direction of the linkages. The significance of the correlation coefficients was assessed, which helped identify factors that had statistically significant relationships with per capita water consumption. This information was then utilized to guide the remaining phases of the study. This study's meticulous implementation of correlation analysis established a basis for comprehending the initial associations between two variables. It directed the choice of relevant independent variables for the following analysis using the multiple linear regression method. Utilizing this methodological technique enhanced the overall strength and credibility of the study's investigation of the diverse aspects that impact water consumption patterns. This research used the “correlation analysis” command in SPSS to apply Pearson Correlation Analysis.

The selected analytical methodology, multiple linear regression analysis, is a robust statistical technique to investigate the association between a dependent variable and numerous independent variables. Within the framework of this research about water consumption, the variable under investigation is per capita water consumption, which serves as the dependent variable and signifies the focal point of interest. The research comprehensively examines 13 independent variables divided into three unique categories. These categories represent various factors that might potentially influence the variances seen in water consumption habits. Using multiple linear regression enables the investigation of the relationship between alterations in one or more independent variables and corresponding changes in the dependent variable, providing valuable insights into the quantitative influence of each element. The overarching objective is to construct a regression model that effectively represents the combined impact of these factors on per capita water consumption. The coefficients in the model represent the magnitude and direction of these impacts, offering a detailed comprehension of the complex dynamics in operation. SPSS software was used as the analytical tool to perform the multiple linear regression analysis.

The results of spatial dependence tests test the assumption of independence between data in a model. The presence of geographical dependency not only impacts the accuracy of statistical inference but also provides valuable information on the spatial distribution of the phenomena under investigation. GeoDa software was used to perform LM tests.

4.2. Data and Materials

The investigation utilized cross-sectional data collected in the year 2019. The dependent variable is per capita water consumption. The study encompasses 13 independent variables, classified into three distinct categories. The three categories, including independent variables, are classified as demographic, socioeconomic, and urban variables. Five variables are in the demographic variables category, four are in the socioeconomic variables category, and four are in the urban variables category. All variables consist of continuous variables. Table 3 shows the names of the dependent and independent variables, their definitions, and their data sources. The literature review in Chapter 2 was used effectively in selecting variables. Since this study does not use time series data, climate and price variables are not included in the data set. Additionally, since the aim of this study is not to examine the policy dimension of water consumption management, the price variable was not included in the data set.

The 2019 residential water consumption data of the İzmir Water and Sewerage Administration and population data of the Turkish Statistical Institute were used to obtain the dependent variable. The per capita water consumption was obtained by dividing the total residential water consumption by the population. According to the graph of sectoral water consumption that the İzmir Water and Sewerage Administration generated, the residential water consumption rate was found to be the highest rate (Fig. 6). Because of this, the quantity of per capita water consumption in the study was determined by using residential water consumption as the basis for the calculation.

This study benefited from the 2019 database of the Turkish Statistical Institute in calculating demographic variables such as population density, children population ratio, active population ratio, elderly population ratio, and average household size. The population density was calculated by dividing the population by the built-up area. The children population ratio represents the ratio of the 0-14 age group in the total population; the active population ratio is the ratio of the 15-64 age group in the total population; The elderly population ratio represents the ratio of the 65+ age group in the total population. Average household size refers to the ratio of the total population to the number of households.

The Turkish Statistical Institute 2019 database was used for primary school, higher school, and CWR variables in the socioeconomic variables. For the square meter sales price, 2019 data from "sahibinden.com" and "endeksa.com" real estate websites were used. The primary school graduate population ratio was calculated by dividing the primary school graduate population by the total population. This variable was used to express the low level of education. The higher education graduate population ratio was calculated by dividing the population with bachelor’s, master's, and doctoral degrees by the total population. This variable represents higher education level. The child-woman ratio divides the number of children in the age group 0-4 by the number of women of 15-49 years and then multiplying by 1000. The square meter sales price represents the average annual unit housing sales price in 2019. The square meter sales price is used to refer to the income level.

In the category of urban variables, there are spectral indices such as the NDISI, which represents the impervious rate; the NDBI, which defines the built-up area; and the NDVI. In addition to spectral indices, the LST variable is included in the urban variable category. It aims to evaluate urbanization's impact and its effects on per capita water consumption through urban variables.

Normalized difference impervious surface index is used to analyze impervious surfaces. The impervious surface increases as the value is close to 1[96].

The NDISI can be calculated using this eq. (8):

$$NDISI = \frac{\mathrm{TIR} - (\mathrm{MNDWI} + \mathrm{NIR} + \mathrm{MIR1})/3}{\mathrm{TIR} + (\mathrm{MNDWI} + \mathrm{NIR} + \mathrm{MIR1})/3} \tag{8}$$

The near-infrared, mid-infrared1, and thermal-infrared bands of the Landsat8 images are denoted as NIR, MIR1, and TIR, respectively. The Modified Normalized Difference Water Index (MNDWI) utilizes the enhanced normalized water body index, as suggested by Xu[97].

It can be computed by employing the following eq. (9):

$$MNDWI = \frac{\text{Green} - \text{MIR1}}{\text{Green} + \text{MIR1}} \tag{9}$$

where Green is the green light band. Landsat 8 satellite images from August 2019 were obtained through USGS Earth Explorer to obtain the NDISI.

The normalized difference built-up index was used for analysis of the built-up area. The NDBI is a remote sensing technique that leverages the Near-Infrared (NIR) and Short-Wave Infrared (SWIR) bands to accentuate areas characterized by human-made structures and urban development. The approach is focused on utilizing ratios to address the challenges posed by variations in terrain illumination and atmospheric conditions. The concept of normalizing the difference The Build-up Index value ranges from -1 to +1. A negative number denotes aquatic environments, whereas a greater value signifies urbanized regions[98]. The NDBI can be calculated using this eq. (10):

$$NDBI = (\text{SWIR} - \text{NIR}) / (\text{SWIR} + \text{NIR}) \tag{10}$$

where SWIR is the Band 6. NIR is the Band 5. Landsat 8 satellite images from August 2019 were obtained through USGS Earth Explorer to get the NDBI.

NDVI is widely employed as a vegetation index to monitor vegetation globally. NDVI values range from -1 to 0 and indicate water bodies. NDVI values range from -0.1 to 0.1, indicating areas characterized by barren rocks, sand, or snow. NDVI values ranging from 0.2 to 0.5 indicate shrubs, grasslands, or crops in a senescing state. The range of NDVI values between 0.6 and 1.0 means areas characterized by dense vegetation, such as tropical rainforests[99].

NDVI is calculated as eq. (11):

$$NDVI = (\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red}) \tag{11}$$

where NIR is the Band 5. Red is the Band 4. Landsat 8 satellite images from August 2019 were obtained through USGS Earth Explorer to get the NDVI.

Lastly, data obtained from Landsat 8 satellite images in RsLab were used for the LST variable in the Urban variables category. The Remote Sensing Laboratory, located inside the FORTH Institute of Applied and Computational Mathematics, studies climate change and urbanization[100].

Table 3. Definition of Data

Variable Type	Variable Name	Description	Source
Dependent Variable	Per Capita Water Consumption	The residential water consumption per person	İzmir Water and Sewerage Administration, 2019 TURKSTAT, 2019
DEMOGRAPHIC VARIABLES			
Independent Variable	Population Density	Number of individuals per unit	TURKSTAT, 2019
Independent Variable	Children	Ratio of population aged 0-14 within the total population	TURKSTAT, 2019
Independent Variable	Active	Ratio of population aged 15-64 within the total population	TURKSTAT, 2019
Independent Variable	Elderly	Proportion of population aged 65+ within the total population	TURKSTAT, 2019
Independent Variable	Average Household Size	Average number of individuals forming households	TURKSTAT, 2019
SOCIOECONOMIC VARIABLES			
Independent Variable	Primary School	Ratio of population with primary education.	TURKSTAT, 2019
Independent Variable	Higher School	Ratio of population with higher education	TURKSTAT, 2019
Independent Variable	CWR	Ratio of women and children	TURKSTAT, 2019
Independent Variable	M² Price	Unit selling price of residences	“Sahibinden.com” , 2019 “Endeksa.com”, 2019
URBAN VARIABLES			
Independent Variable	NDISI	Normalized Difference Impervious Surface Index	USGS earth explorer, 2019
Independent Variable	NDBI	Normalized Difference Built-up Index	USGS earth explorer, 2019
Independent Variable	NDVI	Normalized Difference Vegetation Index	USGS earth explorer, 2019
Independent Variable	LST	Land Surface Temperature	“rslab.gr”, 2019

CHAPTER 5

RESULTS AND DISCUSSION

This part of the study includes analysis results and a discussion section. This section consists of two main parts. The first part examines the spatial pattern of per capita water consumption and driving factors in the study area. The spatial distribution of driving factors (demographic, socioeconomic, and urban variables) and the spatial autocorrelation of per capita water consumption were examined in this regard. While the spatial distribution of driving factors was examined by cluster analysis, Global Morans' I and Local Morans' I were used to investigating the spatial autocorrelation of per capita water consumption. Findings have revealed that the per capita water consumption showed a tendency to cluster. If shown cluster tendency, the characteristic features of the regions where high and low consumption are clustered were determined. In the second section, factors affecting per capita water consumption were examined. In this regard, correlation analysis was used to investigate the relationship between per capita water consumption and driving factors. Multiple linear regression analyses examined the causality between variables, showing a linear relationship with per capita water consumption. The multiple linear regression analysis included driving factors that showed a significant linear relationship with per capita water consumption. The assumptions of multiple linear regression analysis are tested in this section.

5.1. Understanding The Spatial Pattern of Per Capita Water Consumption and Driving Factors

The study conducted a cluster analysis to improve the comprehensibility of unique characteristics within the designated geographical region. This analysis aims to categorize the study area into coherent clusters, enabling a more intricate comprehension of its attributes. A cluster was utilized for this objective, which was conducted automatically through SPSS software. The two-step cluster technique is primarily intended for analyzing extensive datasets. The program employs a clustering technique to group the data based on a statistical proximity. The methodology uses an agglomerative hierarchical clustering technique.

In contrast to traditional approaches in cluster analysis, the two-step method can handle both continuous and categorical characteristics. Applying this technique allowed the automatic identification of two distinct clusters and provided information about the characteristics of the study area. Clusters were mapped for the study area via ArcMap 10.8.2 to examine the spatial distribution of the identified features.

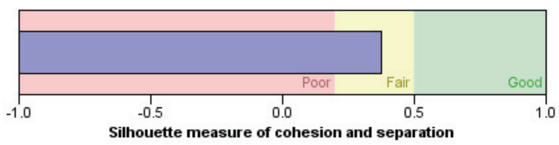
The Silhouette Score is a statistic used to evaluate the clustering quality by measuring the degree of distinctiveness and separation across clusters. Computed for every data point, it considers the mean distance inside its designated cluster (cohesion) and the minimum mean distance between points in other clusters (separation). The Silhouette Score, which ranges from -1 to 1, measures cluster distinctiveness. A higher score implies well-separated clusters, whereas a lower score denotes clusters that overlap or are poorly divided. This measure facilitates the assessment of clustering algorithms by offering insights into the compactness and uniqueness of the detected clusters[101]. The quality of the clusters is seen as 0.4. This value shows that the clusters are statistically acceptable (Table 4).

Table 4. Model Summary of Cluster Analysis

Model Summary

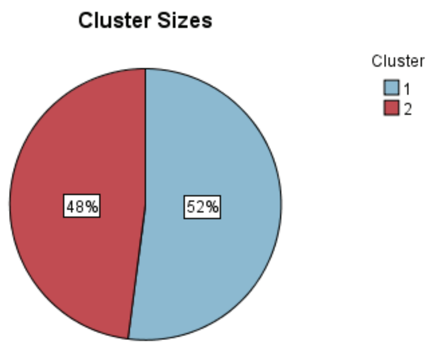
Algorithm	TwoStep
Inputs	13
Clusters	2

Cluster Quality



The direct marketing tool employs a cluster analysis approach that utilizes an automated algorithm for the clustering process. Given that the dataset comprises continuous variables, the Log-likelihood distance measurement was chosen as the preferred method. Cluster analysis is a statistical technique that divides neighborhoods into separate groups based on statistical divergence, thereby revealing unique characteristics associated with each cluster. Two options for specifying the number of clusters in cluster analysis: determine automatically and specify fixed. The determine automatically option was chosen to determine the most accurate number of clusters according to the nature of the dataset. As a result, two clusters were automatically created.

Figure 9 shows the size of the clusters.



Size of Smallest Cluster	108 (48%)
Size of Largest Cluster	117 (52%)
Ratio of Sizes: Largest Cluster to Smallest Cluster	1.08

Figure 9. Cluster Sizes

Quantile-based clustering utilizes ideally selected quantiles to describe the clusters[102]. When comparing clusters using a quantile plot, using median values aids in assessing the central tendency of each cluster and analyzing differences across clusters. Figure 10 shows the median values of the variables in Cluster 1 and Cluster 2. This comparison offers valuable insights into the disparities in different characteristics between the two clusters, aiding in the characterization and comparison of the clusters based on the provided variables. As a result of the cluster analysis, remarkable results were obtained in terms of demographics and socioeconomics. There is no clear clustering in terms of urban variables. This may be because the neighborhoods in the study area have similar urban characteristics. Population density, active population rate, and LST values of Cluster 1 and Cluster 2 are similar to each other.

Accordingly, the properties of the clusters are as follows: Cluster 1 has a lower median household size than Cluster 2, indicating smaller households in Cluster 1. The median values for the elderly population ratio are higher in Cluster 1, indicating a higher elderly ratio in that cluster. In contrast, Cluster 1 has a lower children population ratio. Cluster 1 has a higher average Population Density than Cluster 2; This indicates that Cluster 1 is more densely populated. Cluster 1 has higher median values for a higher education population ratio than Cluster 2. This indicates that Cluster 1 has more individuals with higher education levels. Cluster 1 has a high income level. Cluster 1 has a lower median value for CWR, suggesting a smaller child-woman ratio in this cluster. A low CWR value indicates a high socioeconomic status. Both clusters have relatively high NDISI values, but Cluster 1 has a higher median, indicating the presence of more impervious surfaces.

When Cluster 2 is examined from a demographic perspective, it is seen that the average household size and children population are higher. In short, crowded families live in this region. From socioeconomic variables, lower levels of education and income are notable. Concurrently, the high value of the CWR indicates a lower socioeconomic status. Cluster 2 represents a region with a low socioeconomic status. Relatively low NDISI values are observed in Cluster 2.

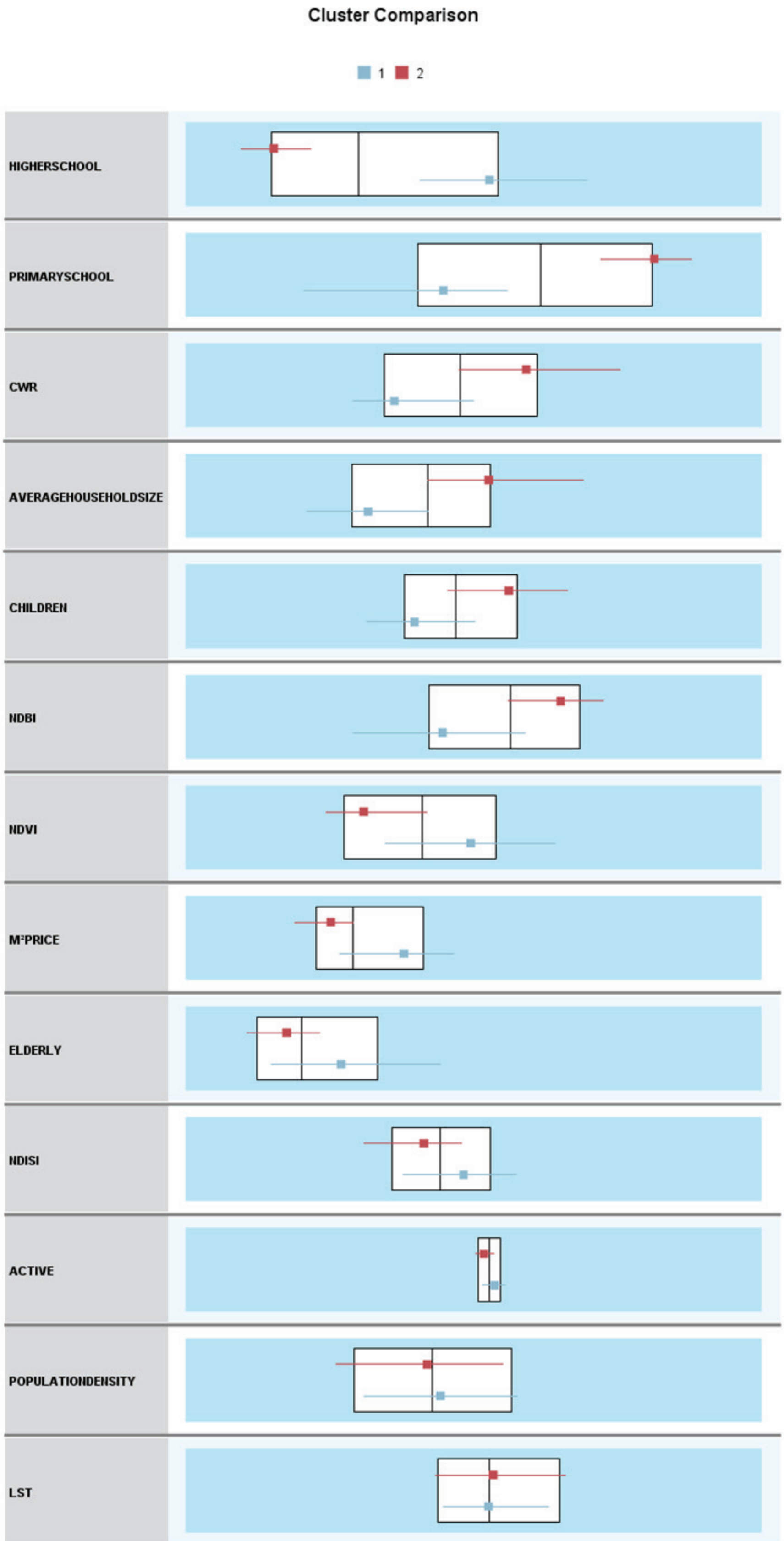


Figure 10. Cluster Comparison

The spatial distribution of the clusters on the map (Figure 11) shows that the neighborhoods belonging to Cluster 1 encompass Çiğli, Narlıdere, Balçova, Güzelbahçe, Karşıyaka Districts, and part of Karabağlar and the coastal part of Konak district. Cluster 2 encompasses Buca, Bornova, Bayraklı, and Karabağlar Districts.

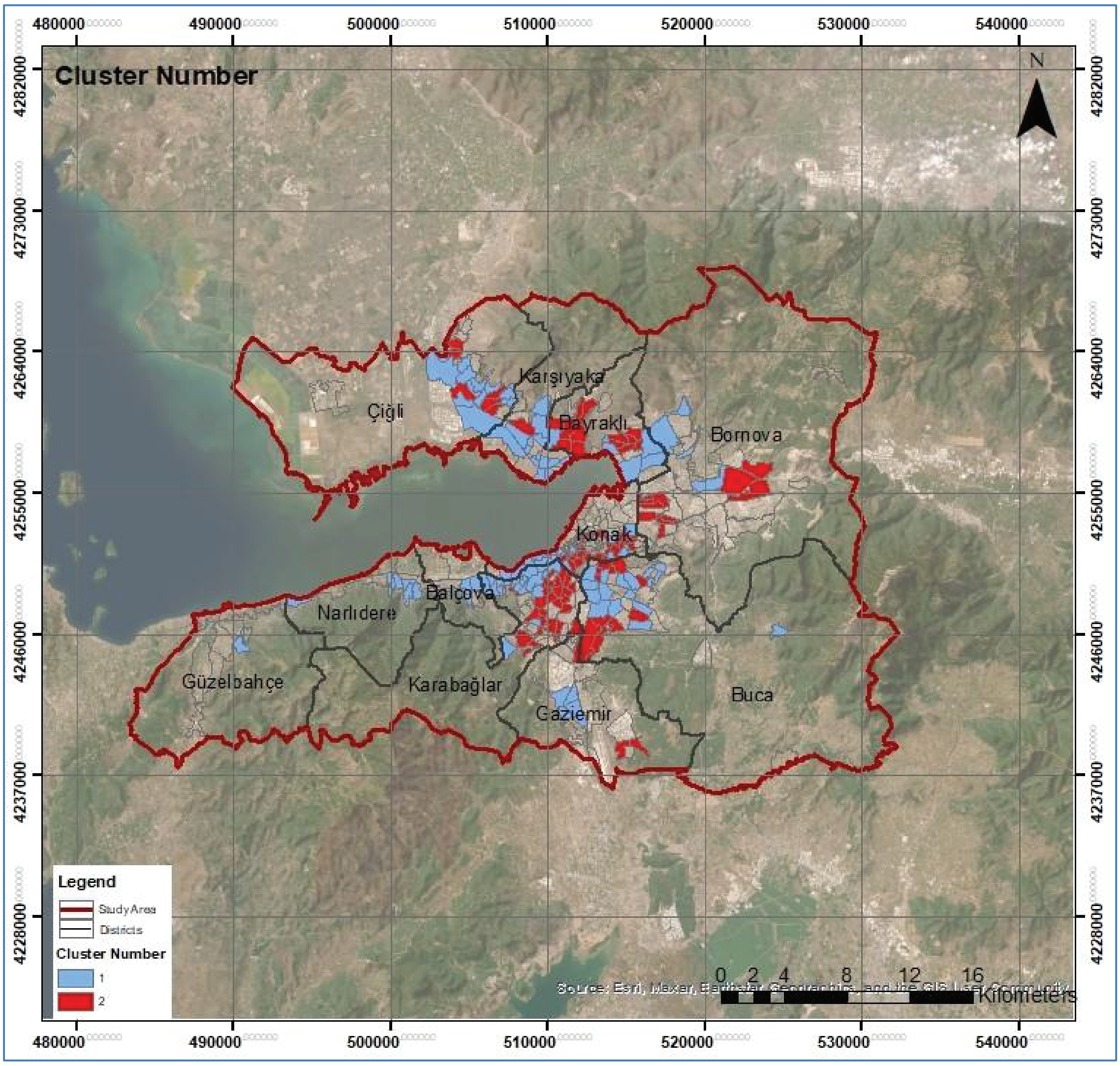


Figure 11. Cluster Number

Distributions of elderly population ratio, average household size, higher education ratio, square meter sales price, and impervious surface ratio according to clusters are shown on the maps. The blue circle represents Cluster 1. The red circle represents Cluster 2.

Figure 12 shows the distribution of the elderly population ratio by cluster. The elderly population ratio increases from light to dark color. While the lowest elderly population ratio is 0.04, the highest is 0.34. It is seen that Cluster 1 increases in regions where the elderly population ratio increases.

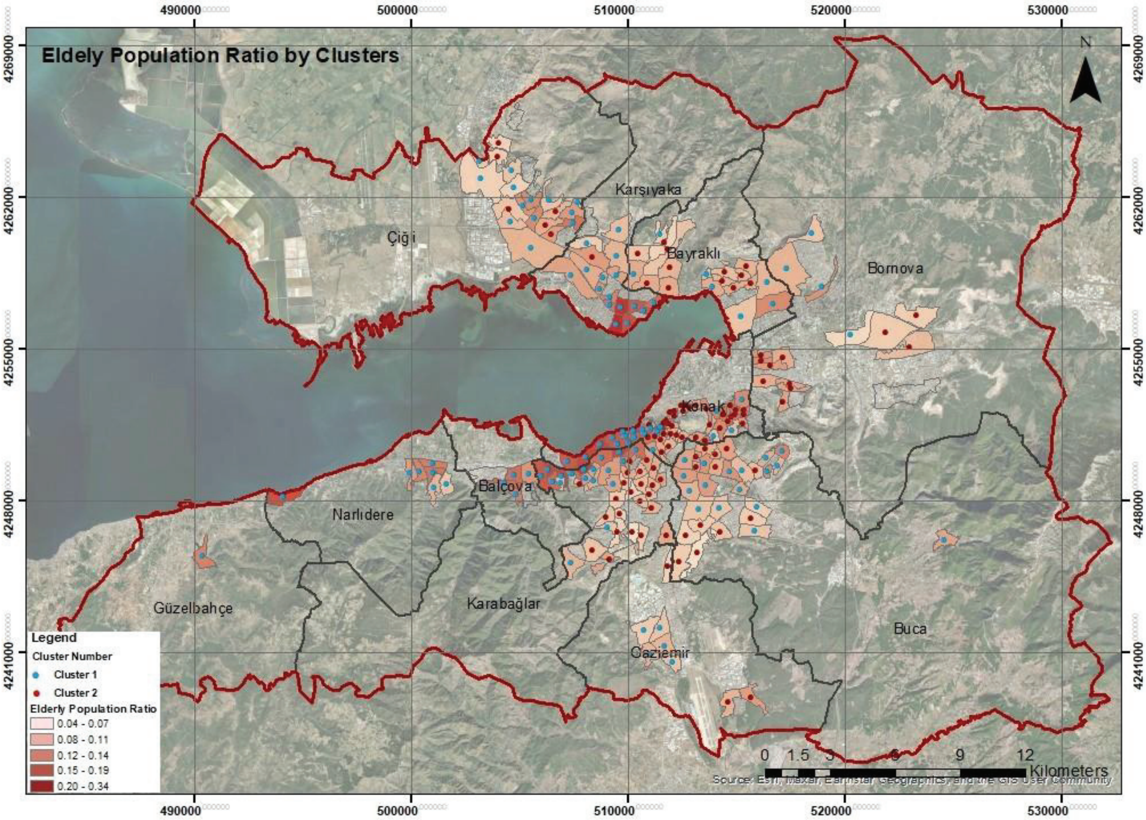


Figure 12. Elderly Population Ratio by Clusters

Figure 13 shows the distribution of average household size by cluster. Blue colors represent values between 2.10 and 2.62. Light green colors represent values between 2.63 and 2.91. Light orange colors represent values between 2.92 and 3.17. Orange colors represent values between 3.18 and 3.50. Red values represent values between 3.51 and 4.10. Cluster 2 is increasing in regions where the average household size is increasing.

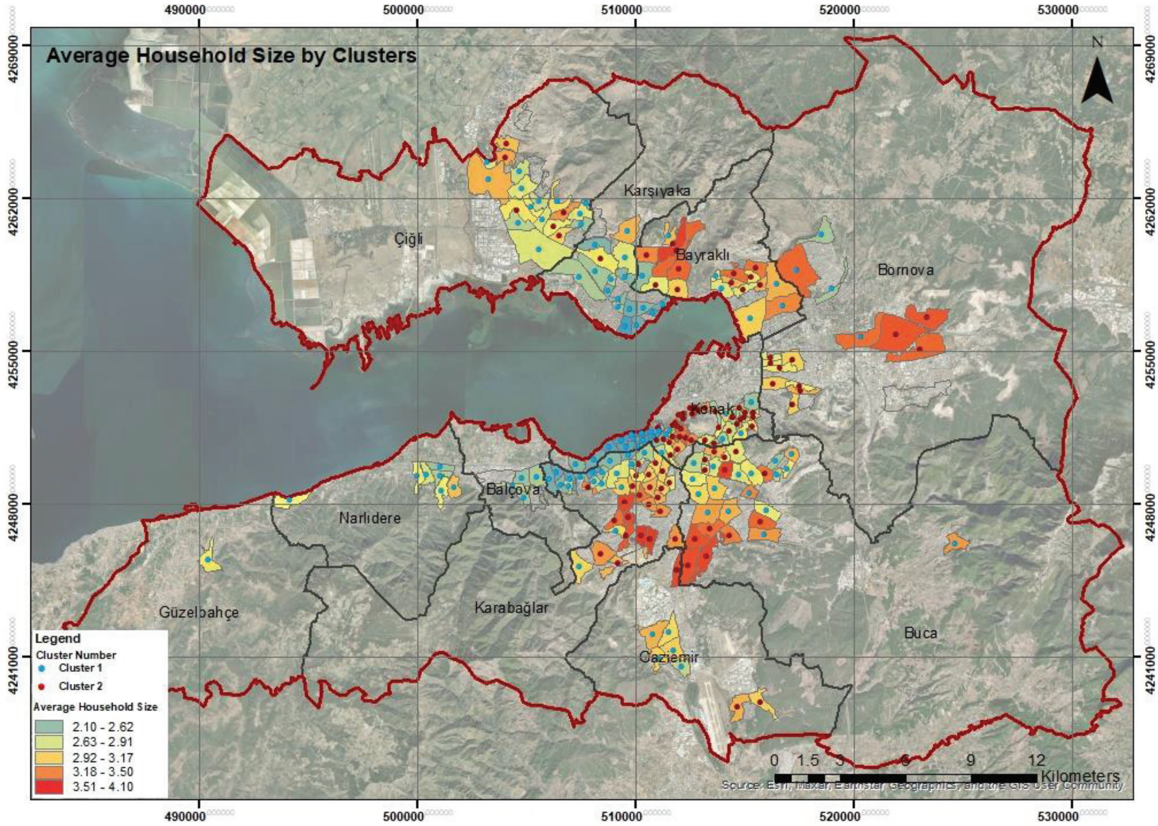


Figure 13. Average Household Size by Clusters

Figure 14 shows the distribution of higher education ratio by cluster. Green colors represent values between 0 and 0.10. Yellow colors represent values between 0.11 and 0.20. Orange colors represent values between 0.21 and 0.32. Dark pink colors represent values between 0.33 and 0.53. Light pink colors represent values between 0.54 and 0.88. According to the map, Cluster 2 shows an increase in regions with a low higher education ratio.

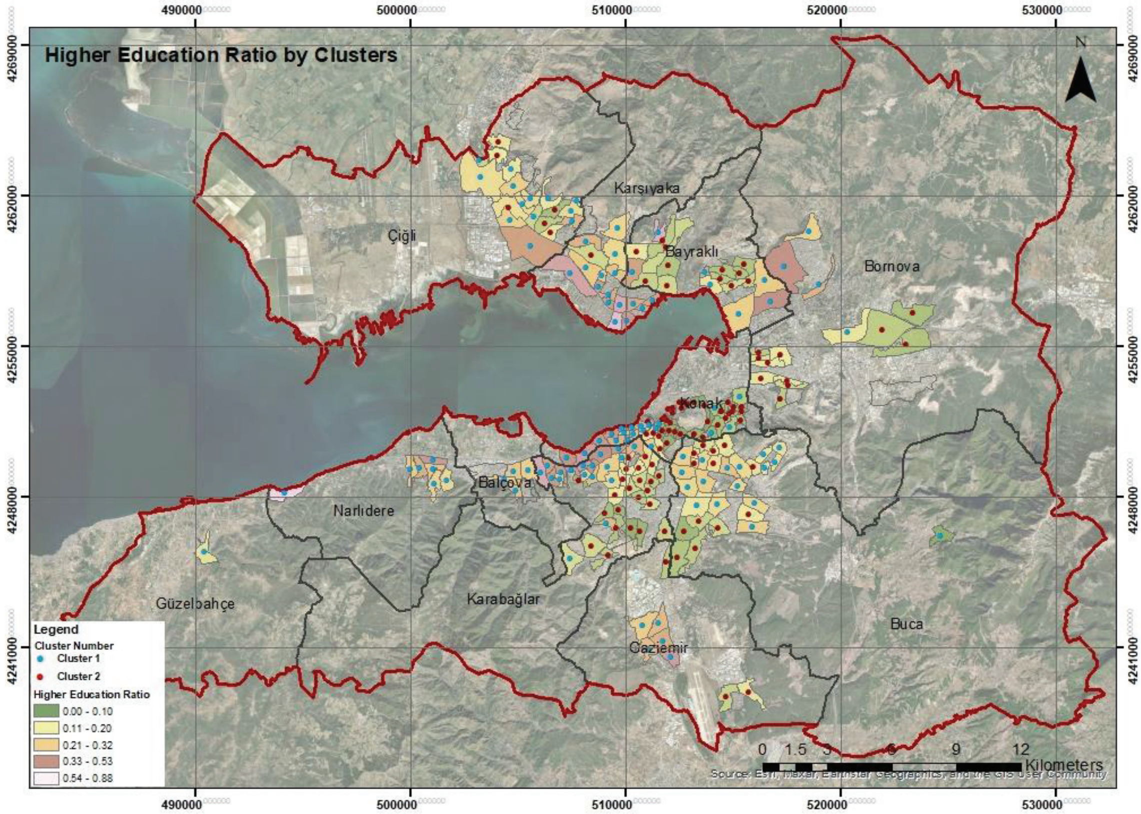


Figure 14. Higher Education Ratio by Clusters

Figure 15 shows the distribution of square meter sales price by cluster. Square meter sales prices increase from light blue to dark blue. While the lowest square meter sales price is 1129.58 Turkish Liras, the highest square meter sales price is 6164.08 Turkish Liras. Cluster 1 shows an increase in regions where square meter sales prices increase.

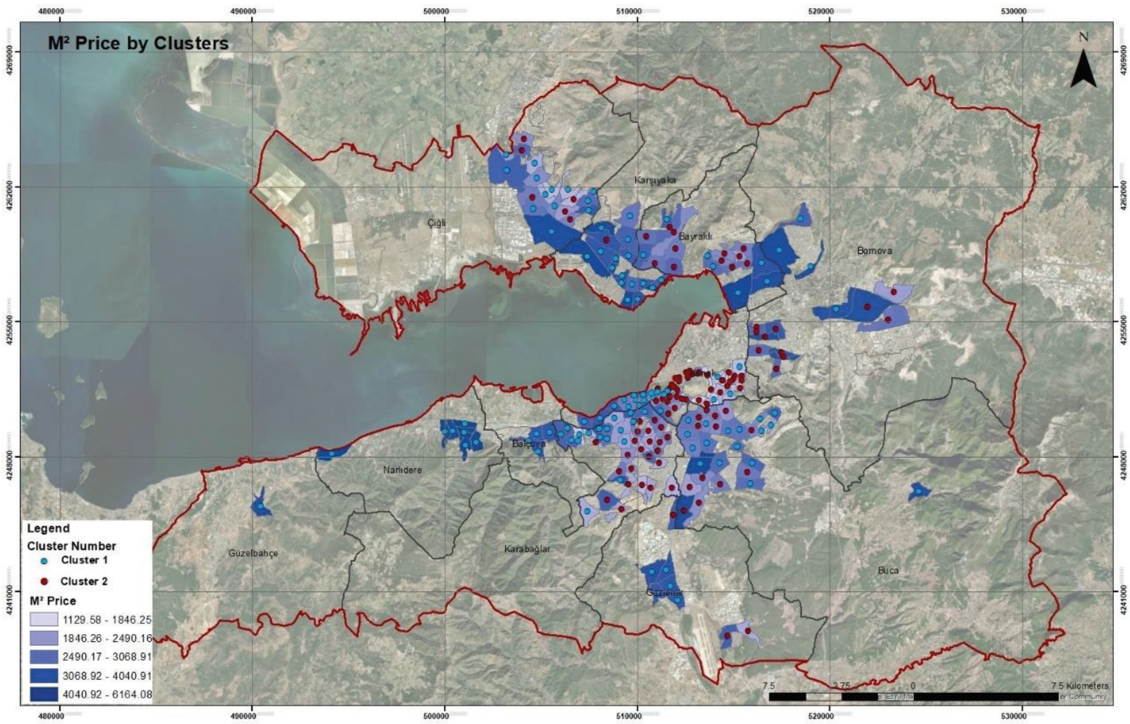


Figure 15. Square Meter Sales Price by Clusters

Figure 16 shows the distribution of impervious surface ratio by cluster. Dark green colors represent values between 0.46 and 0.48. Light green colors represent values between 0.49 and 0.50. Yellow colors represent values between 0.51 and 0.52. Orange colors represent colors between 0.53 and 0.54. Red colors represent values between 0.55 and 0.56. However, there is no precise distribution in clusters with similar urban characteristics; Cluster 1 increases in regions with a higher impervious surface ratio.

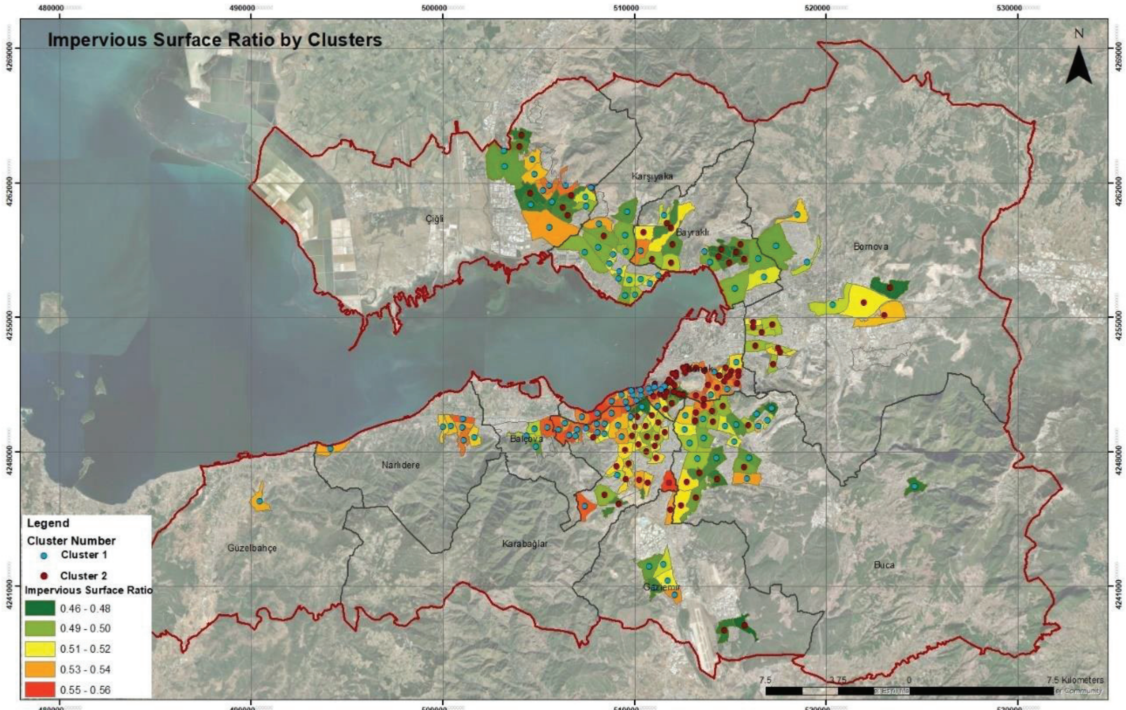


Figure 16. Impervious Surface Ratio by Clusters

Finally, Cluster 1 is characterized by an elderly population, low average household size, and high socioeconomic status. Cluster 2 is characterized by a high child population ratio, high average household size, and low socioeconomic status.

When examining the spatial distribution of driving factors with cluster analysis, it was observed that there was a tendency to cluster. Similarly, spatial autocorrelation analysis was used as a spatial statistics method to examine the spatial dependence and spatial pattern of per capita water consumption. The "Inverse Distance" method conceptualized spatial relationships in the spatial autocorrelations analyses. In this approach, proximity to surrounding features has a greater impact on the calculations for a target feature than distant features. The Euclidean Distance method for calculating distance was used. Global Moran's I, a measure of spatial autocorrelation, evaluates whether the observed water consumption pattern exhibits clustering, dispersion, or random distribution throughout the study area. Figure 17 contains the results of spatial autocorrelation. The spatiality of per capita water consumption has been studied. The z-score value, indicate that water consumption across the study area is not randomly distributed. Moran's I value close to 1 shows a positive autocorrelation. As a result, there is a spatial auto-correlation between per capita water consumption in neighborhoods.

With a z-score of 11.8071070006, the probability of this clustered pattern occurring by random chance is less than 1%.

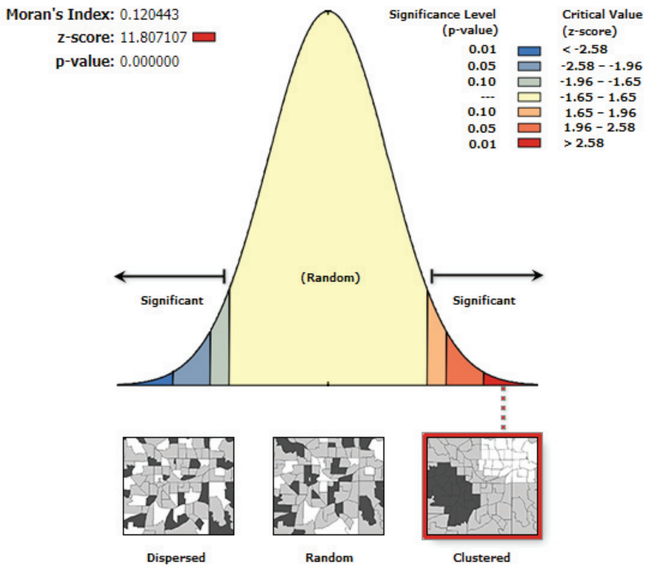


Figure 17. Global Moran's I

Local Moran's I aims to conduct a thorough spatial autocorrelation analysis by evaluating the concentration or dispersion of variable values at a local scale within a designated research region. Contrary to Global Moran's I, which assesses spatial autocorrelation for the whole research region, Local Moran's I specifically identifies places where clustering or outlier patterns are present. This statistic is especially valuable in water consumption research as it identifies specific areas with strong spatial relationships. It facilitates a more detailed comprehension of localized per capita water consumption patterns. The outcomes of Local Moran's I can determine if certain regions form clusters characterized by comparable consumption levels (high-high or low-low clusters) or whether they diverge from surrounding regions (high-low or low-high outliers). According to the results of the local spatial autocorrelation (Fig. 18), local-level spatial dependence is observed in the neighborhoods located in the western axis of İzmir. It is seen that the neighborhoods in Güzelbahçe, Narlıdere, Balçova, and Karabağlar Districts are hotspots of per capita water consumption. It is seen that there are coldspots of per capita water consumption in the neighborhoods located in Buca District and Konak District. On the contrary, a negative correlation exists between Buca District and Bayraklı District neighborhoods.

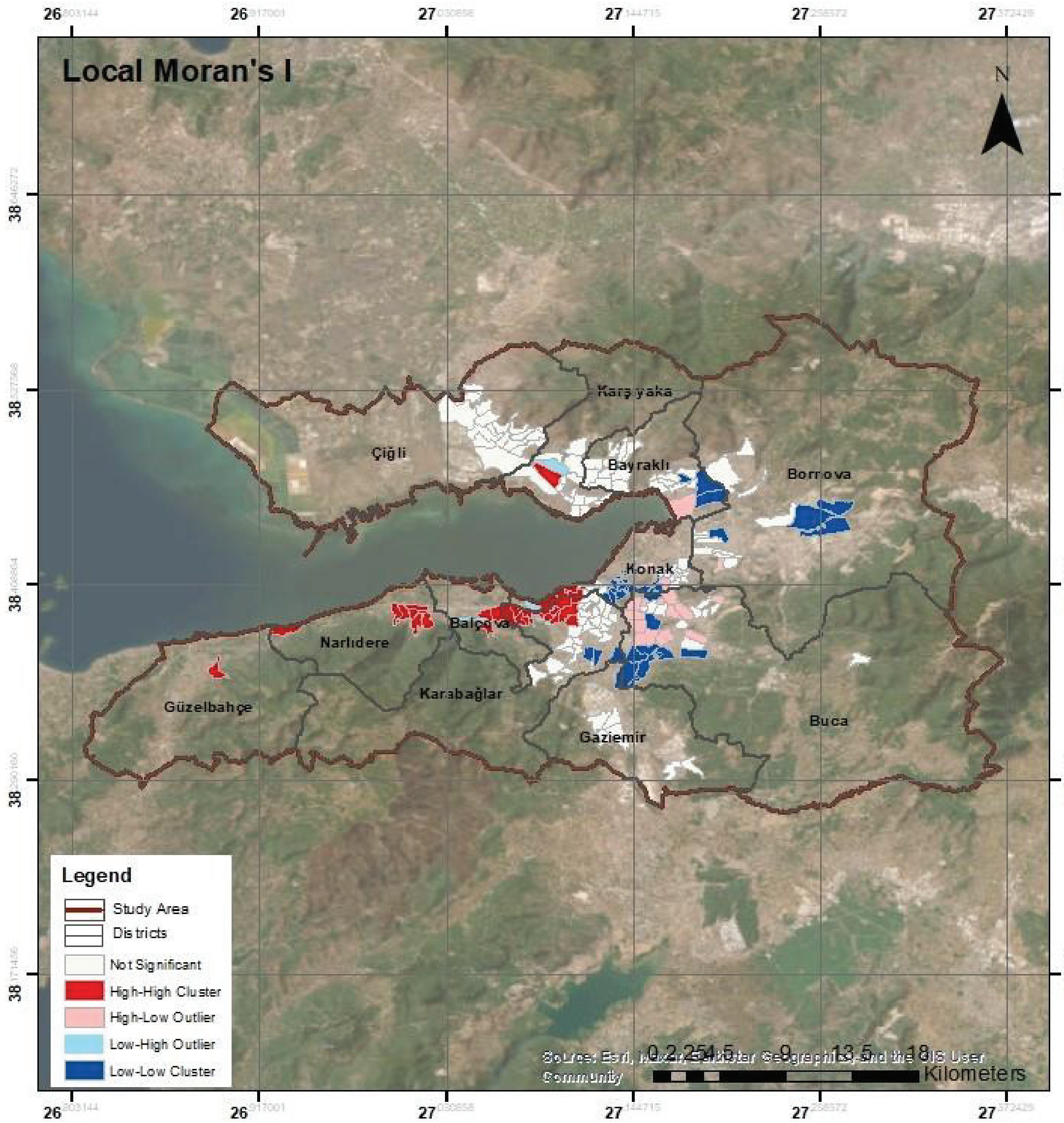


Figure 18. Local Moran's I

A comparison of which statistical cluster of the previous assessment coincides with the hotspot and coldspot regions is given in Table 5. All hotspots are included in Cluster 1. Per capita, water consumption is high in areas where older people live, and there are smaller-sized households. This region also attracts attention with its high socioeconomic level. High education, high income, and low CWR levels characterize a higher socioeconomic status. High socioeconomic status is frequently linked to high financial capacity and availability of diverse luxuries, including more water-intensive appliances and lifestyles. Cluster 1 is characterized by a significant presence of impervious surfaces, such as pavements and roads, but a relatively low built-up area. Additionally, this cluster has urban landscape characteristics. On the contrary, Cluster 2, where cold spots (low per capita water consumption) are concentrated at 33%, describes a region where crowded families with children live. At the same time, individuals with low socioeconomic status have been associated with low per capita water consumption. These regions also have impervious surfaces lower than in Cluster 1. Regions with low per capita water consumption are those with low impervious surface ratio.

Table 5. Neighborhoods by Clusters

Cluster Number	Cluster Size (number of neighborhoods)	Hotspots (number of neighborhoods)	Coldspots (number of neighborhoods)
1	117	30	7
2	108	0	36
TOTAL	225	30	43

5.2. Assessment of The Relationship Between Per Capita Water Consumption and Factors

The study's second objective is to assess the relationship between per capita water consumption and driving factors with correlation and multiple regression analyses. Correlation analysis, a fundamental statistical technique, was selected to examine the relationships between per capita water consumption (the dependent variable) and identified independent variables. This approach enabled a comprehensive comprehension of the magnitude and orientation of connections, revealing noticeable patterns among the factors. The Pearson correlation coefficients were calculated to measure linear relationships, offering valuable insights into the strength and direction of these linkages. Statistical analyses were conducted to determine the significance of these correlation coefficients, which identified characteristics that had statistically significant associations with per capita water consumption. This information influenced the following stages of the investigation, where correlation analysis not only established the basis for comprehending early connections between variables but also led to the choice of relevant independent variables for later multiple linear regression analysis. The careful implementation of this systematic methodology enhanced the overall strength and dependability of the study's investigation of the many aspects that affect water consumption patterns.

Before completing multiple linear regression analysis, a correlation analysis was undertaken to ascertain the presence of a linear connection between the dependent and independent variables. The presence of "**" denotes a statistically significant association at the 0.01 level. The symbol "*" denotes that the association is statistically significant at the 0.05 significance level. The correlation study includes 225 cases. Correlation analysis results are given in Table 6, first examining the correlation between per capita water consumption and demographic factors. The correlation study reveals a weak but statistically significant positive association ($r = 0.168$, $p < 0.05$) between per capita water consumption and population density. This situation suggests that regions with higher population density consume more water per capita.

On the other hand, there is a significant negative association ($r = -0.449$, $p < 0.01$) between the amount of per capita water consumption and the children population ratio. This result suggests that areas with a greater proportion of children often have lower per capita water consumption. Furthermore, a notable positive association ($r = 0.292$, $p < 0.01$) between per capita water consumption and the number of older people has been seen. This result shows that regions with more older people tend to exhibit higher levels of water consumption. This correlation may be related to the correlation between the elderly population and average household size. The negative correlation of the increase in the elderly population in the average household may be the underlying reason for the relationships. The negative correlation between average household size and per capita water consumption indicates that a greater number of people sharing a home tend to have lower per capita water consumption. This result might be attributed to the distribution of water consumption across more persons ($r = -0.577^{**}$, $p < 0.01$).

An analysis of the correlation between per capita water consumption and socioeconomic characteristics yielded significant findings. Higher education and income levels represent an increase socioeconomic status. A low CWR indicates a high socioeconomic status. This result means regions with more educated populations, wealth, and higher socioeconomic status tend to have higher per capita water consumption. The correlation coefficients for these relationships are as follows: Higher School: $r = 0.648^{**}$, $p < 0.01$; M^2 Price: $r = 0.405^{**}$, $p < 0.01$; CWR: $r = -0.475^{**}$, $p < 0.01$. The negative association between primary school education and per capita water consumption shows that places with greater rates of primary school education, an indicator of low level of education, may have lower levels of per capita water consumption (Primary School: $r = -0.361^{**}$, $p < 0.01$).

Notable trends emerged from investigating the correlation between per capita water consumption and urban characteristics. The data showed a positive connection between per capita water consumption and NDISI. This result suggests that places with higher impervious surface ratios, which indicate more urbanization, tend to have higher per capita water consumption ($r=0.299^{**}$, $p < 0.01$). On the other hand, a negative connection was found between NDBI and per capita water consumption. This result suggests that places with lower built-up indices, which may indicate less building and urban growth, tend to have greater water consumption ($r= = -0.231^{**}$, $p < 0.01$). The increase in the proportion of impervious surfaces such as roads and pavements means that the built-up area does not increase. A modest positive correlation ($r= 0.150^{*}$, $p < 0.05$) exists between NDVI and per capita water consumption. A correlation between per capita water consumption and NDVI implies that regions with greater vegetation and plant life typically exhibit elevated water consumption. The positive relationship between NDVI and educational and income levels may be associated with the inclination of individuals with higher socioeconomic status to reside in neighborhoods with high green space. Individuals with higher socioeconomic status may tend to choose better living spaces. A negative relationship is observed among variables defining average household size and high socioeconomic status. These relationships may imply indirect associations underlying per capita water consumption.

Table 6. Correlation Analysis Results

Correlations															
		DEMOGRAPHIC VARIABLES						SOCIOECONOMIC VARIABLES				URBAN VARIABLES			
		Per Capita Water Consumption	POPULATION DENSITY	CHILDREN	ACTIVE	ELDERLY	AVERAGE HOUSEHOLD SIZE	PRIMARY SCHOOL	HIGHER SCHOOL	CWR	M²PRICE	NDISI	NDBI	NDVI	LST
Per Capita Water	Pearson	1	.168*	-.449**	0.067	.292**	-.577**	-.361**	.648**	-.475**	.405**	.299**	-.231**	.150*	-0.109
POPULATION DENSITY	Pearson	.168*	1	-.197**	0.050	.256**	-.242**	-0.075	.282**	-.208**	0.003	.195**	.435**	-.454**	-.171*
CHILDREN	Pearson	-.449**	-.197**	1	.236**	-.667**	.797**	.244**	-.557**	.804**	-.174**	-.261**	0.108	-0.108	.178**
ACTIVE	Pearson	0.067	0.050	.236**	1	0.078	-0.028	-0.117	0.050	-0.107	0.118	0.043	-0.104	0.044	0.077
ELDERLY	Pearson	.292**	.256**	-.667**	0.078	1	-.705**	-.202**	.430**	-.621**	0.122	.368**	0.026	0.025	-.383**
AVERAGEHOUSEHOLDSIZ	Pearson	-.577**	-.242**	.797**	-0.028	-.705**	1	.271**	-.571**	.718**	-.155*	-.374**	0.109	-0.096	.193**
PRIMARYSCHOOL	Pearson	-.361**	-0.075	.244**	-0.117	-.202**	.271**	1	-.610**	.309**	-.508**	-.206**	.288**	-.237**	0.100
HIGHERSCHOOL	Pearson	.648**	.282**	-.557**	0.050	.430**	-.571**	-.610**	1	-.652**	.550**	.236**	-.380**	.311**	-0.028
CWR	Pearson	-.475**	-.208**	.804**	-0.107	-.621**	.718**	.309**	-.652**	1	-.301**	-.215**	.194**	-.157*	0.104
M²PRICE	Pearson	.405**	0.003	-.174**	0.118	0.122	-.155*	-.508**	.550**	-.301**	1	-0.022	-.324**	.215**	-0.030
NDISI	Pearson	.299**	.195**	-.261**	0.043	.368**	-.374**	-.206**	.236**	-.215**	-0.022	1	-.134*	0.057	-.316**
NDBI	Pearson	-.231**	.435**	0.108	-0.104	0.026	0.109	.288**	-.380**	.194**	-.324**	-.134*	1	-.865**	-0.101
NDVI	Pearson	.150*	-.454**	-0.108	0.044	0.025	-0.096	-.237**	.311**	-.157*	.215**	0.057	-.865**	1	0.078
LST	Pearson	-0.109	-.171*	.178**	0.077	-.383**	.193**	0.100	-0.028	0.104	-0.030	-.316**	-0.101	0.078	1

Investigating the link between per capita water consumption and its driving variables requires a dual analytical technique that combines correlation and multiple regression analysis. Correlation analysis was a foundation for comprehending the early associations between per capita water consumption and demographic, socioeconomic, or urban characteristics. Multiple linear regression analysis expands upon the study by examining the multivariate connections between per capita water consumption and independent factors. This approach facilitates the recognition of significant factors and their distinct impacts on water consumption patterns.

Based on the presented findings, statistically significant variables were included in multiple linear regression analyses to investigate their impact on per capita water consumption. Children population ratio, elderly population ratio, and average household size, among demographic variables, showed statistically significant relationships with per capita water consumption. The active population did not show significant correlations. Among the socioeconomic variables, primary school graduate population ratio, higher education graduate population ratio, square meter sales price, and CWR showed significant correlations. While urban variables such as NDISI and NDBI, which are among the urban variables, showed significant correlations, LST did not show significant correlations. As a result, children population ratio, elderly population ratio, average household size, primary school graduate population ratio, higher education graduate population ratio, square meter sales price, CWR, NDISI, and NDBI variables were included in the regression analysis. Evaluating regression assumptions is vital in guaranteeing the accuracy and dependability of regression analysis. Firstly, the linearity study evaluates whether the connection between the independent and dependent variables is well represented by a linear model (Table 6). A Pearson r of approximately 0.20-0.30 is expected between the dependent and independent variables.

The forward method in multiple regression analysis is a systematic procedure for constructing a predictive model by progressively picking independent variables that impact the model's explanatory capacity the most. The process starts with an absence of variables in the model, and at each phase, the variable that demonstrates the most robust correlation with the dependent variable is included. This incremental incorporation process persists until no other variables substantially enhance the model's adequacy. The forward technique aids in identifying the most influential predictors and streamlines the model by including only those variables that significantly explain the variation in the dependent variable. This methodology was preferred because it creates short and understandable regression models and increases the overall predictive ability of the model.

Another assumption of multiple linear regression analysis is the condition of non-multicollinearity. Therefore, the VIF value was checked. If the VIF value is below 4, it is considered that there is no multicollinearity problem[103]. There is no multicollinearity problem between the variables (Table 7).

Table 7. Table of Coefficients

Coefficients[a]											
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	33.503	0.309		108.515	0.000					
	HIGHERSCHOOL	19.951	1.558	0.654	12.807	0.000	0.654	0.654	0.654	1.000	1.000
2	(Constant)	42.556	1.739		24.473	0.000					
	HIGHERSCHOOL	14.644	1.781	0.480	8.222	0.000	0.654	0.486	0.396	0.682	1.467
	AVERAGEHOUSEHOLDSIZE	-2.704	0.512	-0.308	-5.281	0.000	-0.579	-0.336	-0.254	0.682	1.467
3	(Constant)	49.056	2.634		18.622	0.000					
	HIGHERSCHOOL	15.184	1.752	0.497	8.667	0.000	0.654	0.506	0.409	0.676	1.480
	AVERAGEHOUSEHOLDSIZE	-4.196	0.681	-0.478	-6.159	0.000	-0.579	-0.385	-0.290	0.369	2.709
	ELDERLY	-18.088	5.594	-0.236	-3.233	0.001	0.367	-0.214	-0.152	0.416	2.401
4	(Constant)	48.681	2.604		18.694	0.000					
	HIGHERSCHOOL	11.928	2.134	0.391	5.589	0.000	0.654	0.355	0.260	0.443	2.256
	AVERAGEHOUSEHOLDSIZE	-4.521	0.684	-0.515	-6.610	0.000	-0.579	-0.409	-0.308	0.357	2.802
	ELDERLY	-17.609	5.525	-0.230	-3.187	0.002	0.367	-0.211	-0.148	0.416	2.404
	M²PRICE	0.001	0.000	0.151	2.602	0.010	0.402	0.174	0.121	0.646	1.548
5	(Constant)	33.300	6.580		5.061	0.000					
	HIGHERSCHOOL	11.413	2.118	0.374	5.389	0.000	0.654	0.344	0.248	0.439	2.276
	AVERAGEHOUSEHOLDSIZE	-4.299	0.681	-0.490	-6.311	0.000	-0.579	-0.395	-0.290	0.351	2.849
	ELDERLY	-19.236	5.494	-0.251	-3.501	0.001	0.367	-0.232	-0.161	0.410	2.437
	M²PRICE	0.001	0.000	0.169	2.929	0.004	0.402	0.195	0.135	0.636	1.572
	NDISI	28.748	11.319	0.128	2.540	0.012	0.310	0.170	0.117	0.829	1.207

a. Dependent Variable: Per Capita Water Consumption

Detection of outliers is essential in regression analysis. The first option to identify outliers is to check the maximum value of "std.Residual." This value should be in the range of -3.29 to +3.29. Accordingly, the number of outliers is in the "Casewise Diagnostics" table (Table 8). The second option to identify outliers is to check the Mahalanobis, Cook's, and Leverage values in the residual statistics (Table 9).

Table 8. Casewise Diagnostics

Casewise Diagnostics[a]				
Case Number	Std. Residual	Per Capita Water Consumption	Predicted Value	Residual
213	3.270	50.872975277067300	42.727118938821700	8.145856338245600
a. Dependent Variable: Per Capita Water Consumption				

The maximum "Std. Residual" value should be between "-3.29 and +3.29"[104]. However, it was determined that case number 213 was an outlier in the "Casewise Diagnostics" table.

Table 9. Residuals Statistics

Residuals Statistics[a]					
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	30.497924804687500	43.228572845459000	36.762596150676100	2.694890477416360	225
Std. Predicted Value	-2.325	2.399	0.000	1.000	225
Standard Error of Predicted Value	0.179	1.235	0.386	0.130	225
Adjusted Predicted Value	29.702882766723600	42.622253417968700	36.762555567590100	2.694670081370910	225
Residual	-6.030695438385010	8.145855903625490	0.000000000000018	2.463150660849090	225
Std. Residual	-2.421	3.270	0.000	0.989	225
Stud. Residual	-2.451	3.374	0.000	1.006	225
Deleted Residual	-6.305531978607180	8.669904708862300	0.000040583086069	2.552430558465990	225
Stud. Deleted Residual	-2.480	3.457	0.001	1.012	225
Mahal. Distance	0.166	54.073	4.978	4.941	225
Cook's Distance	0.000	0.122	0.006	0.015	225
Centered Leverage Value	0.001	0.241	0.022	0.022	225
a. Dependent Variable: Per Capita Water Consumption					

In addition, Mahalanobis distance, Cook's distance, and Leverage value are checked. The chi-square table is used to consult concerning the number of independent variables for the Mahalanobis value. The value of 0.001 is checked. Since nine independent variables are included in the analysis, the maximum Mahalanobis value should be 27.878. The Cook's distance value is tested using the formula 4/n-k-1, where n represents the number of cases and k represents the number of independent variables[105]. The Leverage value is tested using the formula 2k+2/n, where n represents the number of cases and k represents the number of independent variables. Accordingly, the maximum Cook's Distance value is 0.02; the Leverage Value should be 0.09. Cases above these values were removed from the data set.

Histogram and P-P plot graphs were examined to examine whether the errors were normally distributed. It was observed that the errors are distributed in a normal distribution (Fig. 19 and Fig. 20).

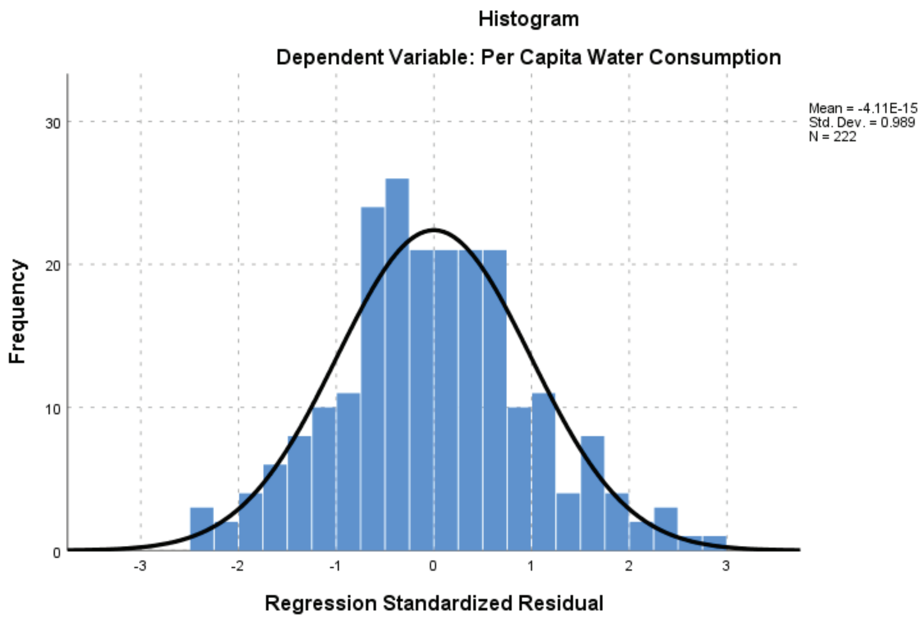


Figure 19. Histogram Graph

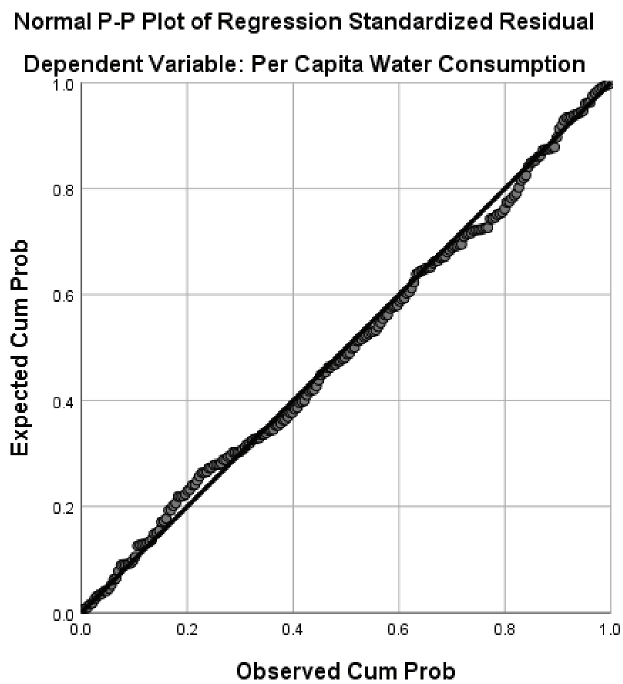


Figure 20. Normal P-P Plot of Regression Standardized Residual

Homoscedasticity, one of the assumptions of regression analysis, was examined. As a result, points should be spread as evenly as possible and have a rectangular distribution. The Homoscedasticity condition was satisfied (Fig. 21).

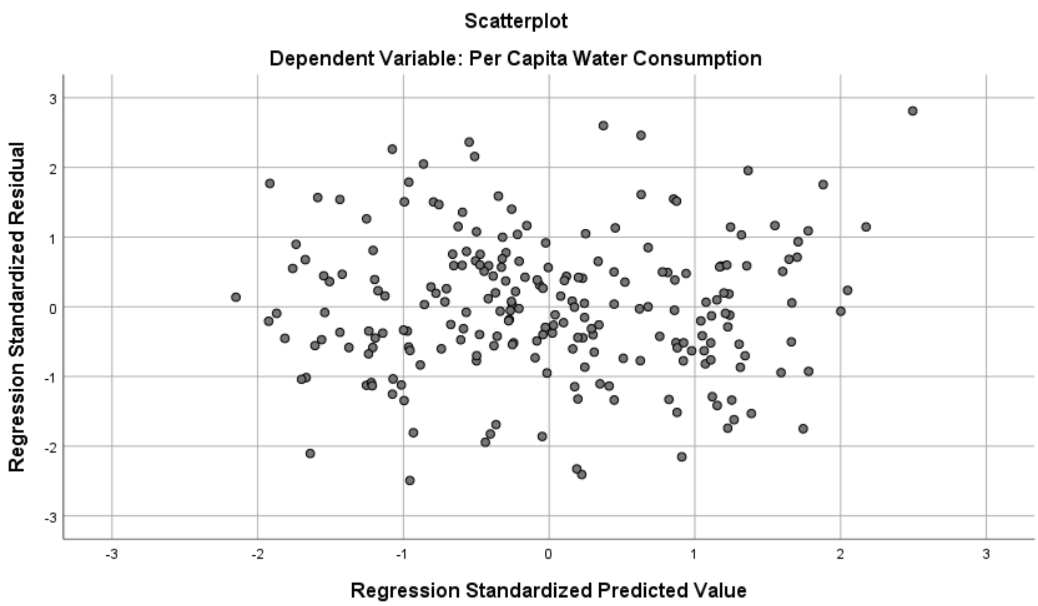


Figure 21. Scatterplot of Regression Analysis

The Durbin-Watson coefficient determines the independence of errors. This coefficient should fall between 1 and 3 (Table 11). The coefficient in the model indicates that the errors are independent. All assumptions of the regression analysis have been met. Ensuring that multiple linear regression analysis assumptions are met is crucial to generating reliable and accurate findings. The accuracy of parameter estimations and the robustness of forecasts are influenced by the assumptions that form the basis of the statistical inferences taken from the model. Ensuring that certain requirements, such as linearity, independence of errors, and homoscedasticity, are met is essential for accurately interpreting regression coefficients and increasing the capacity to apply the findings to a broader population. Furthermore, following assumptions about normality and multicollinearity enhances parameter estimations' accuracy and statistical conclusions' general reliability.

Whether the residuals show spatial dependence was tested with the LM test. K-Nearest Neighbors weight matrix was used. The LM test results are listed in Table 10. The results did not exhibit any spatiality. The validity of the generated regression model is acknowledged in terms of its accuracy and robustness.

Table 10. Diagnostics For Spatial Dependence

REGRESSION DIAGNOSTICS			
MULTICOLLINEARITY CONDITION NUMBER 158.448816			
TEST ON NORMALITY OF ERRORS			
TEST	DF	VALUE	PROB
Jarque-Bera	2	2.5887	0.27407
DIAGNOSTICS FOR HETEROSKEDASTICITY			
RANDOM COEFFICIENTS			
TEST	DF	VALUE	PROB
Breusch-Pagan test	9	13.4201	0.14450
Koenker-Bassett test	9	11.7367	0.22856
DIAGNOSTICS FOR SPATIAL DEPENDENCE			
FOR WEIGHT MATRIX : dataset			
(row-standardized weights)			
TEST	MI/DF	VALUE	PROB
Moran's I (error)	-0.0648	-1.2463	0.21266
Lagrange Multiplier (lag)	1	0.9682	0.32514
Robust LM (lag)	1	0.0024	0.96100
Lagrange Multiplier (error)	1	1.6978	0.19258
Robust LM (error)	1	0.7320	0.39224
Lagrange Multiplier (SARMA)	2	1.7002	0.42738

Following the assessment of the reliability of the regression analysis, the subsequent step involves the formulation of the equation and the interpretation of the model. The model summary table (Table 11) displays the outcomes of a multiple regression analysis using the forward approach, providing information on the effectiveness and appropriateness of the succeeding models. The Adjusted R Square values indicate the amount of variability in the dependent variable (per capita water consumption) that can be accounted for by the independent factors. As we advance through the models, the Adjusted R Square value increases, reaching 0.533 in the fifth model. This result indicates that the fifth model explains roughly 53.3% of the per capita water consumption variation. The Adjusted R Square accounts for the quantity of predictors and compensates for the intricacy of the model. The Standard Error of the Estimate measures the model's precision, where smaller numbers indicate a more robust match. The Durbin-Watson statistic is utilized to assess the presence of autocorrelation in the residuals. A value around 2 indicates the absence of substantial autocorrelation. The Durbin-Watson value for the fifth model is 1.999, which suggests that there is no considerable autocorrelation. In general, the sequence of models indicates an increase in the ability to explain per capita water consumption when additional factors are incorporated.

In Model 1, the explainability of the independent variables on the dependent variable was 42.4%, 48.7% in Model 2, and 50.8% in Model 3, 52.1% in Model 4. Model 5 contains the final result of the relationship between the dependent and independent variables (Table 11), where the independent variables explained 53.3% of the change in the dependent variable. Higher education graduate ratio, average household size, elderly population ratio, square meter sales price, and impervious surface ratio were included in the model, respectively.

In Model 5, a comprehensive investigation of the driving factors influencing per capita water consumption reveals complex relationships. The model includes two demographic, two socioeconomic, and one urban variable.

Table 11. Model Summary of Regression Analysis

Model Summary[f]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.654[a]	0.427	0.424	2.686229035779980	
2	.701[b]	0.492	0.487	2.535726822953790	
3	.718[c]	0.515	0.508	2.482707309685230	
4	.728[d]	0.530	0.521	2.450490238957400	
5	.737[e]	0.543	0.533	2.420285907070710	1.999
a. Predictors: (Constant), HIGHERSCHOOL					
b. Predictors: (Constant), HIGHERSCHOOL, AVERAGEHOUSEHOLDSIZE					
c. Predictors: (Constant), HIGHERSCHOOL, AVERAGEHOUSEHOLDSIZE, ELDERLY					
d. Predictors: (Constant), HIGHERSCHOOL, AVERAGEHOUSEHOLDSIZE, ELDERLY, M²PRICE					
e. Predictors: (Constant), HIGHERSCHOOL, AVERAGEHOUSEHOLDSIZE, ELDERLY, M²PRICE, NDISI					
f. Dependent Variable: Per Capita Water Consumption					

Based on the standardized beta coefficients in Table 7, the influence of the independent variables on the dependent variable was examined.

The predictors of the independent variables on the dependent variable are average household size, higher education, elderly population ratio, income level, and NDISI values, respectively.

A 1 standard deviation increase in average household size causes a .490 standard deviation decrease in per capita water consumption. As household size increases, per capita water consumption tends to decrease. It was determined that per capita water consumption decreased as the average household size increased (Beta = -0.490, $p < 0.01$). Höglund[40] and Arbues et al.[50] similarly found that per capita water consumption decreases as the average household size increases. This can be explained by the fact that the increase in total water consumption is less than the increase in household size and the increase in common use of individuals.

A 1 standard deviation increase in high education level causes a .374 standard deviation increase in per capita water consumption. The positive coefficient for the rate of higher education graduates (Beta = 0.374, $p < 0.01$) indicates that per capita water consumption increases in regions where the number of people with higher education graduates is high. Fan et al.[27] similarly found that water consumption increased as the education level increased. According to the results of the correlation analysis, there is a linear positive relationship between educational status and square meter sales price. This situation may indicate that as the education level of individuals increases, their income level increases. In this case, it can be explained by the fact that higher education graduates allocate a higher financial budget to water bills.

A 1 standard deviation increase in the elderly population ratio causes a .251 standard deviation decrease in per capita water consumption. The elderly population ratio variable, among the demographic variables, shows a negative relationship with per capita water consumption (Beta = -0.251, $p < 0.01$), which shows that the per capita water consumption of regions with a higher elderly ratio tends to decrease. Arbues et al.[50] obtained similar results in their study. This situation can be explained by the fact that the daily activities of elderly individuals are less than other age groups.

A 1 standard deviation increase in income level causes a .169 standard deviation increase in per capita water consumption. Square meter sales price showed a positive correlation (Beta = 0.169, $p < 0.01$), highlighting that areas with higher square meter prices are related to elevated per capita water consumption. Kostas and Chrysostomos[28] and Mazzanti and Montini[29] established that increased income levels were related to higher per capita water consumption. This situation can be explained by lifestyle and financial capacity. Additionally, a positive relationship was observed between square meter sales price and NDVI in the correlation table (Table 6). Regions with increasing income levels may be regions where outdoor water use increases.

A 1 standard deviation increase in impervious surface causes a .128 standard deviation incrase in per capita water consumption. Among the urban variables, NDISI appears to have a positive relationship with per capita water consumption (Beta = 0.128, $p <0.05$). This result means regions with a higher impervious surface ratio, indicative of increasing urbanization, tend to exhibit higher per capita water consumption. As in Heidari's study[60], impervious surfaces such as pavement, buildings, and roads affected water consumption. It is known that the urban water cycle is less sustainable thanks to impervious surfaces. In this case, planning strategies of urban areas come to the fore to ensure water management.

The relative importance of the independent variables on per capita water consumption is average household size, higher education graduate population ratio, elderly population ratio, square meter sales price, and impervious surface ratio. Understanding the relationships between the dependent and independent variables is crucial for urban water demand management, as it allows policymakers and water resource managers to recognize the key factors affecting water consumption and adopt focused policies toward sustainable water use.

CHAPTER 6

CONCLUSION

This study investigates the factors determining per capita water consumption in 11 districts of the İzmir Metropolitan Area, focusing on the global water scarcity caused by climate change and urbanization. The research employed spatial and statistical analysis and modeling approaches to uncover complex spatial patterns of neighborhood characteristics and per capita water consumption.

Regions characterized by high per capita water consumption, referred to as "hotspots," have been linked to higher population density, higher elderly people, low child-woman ratio, higher education and high-income levels, and higher impervious surfaces. In contrast, regions characterized by low per capita water consumption, referred to as "coldspots," are characterized by a lower population density, higher children population, lower educational level, lower income levels, higher child-woman ratio, and low impervious surfaces.

The correlation analysis revealed that per capita water consumption is associated with various demographic, socioeconomic, and urban variables, including children population, elderly population, higher education graduate population, income level, and impervious surface. Finally, this study determined the importance of the variables affecting per capita water consumption by multiple linear regression analysis. The study found that average household size, high education level, elderly population, high-income level, and impervious surface variables influenced per capita water consumption. The study's findings can guide policymakers in urban water demand management studies and contribute to the understanding of water consumption patterns and their drivers for efficient resource management.

Decision-makers can implement targeted water conservation initiatives in urban areas with high socioeconomic status and higher water consumption.

- İzmir Metropolitan Municipality and İzmir Water and Sewerage Administration, in cooperation, may introduce intelligent water metering systems that provide real-time water usage feedback to wealthy neighborhood residents.

- Public awareness campaigns focusing on water conservation's environmental and economic benefits can be explicitly organized in these areas. It is important to create a multi-stakeholder process in carrying out awareness campaigns. Therefore, district municipalities and neighborhood headmen can be included in the process. Collaborating with community leaders and influencers in these affluent neighborhoods can enhance the effectiveness of awareness campaigns and encourage residents to participate actively in sustainable water management practices.
- Local policies might incentivize the installation of water-efficient appliances.

Implementing these strategies can reduce water consumption in urban areas with higher socioeconomic status.

Various cities worldwide have implemented strategies to address high water consumption. Water agencies have introduced tiered pricing structures in cities like Los Angeles, California, and consumers pay higher rates for excessive water use[106]. This encourages more responsible water usage and discourages wasteful practices. In Singapore, PUB, the national water body of Singapore, launched a water conservation initiative called Water Efficient Homes, aimed at assisting people in conserving water and reducing their water expenses. In conjunction with its 3P partnership strategy, which includes citizens, grassroots leaders, and volunteers, the organization promotes water efficiency among residents by encouraging the installation of water-saving equipment and the adoption of water-saving behaviors. Mobile displays were established to inform and show locals the efficacy of water-saving gadgets and the process of installing them[107]. Target 155 aims to reduce Melbourne's water consumption and average individual consumption. The campaign was designed in collaboration with the municipality and water companies to educate Melbourne residents about using water efficiently[108]. These examples showcase diverse approaches that combine pricing mechanisms, community engagement, and technology to address water consumption patterns in affluent neighborhoods.

It has been found that impervious surfaces increase water consumption. Urban planners and local governments can work to reduce the impact of impervious surfaces on water consumption and promote sustainable urban development practices by adopting a combination of the following measures:

- Developing green areas, parks, and permeable surfaces can be encouraged to increase natural water absorption. Green infrastructure helps reduce runoff and supports groundwater recharge. In Melbourne, Australia, the permeability of the urban environment was increased by replacing impervious surfaces with permeable surfaces. At the same time, regulations have been made in urban areas in order to contribute positively to the water cycle in Melbourne[109]. However, drought-resistant landscaping practices, such as those in Los Angeles, USA, can be implemented in green area arrangements[110]. Thus, outdoor water use has not increased.
- It can be implemented low-impact development techniques (LID) such as rain gardens, permeable pavements, and green roofs that can be incorporated into urban planning and development[110]. These practices help manage stormwater locally, helping to prevent excessive runoff. The rainwater collection method is also supported to prevent surface runoff on impervious surfaces such as asphalt or concrete floors[111]. Many states in the United States inform administrators and the public by organizing guidelines, training programs, and funds to disseminate LID techniques. Widespread implementation of LID practices positively affects rainwater retention, catchment hydrology, and water quality[112].
- Zoning regulations that limit the extent of impervious surfaces in construction projects may be implemented. Adopting urban design principles that prioritize permeability can mitigate the adverse effects of water consumption. Local governments have developed impervious surface regulations to mitigate the negative impacts of urbanization on water resources. These restrictions limit the percentage of impervious surfaces within the total site area[113]. These restrictions, typically in the form of zoning codes, aim to preserve a relatively high level of water absorption by requiring developers to minimize the amount of impervious surface area.

The findings have academic and practical significance, providing valuable insights for politicians and urban planners managing water resources sustainably. This study aims to lay the foundation for specific interventions and policies by including the spatial dimension and understanding the various factors affecting water consumption. Urban areas are intricate systems in which water is a scarce and indispensable resource, and its effective management is crucial for the welfare of people. Gaining insight into the variables that influence water consumption is valuable for efficient urban planning as it enables the development of informed policies and plans. Furthermore, identifying influential elements guarantees the long-term utilization of water resources and aids in developing resilient and flexible urban designs considering the fluctuating factors of population, socioeconomic conditions, and urbanization.

Future research can examine the variables affecting water consumption according to different characteristics by expanding the geographical scope of the study if a healthy and complete data set is created. By adding rural neighborhoods to the scope of the study, water consumption trends of urban and rural neighborhoods can be investigated. By applying Geographically Weighted Regression Analysis as a method, the relationship between the spatial characteristics of neighborhoods and the factors affecting water consumption can be examined in detail. Additionally, if a healthy and complete data set is created in the neighborhoods where urban sprawl is seen, the effect of urban sprawl on water consumption can be examined.

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