DOKUZ EYLÜL UNIVERSITY

GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

ASSESSING SPATIAL BEHAVIOR FOCUSING ON THE DAY AND THE NIGHT DIFFERENCES USING SOCIAL MEDIA, GIS, AND SPATIAL STATISTICS

by

Ezgi TÜKEL

July, 2021

İZMİR

ASSESSING SPATIAL BEHAVIOR FOCUSING ON THE DAY AND THE NIGHT DIFFERENCES USING SOCIAL MEDIA, GIS, AND SPATIAL STATISTICS

A Thesis Submitted to the
Graduate School of Natural and Applied Sciences of Dokuz Eylül University
In Partial Fulfillment of the Requirements for Master of Science in
Geographic Information Systems

by
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July, 2021
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M.Sc THESIS EXAMINATION RESULT FORM

We have read the thesis entitled **"ASSESSING SPATIAL BEHAVIOR FOCUSING ON THE DAY AND THE NIGHT DIFFERENCES USING SOCIAL MEDIA, GIS, AND SPATIAL STATISTICS"** completed by **EZGİ TÜKEL** under supervision of **PROF.DR. K. MERT ÇUBUKÇU** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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ACKNOWLEDGEMENTS

I would like to heartily thank my advisor, Prof.Dr. K. Mert ÇUBUKÇU for his support, guidance, consideration and encouragement throughout my thesis process. Working with him is truly a lifetime experience, he encouraged me from initial to the end to think and imagine all aspects of the topics.

I would also like to thank Assoc.Prof.Dr. Muhammet AYDOĞAN and Assoc.Prof. Görkem GÜLHAN for serving on my committee.

I am also grateful thank to my friend Data Scientist Esma AŞÇIOĞLU for her contributions and assistance to my thesis data process.

Finally, and most importantly, I would like to thank my amazing mother Ayşen TÜKEL. I could not have been where I wanted to be in my life without her excellent patience, support and wisdom.

Ezgi TÜKEL

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ABSTRACT

Nightlife activities of the city indicate a crucial source for urban life. For many years, geographers and urban planners have concerned with studies about human behavior in the city at different hours. In recent years location-based check-in services have allowed seeing users' activity and their locational information. Previous studies examined whether to relate or not spatial behavior and human activity using location-based social media applications. This study fills this gap by using spatial statistical techniques to understand differences in human behavior on different days and at different hours. Foursquare user's check-in data as the main data source was used to understand differences between day and night in the study area.

In this study, three different analyses are conducted. The first is Kernel density used to generalize at different hours of weekday and weekend. The second is quadrat analysis for weekdays and weekends and days and nights to understand whether point distributions are significantly different or not. The last analysis is closest facility, which finds the closest path from Foursquare venues to the bus stops and to understand the differences in accessibility on different day and at different hours.

In conclusion, the density of the Foursquare venues appears to be higher on weekends. The observed check-in patterns are not statistically different both on weekday days and weekday nights and weekend days and weekend nights. Moreover, the levels of accessibility to public transport do not different on weekdays and weekends.

Keywords: Foursquare, spatial behavior, closest facility, quadrat analysis

MEKANSAL DAVRANIŞIN GECE VE GÜNDÜZ FARKLARINA ODAKLANARAK SOSYAL MEDYA, CBS VE MEKANSAL İSTATİSTİK YÖNTEMLERİ İLE İNCELENMESİ

ÖZ

Kentin gece hayatı etkinlikleri, kent yaşamı için önemli bir kaynak olduğunu göstermektedir. Uzun yıllar coğrafyacılar ve şehir plancıları şehirdeki insan davranışları ile ilgili farklı saatlerde yapılan çalışmalarla ilgilendiler. Son yıllarda lokasyon bazlı check-in hizmetleri, kullanıcıların aktivitelerini ve lokasyon bilgilerinin görülmesine olanak sağlamaktadır. Önceki çalışmalar, konum tabanlı sosyal medya uygulamalarını kullanarak mekansal davranış ve insan etkinliğinin ilişkilendirilip ilişkilendirilmediğini incelemiştir. Bu çalışma, farklı günlerde ve farklı saatlerde insan davranışlarındaki farklılıkları anlamak için mekansal istatistiksel teknikler kullanarak bu boşluğu doldurmaktadır. Çalışma alanında gece ve gündüz arasındaki farkları anlamak için ana veri kaynağı olarak Foursquare kullanıcısının check-in verileri kullanıldı.

Bu çalışmada üç farklı analiz yapılmıştır. Birincisi, hafta içi ve hafta sonu farklı saatlerde genelleme yapmak için kullanılan çekirdek yoğunluğudur. İkincisi, nokta dağılımlarının önemli ölçüde farklı olup olmadığını anlamak için hafta içi ve hafta sonları ve günler ve geceler için yapılan kuadrat analizidir. Son analiz, Foursquare mekanlarından otobüs duraklarına en yakın yolu bulan ve farklı gün ve farklı saatlerde erişilebilirlik farklılıklarını anlayan en yakın tesistir.

Sonuç olarak, Foursquare mekanlarının yoğunluğu hafta sonları daha fazla görünmektedir. Gözlemlenen check-in kalıpları, hem hafta içi gündüz ve gece hem de hafta sonu gündüz ve geceleri istatistiksel olarak farklı değildir. Ayrıca toplu taşımaya erişim düzeyleri hafta içi ve hafta sonu farklı değildir.

Anahtar kelimeler: Foursquare, mekansal davranış, en kısa yol, kuadrat analizi

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CHAPTER ONE
INTRODUCTION

Nightlife activities of the city indicate a crucial source for urban life. For many years, geographers and urban planners have concerned with studies about the human behavior in the city at different hours. In recent years location-based check-in services allow seeing users' activity and their locational information.

Previous studies examined whether to relate or not spatial behavior and human activity using location-based social media applications. In addition to spatial behavior aimed to understand preferences for the variety of nightlife of the city. Particularly, nightlife venues enable seeing urban activities and their vitality that are not seen by daytime structures (Farrer, 2008; Pourahmad, Kahaki & Sejodi, 2020). Oldenburg (1989) describes venues as a 'Third Place' term that exception home and workplaces for people in daily life. Hence, using venues at night is a substantial indicator for urban life.

Researchers focusing on spatial behavior have been interested in the behavior of individuals, households, firms, corporations, and institutions. They have aimed to describe these behaviors in a spatial context. According to these studies, human behavior can be described as movement frequencies, distances between origin and destinations of spatial acts. (Golledge & Stimson, 1996).

Since the development of geo-spatial techniques have been possible to collect data for human spatial behavior studies. Location-based mobile applications have become an important source of participant data. Check-in of a specific place, a café for example, reveals the user's preference and activity (Silva, Melo, Almeida, Salles & Loureiro, 2013). Foursquare, a location-based mobile application, has been widely used in such studies.

Some of these studies have used Twitter data to examine urban mobility pattern, while the other studies have compared official urban land use and real-time using geolocated tweets. Furthermore, Instagram datasets were used for locational analyses. Silva et al. (2013) argues that when the Instagram data is compared to the Foursquare data, results show that Foursquare is better than Instagram to understand spatial behavior. Several studies along the course of time developed various techniques based on spatial analyses. The main purpose of these studies is to understand human behavior and how it affects urban mobility patterns and activities.

This study primarily focuses on the differences between weekday and weekend and day and night using various methods including Point Patterns Analysis techniques which are very important to understand spatial behavior at different times. Furthermore, to understand differences in user's preferences between weekday and weekend it is necessary measure accessibility to public transportation stops.

Accessibility has become an important source for the measurement of walking within residential areas. The accessibility measure has become a crucial indicator to evaluate the effectiveness of public transportation access. An important tool measure accessibility is the network analysis approach in GIS. Consist of nodes and links, network analysis enables the solution of various transportation-related problems (Fischer, 2006). This closest facility analysis makes it easy to find the walking distance (from incident to the facility or from the facility to the incident) (Ahmed, Ibrahim & Hefny, 2017).

In this study, the purpose is to analyze the spatial behavior of people using venues at different hours and different days in a populous city and how it is affected by accessibility to public transportation stops. As the main data source, Foursquare user's check-in is used to understand the differences between day-time and night time differences within the study area.

Three different analyses are conducted within this framework to uncover the differences in the day and night of venue check-ins. The first is Kernel density, which is used to generalize at different hours of weekday and weekend days and nights and to assess the pertaining spatial distributions. Furthermore, quadrat analyses are conducted for weekdays and weekends regarding daytime and nighttime hours to understand whether those point distributions are significantly different or not. Quadrat Analysis is one of the point pattern analysis techniques that is used to analyze point distributions in space and presence of difference is tested with a Kolmogrov-Simirnov Test (Cubukcu, 2021). This study important to test the hypothesis that the differences between weekday and weekend and daytime and nighttime venue check-ins and aimed to understand whether these points data are significant or not.

The last analysis is the closest facility technique of network analysis of GIS. The closest facility analysis derives the nearest distance between incidents and facilities. The closest facility technique of network analysis is used in this study to find the closest path from Foursquare venues to the bus stops and to understand the differences in public transportation accessibility on different day and at different hours. The Independent Sample T-test was used to test the walking distance differences.

The remainder of this study is organized as follows. Chapter 2 consists of a literature review. Chapter 3 contains the data with the chosen study area with their explanations. Chapter 4 presents the findings of the analyses. Chapter 5 concludes the research.

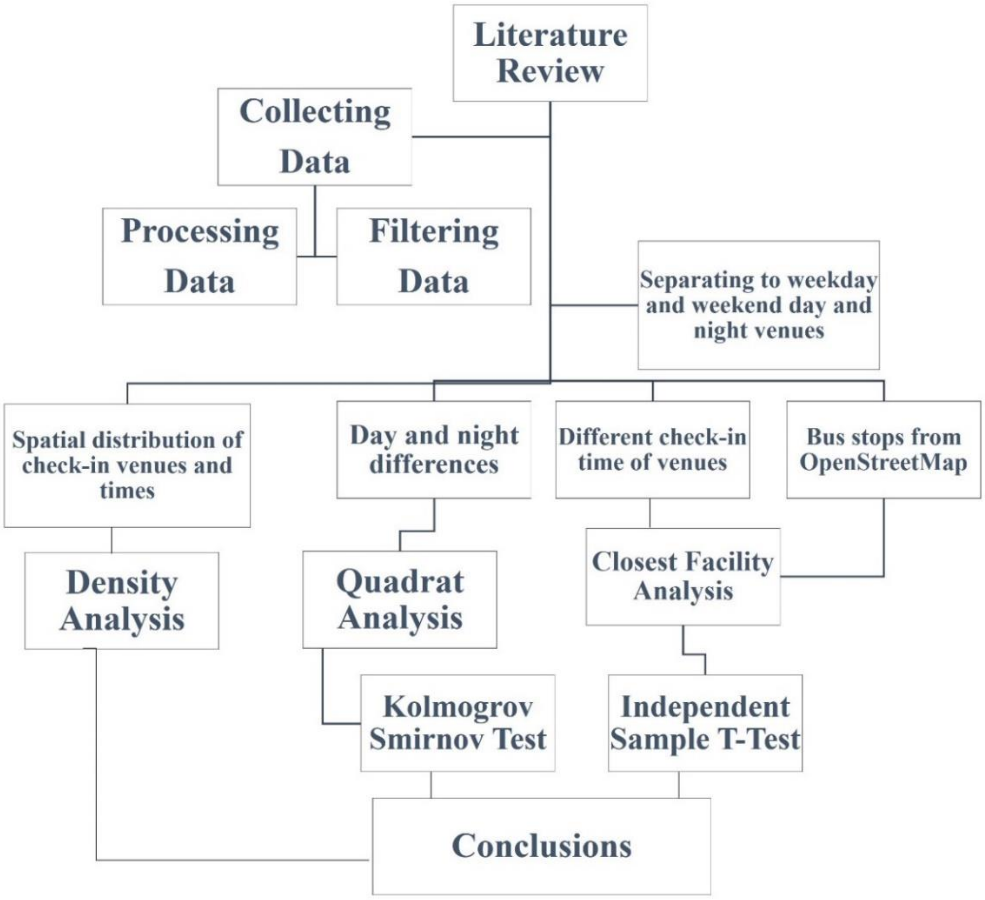

Figure 1.1 Flow chart

CHAPTER TWO
LITERATURE REVIEW

The literature review chapter of this study has been categorized into three main parts. The first part of the literature review section deals with the studies related to nightlife venues and their impact on city life. The second part consists of the relationship between location-based social media applications usage and human spatial behavior. The third part of the literature review section examines the accessibility concept accessibility measure, walking distance and public transportation.

2.1 Nightlife

Using venues at night is a way to reach peace and happiness for many people. The nightlife venues contribute to urban activities and the vitality of the city (Pourahmad et al., 2020). Studying nightlife venues find forms of sociability that are not seen by day or explainable related to daytime structures (Farrer, 2008).

> On a cold winter's night, as you pass the While Horse, and the doors open, a solid wave of conversation and animation surges out and hits you; very warming. The comings and goings from this bar do much to keep our street reasonably populated until three in the morning, and it is a street always safe to come home to (Jacobs, 1961, 40-41).

Limonta (2014) examined the negative impact of nightlife businesses in Milan and gathered information about opening hours and business type to create different maps for the day and the night using Kernel Density Estimation as a geostatistical technique the aim was to see the distribution of nightlife business link on the street. Cosman (2017) investigated preferences for a variety of nightlife and was chosen Chicago as a study area of how these preferences impact the nightlife industry. Nightlife venues were collected using Yelp API then decomposed into the categories to see the distribution of venues on the map. The model (constant elasticity of substitution) was developed to describe consumer preferences. Additionally, Song, Pan & Chen (2016) aimed to understand nightlife consumption in small scale areas like urban villages and examined the effect on public spaces at nighttime. As a case study Pearl River Delta in China was chosen and interviews were conducted with public space users in this area for one day period. According to the user's answers were observed different nighttime activities and applied Importance Performance Analysis (IPA) to evaluate user's perception and to improve public space in urban villages at nighttime.

In addition to the user surveys, there are also studies using demographic data. Some researchers examined student's consumption at the night in the city of Utrecht and Rotterdam using demographic data, gathering data from the online survey and applying T-Test (Brands, Schwanen, & Aalst, 2014). Dong, Ratti & Zheng (2019) examined the daytime and nighttime population, user's consumption of nine Chinese cities using online platforms. They applied the Lasso Regression model to predict variables after calculating a few statistical methods.

There are studies to understand the nightlife pattern of young people. One of these studies was developed a smartphone application and then examined their physical mobility. Study areas are two major cities in Switzerland, Zurich and Lausanne the data is collected with crowdsourcing, which are place, video and drink survey, then they combined. The results show that bar and clubs are more crowded and louder than the rest of public places at night (Santani et al., 2016). In another study, it is aimed to explore spatial practices of adolescents related to leisure and nightlife. Young people (14-16 years old) were interviewed in Barcelona, Spain. It is concluded that since festival places have more flexible management time and far from family control, these places play an important role in getting socializing in contrast to leisure places, such as malls, restaurants and movie theatres for young people (Mecca, 2020).

On the other hand, there are many studies about outside night venues. The term 'Third Place' was used by Oldenburg (1989) to indicate "great, good places" that exception home and work venues for people in daily life. Nowadays, people spend time in venues outside of work and home, hence third places affect the quality of life in the community (Jeffres, Bracken, Jian & Casey, 2009). Studies on show that ‘'third places’’:

- Social activities are related to where clustering economic activities in the city.
- Neighborhoods with upper income associated with a high level of consumption building while neighborhoods with lower income linked to open public spaces.
- Addition to the last decade, nowadays new places are added to third places, such as gas station, bus station etc. (Adelfio, Serrano-Estrada, Martí-Ciriquián, Kain & Stenberg, 2020).

2.2 Spatial Behavior and Social Media Analyses

Geographers and urban planners have been concerned with studies about human behavior in the city. They have studied distributions, network connections, patterns, surface properties of spatial systems (Golledge & Stimson, 1996). Haggett (1965) describes the spatial system is composed of five elements: (A) movements, (B) networks (paths), (C) nodes (intersections), (D) hierarchies and (E) surfaces (areas) (Figure 2.1).

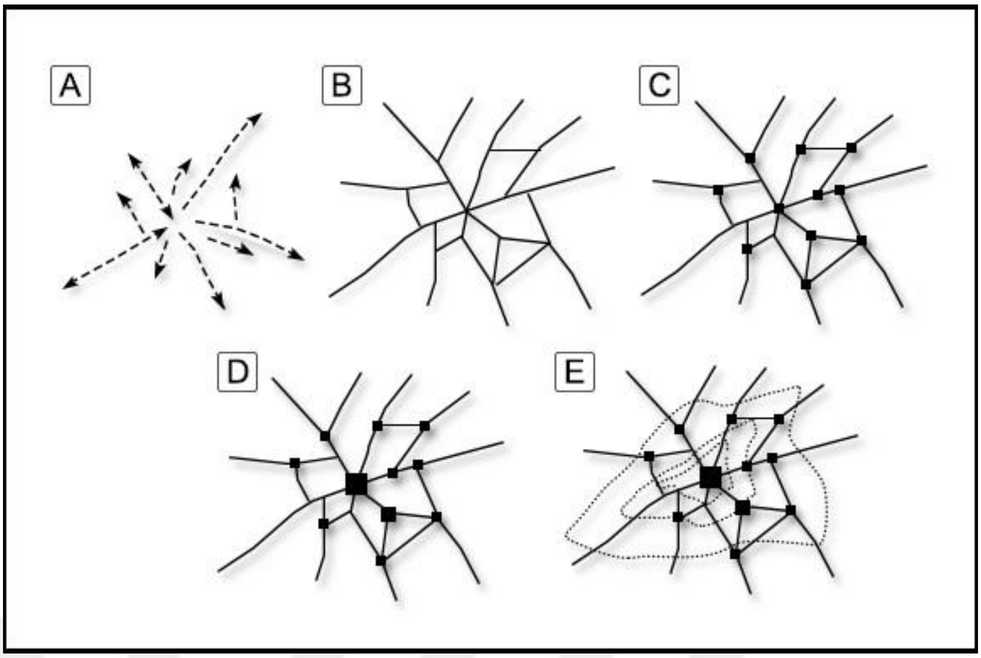

Figure 2.1 The elements of spatial systems (adopted from Haggett,1965)

In the past, due to the lack of geo-computational tools and algorithms, it was quite difficult to improve the model of human spatial behavior. Furthermore, without using GIS-based methods, modeling spatial behavior using accessibility measures was limited. Over time, the increasing availability of geo-referenced data has allowed using this data in human spatial behavior studies. In addition to acquiring the data, the development of spatial analysis tool in the GIS environment has contributed to future studies (Kwan, 2000). Location-based data services are examples obtaining of participant data. Check-in of a specific place shows that for instance a cafe is also the user's preference. To understand human behavior better, Foursquare and Instagram dataset findings are compared. But, results show that both are compatible in finding popular regions of cities or regions and Foursquare is better than Instagram to express typical places for people (Silva et al., 2013).

Foursquare, a location-based application, has been widely used in such studies. Hong (2015) analyzed the spatial distribution of venues in Seoul using Foursquare check-in data and applied hotspot analysis. The results show that the distribution of social media venues is related to the daytime population. In another research examined there is a relation between spatial analysis and human activity. This research used Foursquare check-in data, and the activities are separated into different categories to understand which activity is observed more intensively at different times of the day (Hasan, Zhan & Ukkusuri, 2013). In the study of Austin TX, Foursquare data was used to estimate home-based work trips and home-based retail trip and then they compared the Capital Area Metropolitan Planning Organization (CAMPO) and Foursquare data (Jin, Yang, Cebelak, Ran & Walton, 2013). Agryzkov et al. (2016) aimed to understand how to relationship urban street network and venues via Network Analysis. They examined the Foursquare data and user's demographics and introduced the urban networks of Murcia and was used the PageRank Algorithm. In another study investigated how to impact user's choice according to the most common check-in venues on Swarm and Foursquare in Ankara. It was made an interview with users and aimed to estimate the user's venue preferences (Büyükdemirci & Ercoşkun, 2017).

Several studies used geolocated tweets while examining human behavior in venues. Salas-Olmedo & Quezada (2017) aimed to bring a new approach for urban planning and public transport systems to improve them in Chile. They mapped using geo-localized Twitter data and Python used as a methodology. Then tweets transformed to point data in the GIS database. Consequently, they compared the results of the map from tweets data and the normal map to understand mobility patterns. In another research, a model of smart urban tourism is developed using Twitter messages. They gathered 600.000 Twitter messages using a text mining technique for San Francisco and applied Kernel Density Estimation to observe spatial behavior (Brandt, Bendler & Neumann ,2017). There are also studies about tourism planning and tourist preferences using social media rating sites such as TripAdvisor and Booking. Tourist's rating and comments from these online sites were obtained their spatial distributions are mapped using Hotspot analysis (Campagna, Floris, Massa, Girsheva & Ivanov, 2015). To understand the demand for tourism, the use of Instagram photos to analyze Venice's tourism consumption was investigated. After the dataset collected, it is divided into different categories and the spatial distribution is examined on the map (Rossi, Boscaro & Torsello, 2018). Hasnat & Hasan (2018) analyzed tourist travel behavior using geo-tagged Tweets and applied various methods in Florida region. The K-means clustered results revealed users' activities and destination preferences.

There are the studies to relate Twitter data and examined to compare official urban land use and real-time geolocated tweets in Manhattan, NYC. Weekend and weekday tweets were collected and the Davies-Bouldin clustering index was applied to see tweet categories on the map such as business, leisure, nightlife, and residential (Frias-Martinez, Soto, Hohwald & Frias-Martinez,2012). In another study Twitter data was analyzed throughout the day in Madrid and its relationship to land use (García-Palomares et al., 2017).

There are other studies to understand human spatial behavior. D'Antonio & Monz (2016) examined the visitor spatial behavior in off-trail areas of recreation use. They collected GPS-based visitor tracking points and applied spatial analysis and statistical techniques. They found the median the center and directional ellipse then calculated the average Euclidean distance from the median center points. These averages were compared using the two-sample t-test. Results show that visitor behavior does not change in some recreation locations such as mountain summits but, in other locations the visitor behavior is observed to change.

2.3 Accessibility to Public Transportation

Accessibility is a crucial concept for urban planners because it shows activities available to residents of a neighborhood of a city. Accessibility is determined by potential destinations, the ease of reaching each destination, and the quality, magnitude and character of the activities found there. The concept of accessibility redress a balance between land-use and transportation policies (Handy & Niemeier, 1997 ; Handy & Clifton, 2002).

The measure of accessibility has a wide literature. Pirie (1979) examined the past studies on the measure of accessibility. These can be classified into four types;

topological measures, distance measures, gravity measures and cumulative-opportunity measures.

In recent years, the development of practical techniques has contributed to addressing accessibility measure. An important one of these techniques is the network analysis approach. Consist of nodes and links GIS based applications enables the solution of various transportation-related problems, such as traveling-salesman problem, vehicle-routing problem, and shortest-path problem based on network structure (Fischer, 2006).

Shifting from private car to public transportation, walking and cycling can increase the sustainability of transport and ultimately, it can help to improve the environment, economy and public health problems (Elias & Shiftan, 2012). Saif, Zefreh, & Torok (2019) concluded that public transportation planning not only its performance but also its impact on other social aspects such as mobility, sustainability, public health etc. Accordingly, there are many studies related to public transport accessibility. A public transport network model is developed as a new measure between public transport service frequency and population density in Melbourne, Australia. The findings show that there is a high level of public transport index associated with the high level of the region population (Saghapour, Moridpour & Thompson, 2016). In the case of Nanjing Metro Station, the relationship between walking access to the metro and the demographic characteristics of the passengers was examined. More than one technique is used as a method including network analysis of routes, K-means cluster analysis, survey with the passenger of the metro station. Hereby, this research aimed to explore urban demographic characters the effect of metro passenger's walking behavior (He, Zhang, Huang & Xi ,2018). In past studies, different methods were used to find the spatial accessibility of public transport stops. One of the methods is the buffer analysis and the other is the isoline method using geographic information systems to find new stops for the need in the case area (Kraft, 2016).

Considering that human behavior is associated with public transport data, location-based data contributes to public transport choice as a new perspective. Rybarczyk, Banerjee, Starking-Szymanski & Shaker (2018) examined people's travel behavior using a semantic analysis method for each travel tweet. Accordingly, pedestrian and water travel are associated with positive valences in addition to bicycling travel.

Walking has different purposes according to the difference between natural and built environment. Studies concluded that transport-related walking is associated with land-use diversity and accessibility of daily destinations (workplace, shop etc.), while recreational walking is related to side-walks and leisure time activity (Saelens & Handy, 2010; Smith et al., 2017). Furthermore, Gao, Kamphuis, Helbich & Ettema (2020) investigated how walking differs on weekdays and weekends related to natural and built environmental characteristics. Higher density areas are associated with transport walking on weekdays and weekends, whereas lower density areas are related to recreational walking on weekdays. Thus, walking behavior is related to public transportation planning. There is a lot of variances in people's walking distance to public transport stops. One of the adopted aspects is walking distance to 400 m for buses and 800 m for rail transport based on observations (Canepa, 2007).

Many walkability studies have focused on measuring and predicting distance to public transportation. Sarker, Mailer & Sikder (2019) aimed to explore the actual walking distance to public transport stations in Munich, Germany. They made a survey with public transport passengers from the started station to the destination station and collecting respondents were converted to point feature on the ArcMap. They applied service area of network analysis of GIS to analyze walking distance and walking time to the stations. Moreover, an independent t-test was conducted to understand walking time for two different modes and then calculated to measure the magnitude of the difference of the public transport modes. The results indicate that the passengers walking patterns can change according to the different public transport modes. In addition to walking distance to public transport, there are a number of studies factors influencing accessibility to public transport. The average walking distance to the public transport stop is associated with demographic characteristics, such as gender, age, income, labor force status, the presence of a child in the household and car ownership (Daniels & Mulley 2013).

As it is clear from the literature reviewed, social media applications are the important indicators about spatial human behavior and users' preferences studies. Some of these studies have used Twitter data to examine urban mobility pattern, while the other studies have used Foursquare data to investigate users' preferences. In addition to spatial behavior there are many studies about accessibility measure using network analyses. The aim of this studies to measure people's walking distance from various starting points to public transportation destinations. There are no studies on human spatial behavior in terms of different times of the city using location-based social media applications and how it is affected walking distance to the public transportation stops. This study fills this gap by using spatial statistical techniques to understand differences on different days and at different hours. Furthermore, network analysis technique is used in this study to understand the differences in public transportation accessibility on different days and at different hours.

CHAPTER THREE

DATA

Foursquare user's check-in data as the main data source was used to understand differences between day and night in the study area. Kadikoy district was chosen as a case study since has advanced transportation opportunities and a variety of using places. The dataset was obtained from Foursquare API between the 28th of June and the 30th of July 2020 using Python. Then this dataset was converted to a GIS database including Latitude and Longitude information. Additionally, public transport data was obtained from QGIS open sources. The measures of accessibility for this study are based on the location of bus stations, the streets, and the location of venues on Foursquare and the networks developed using ArcGIS packages.

3.1 Study Area

Kadikoy district is an advanced area with extensive transportation opportunities and user variety. Kadikoy district is on the east side of the Istanbul metropolitan area. Kadikoy has Atasehir and Uskudar districts in the north, the Marmara Sea in the south, the Bosphorus in the west, and the highway to the European side in the east. With the seaway, railway, and metro transportation as well land use variety, the district is a social attraction area (Üsküplü & Çolakoğlu, 2019).

Kadikoy district was chosen as a study area since it has different transport opportunities and land use variety (Figure 3.1). Moreover, according to the Foursquare Turkey Statistics (2015) Kadikoy has the most check-in number in Istanbul (Figure 3.2).

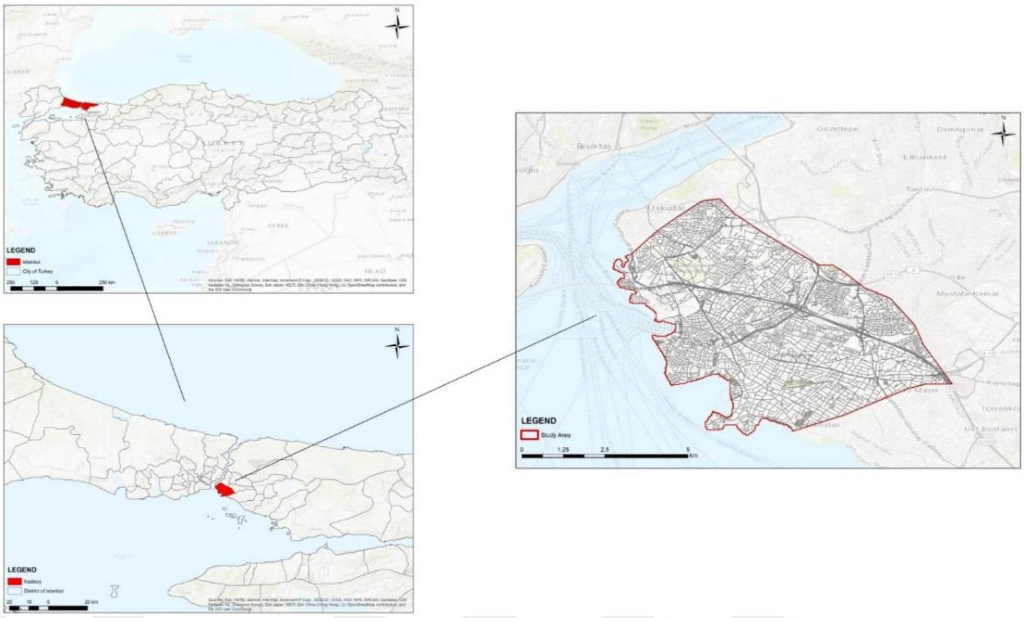

Figure 3.1 Study area

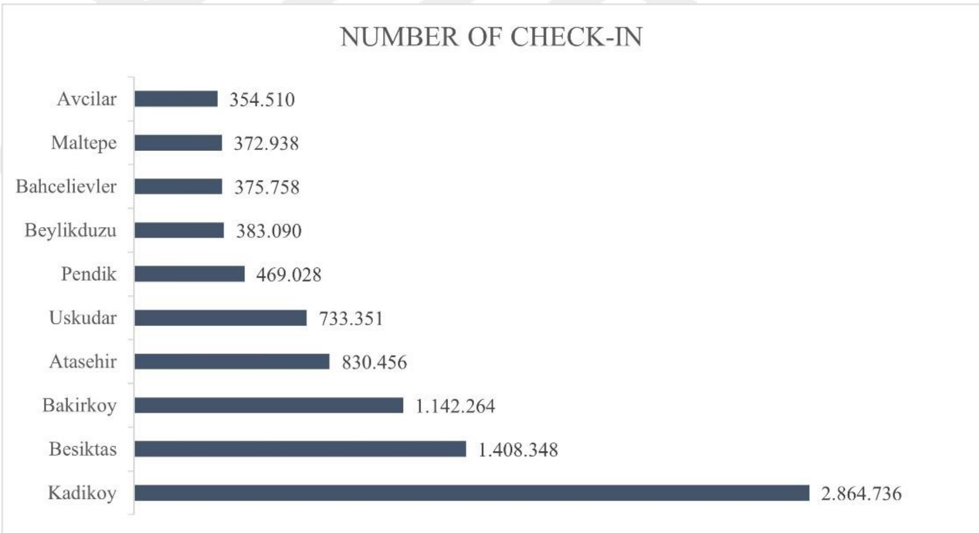

Figure 3.2 Number of check-in in Istanbul

3.2 Data Sources

3.2.1 Foursquare Check-in Data

According to the Intelligencer (2019) report, the Foursquare database includes 105 million venues and 14 billion check-ins. Furthermore, the Foursquare application has

1 billion check-ins per year. Statista (2020) research shows that 47% of Foursquare users in the US are aged between 25 and 34 years old while 29% are aged between 35 and 44 years old. Foursquare user demographics are shown in Figure 3.3.

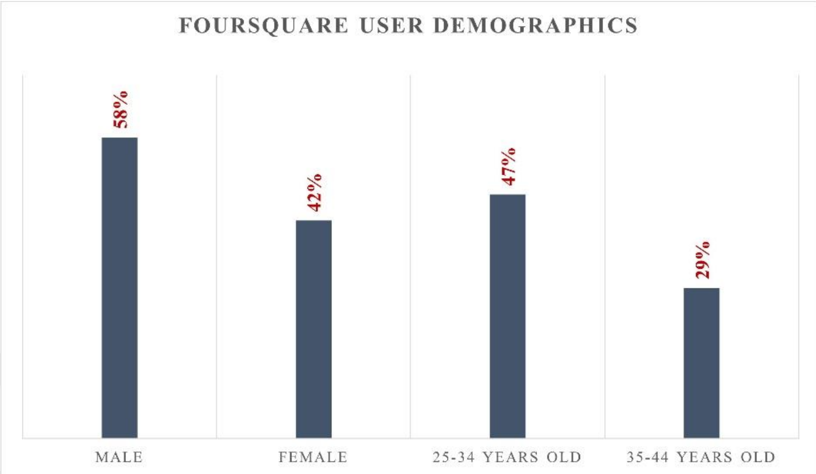

Figure 3.3 Foursquare user demographics

The location-based Foursquare check-in data was chosen as a data source since it is public and accessible using Foursquare API. Because Foursquare API limits the number of requests, the dataset was collected one month, which is between the 28th of June and the 30th of July 2020.

A point grid was created in QGIS and a Python script was used to get requests according to the latitude and longitude of grid points of the study area. When collecting the dataset, it was transferred to the PostgreSQL table at the same time. Lastly, requesting table was transferred to the ArcGIS 10.3 to analyze the dataset (Figure 3.4).

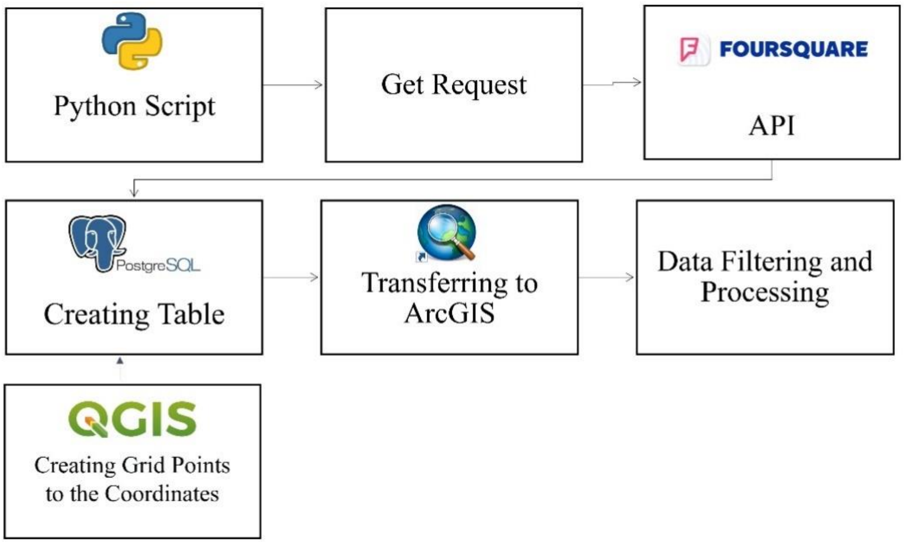

Figure 3. 4 Process of data collection

According to the requested fields in Foursquare API, the dataset included different fields and these fields are shown in Table 3.1.

Table 3.1 Fields of dataset

Field	**Description**
id	A unique identifier for this check-in
name	The name of the venue
category	The tip of venue (café, bar, park etc.)
likes	The count of users who have liked this check-in
latitude	Latitude of coordinates
longitude	Longitude of coordinates
address	Address detail of venue
date	User's check-in date

In past studies, the data was divided into categories and subcategories. Indeed, separated social media data, such as Foursquare, is facilitated for dataset filtering and processes (Martí, García-Mayor, Nolasco-Cirugeda & Serrano-Estrada, 2020). First, the dataset was filtered according to the case study area and then divided into categories to examine. The number of original dataset check-in venues are 1898. After filtering to the study area, the number of study area dataset check-in venues is 1.180. The number of original dataset and the number of the study area dataset are shown in Table 3.2 and presented in Figures 3.5 and 3.6.

Table 3.2 The number of check-in venues data

	Number of Check-ins
Original check-in dataset	1898
Check-in dataset of study area	1180

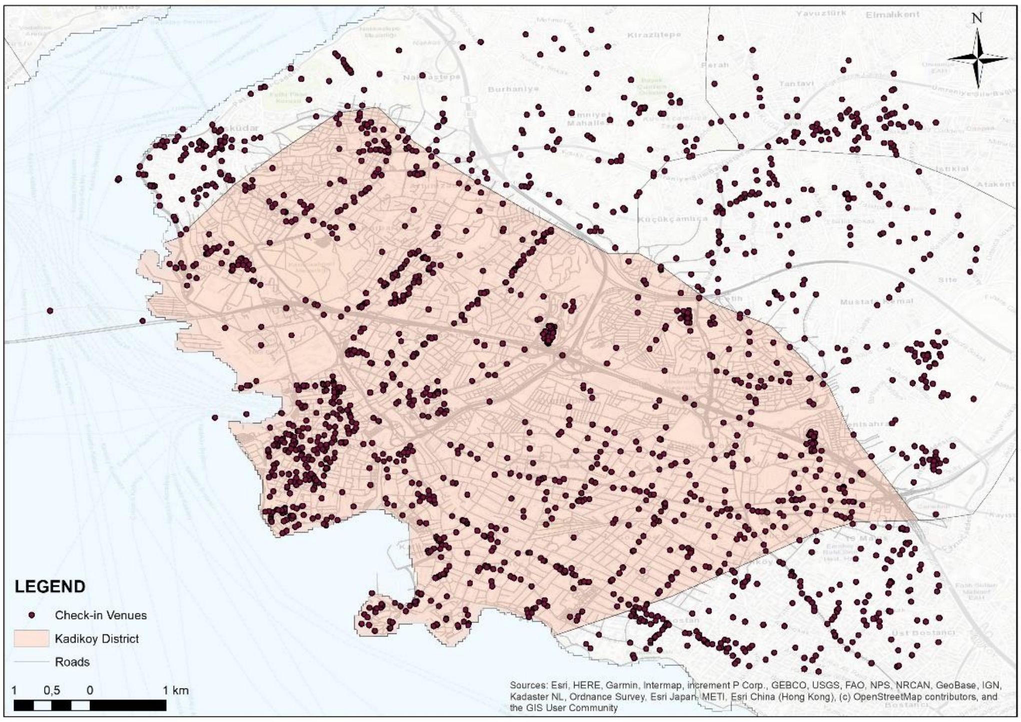

Figure 3.5 Original check-in dataset

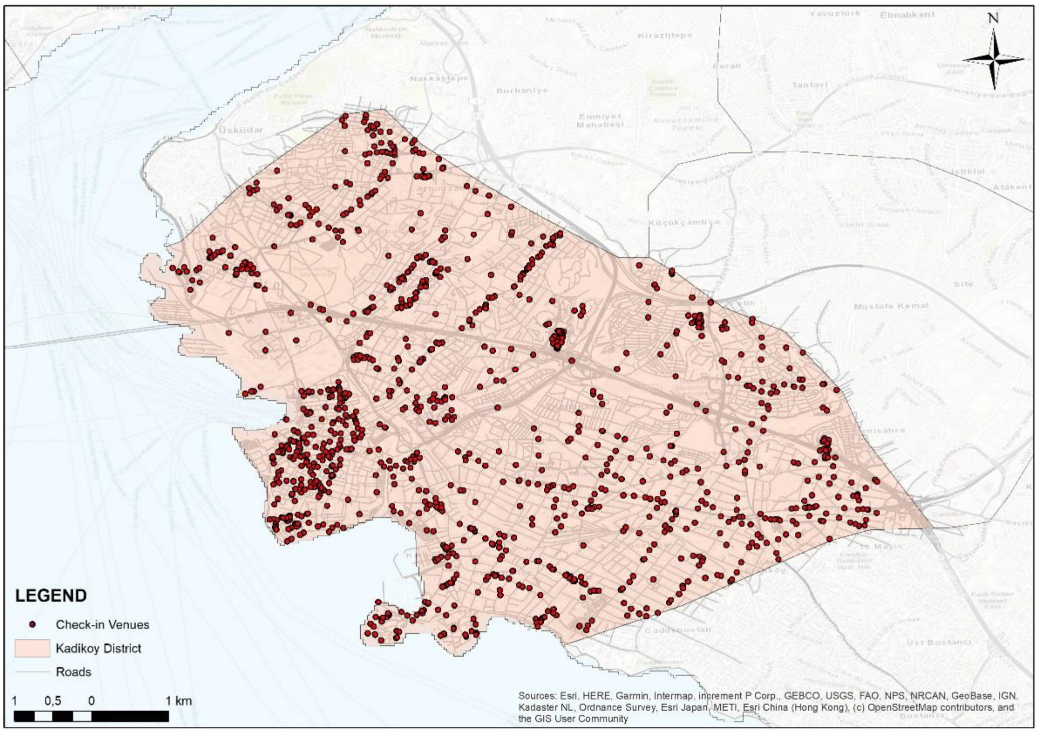

Figure 3.6 Check-in dataset of study area

Foursquare check-in data has a lot of venues category and these category fields were four classified: Drinking & Eating, Entertainment, Recreation and Shopping (Hasan et al., 2013). The categories were classified in PostgreSQL using the Query tool. For example:

UPDATE foursquare_places

SET tip='Shopping' WHERE category IN ('Accessories Stores').

The classification of the check-in venues category is shown in Table 3.3 and illustrated in Figure 3.7.

Table 3.3 Check-in data category classification

The classified check-in venues category	**Check-in venues category**
Drinking & Eating	Café, Restaurant, Bistro, Diner, Pub, Tea Room, etc.
Entertainment	Art Gallery, Museum, Gym, Theater, Opera House, Yoga Studio, etc.
Recreation	Court, Pool, Stadium, Garden, Park, Playground, Mosque, etc.
Shopping	Store, Boutique, Shop, Market, Mall, etc.

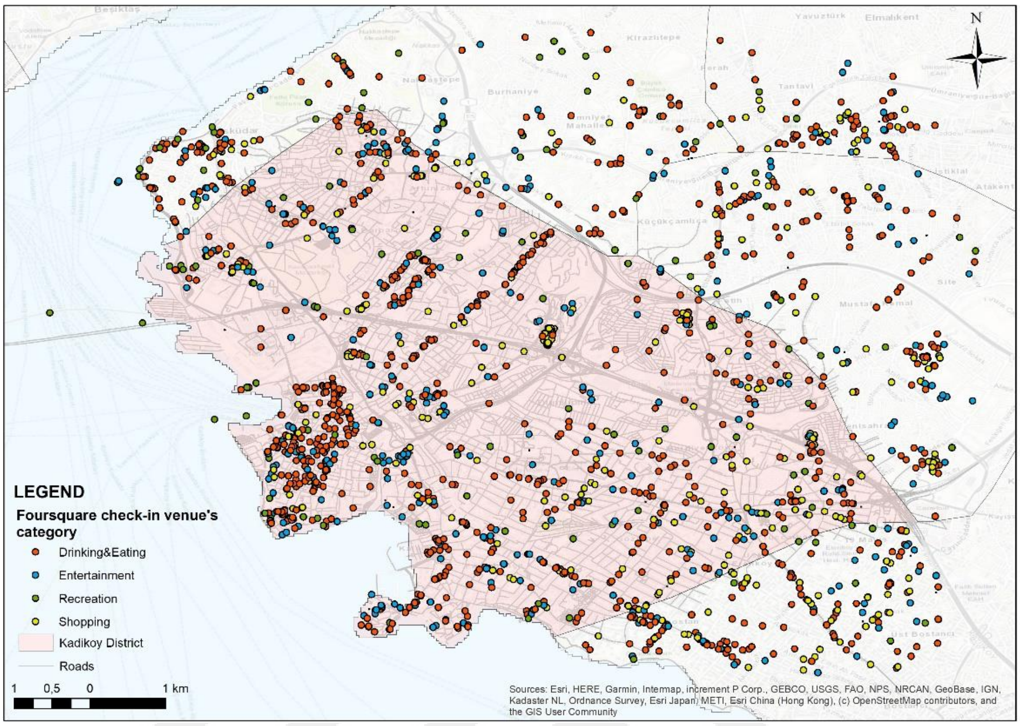

Figure 3.7 The classification of check-in venues categories

Foursquare check-in venues are separated into weekday and weekend and, also day and night categories regarding the check-in hours. Since a check-in venue may have been both day and night or both weekday and weekend, the number of check-in venues is increased. In Table 3.4, the total number of Foursquare check-in venues that are separated into weekday and weekend and day and night categories are presented. Additionally, Foursquare check-in venues are illustrated in Figures 3.8, 3.9, 3.10 and 3.11.

Table 3.4 Check-in time and check-in numbers

Check-in Time of Venues	**Check-in Numbers of Venues**
Weekday Day	896
Weekday Night	92
Weekend Day	843
Weekend Night	785
Total	2616

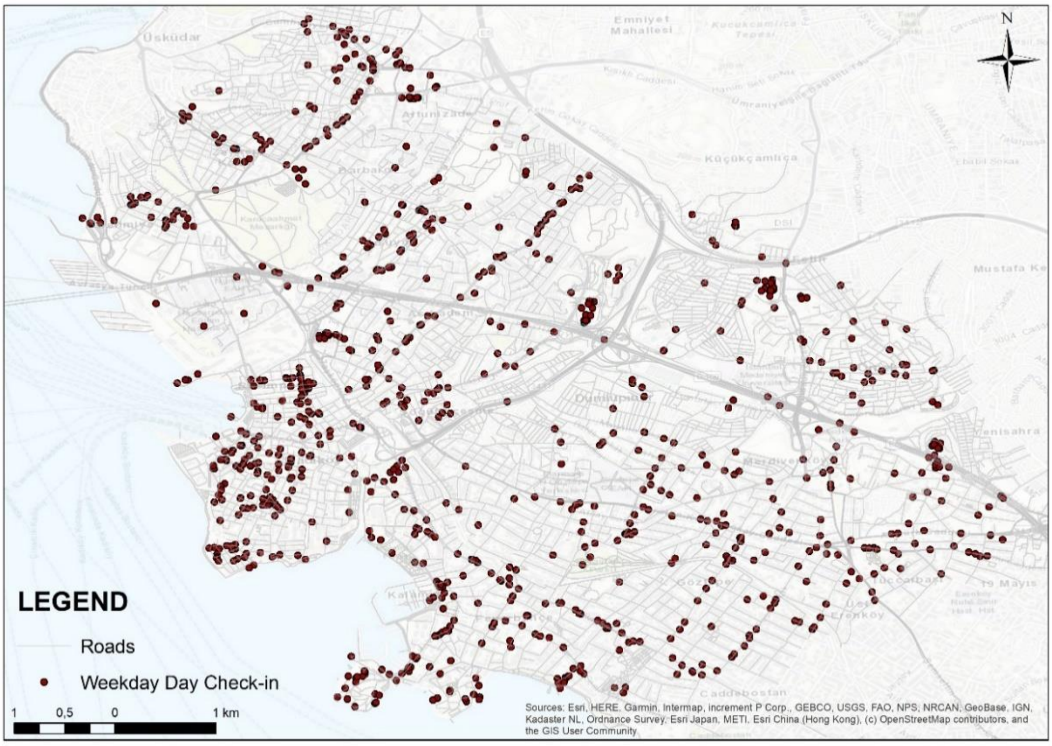

Figure 3.8 Check-in locations of weekday day venues

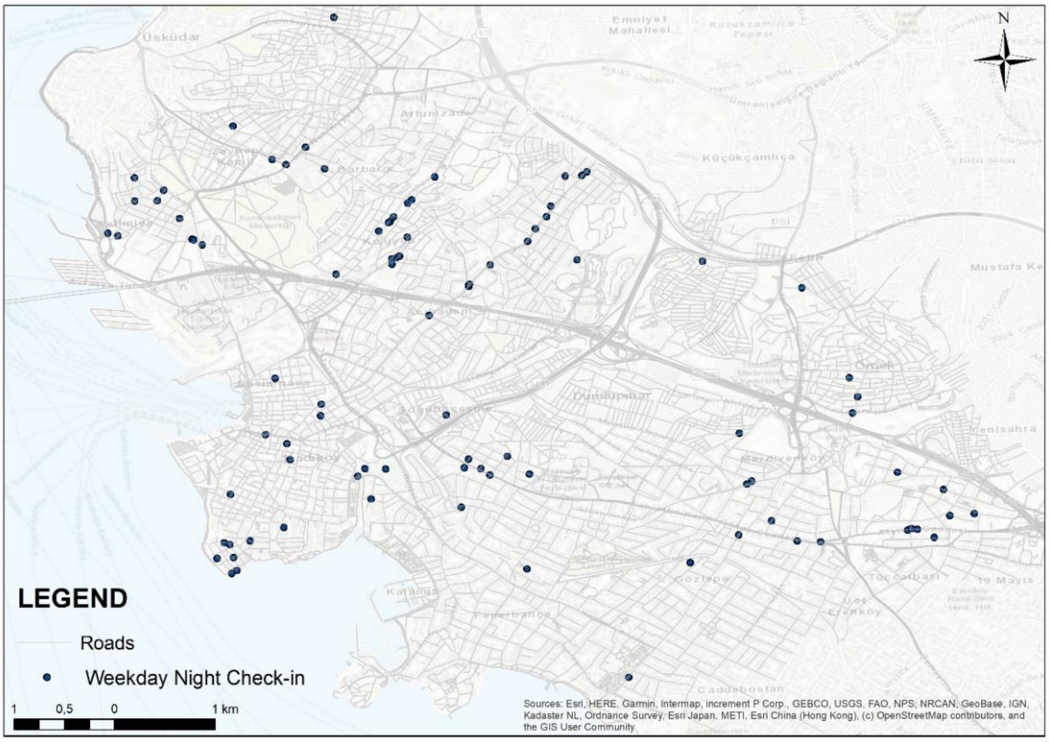

Figure 3.9 Check-in locations of weekday night venues

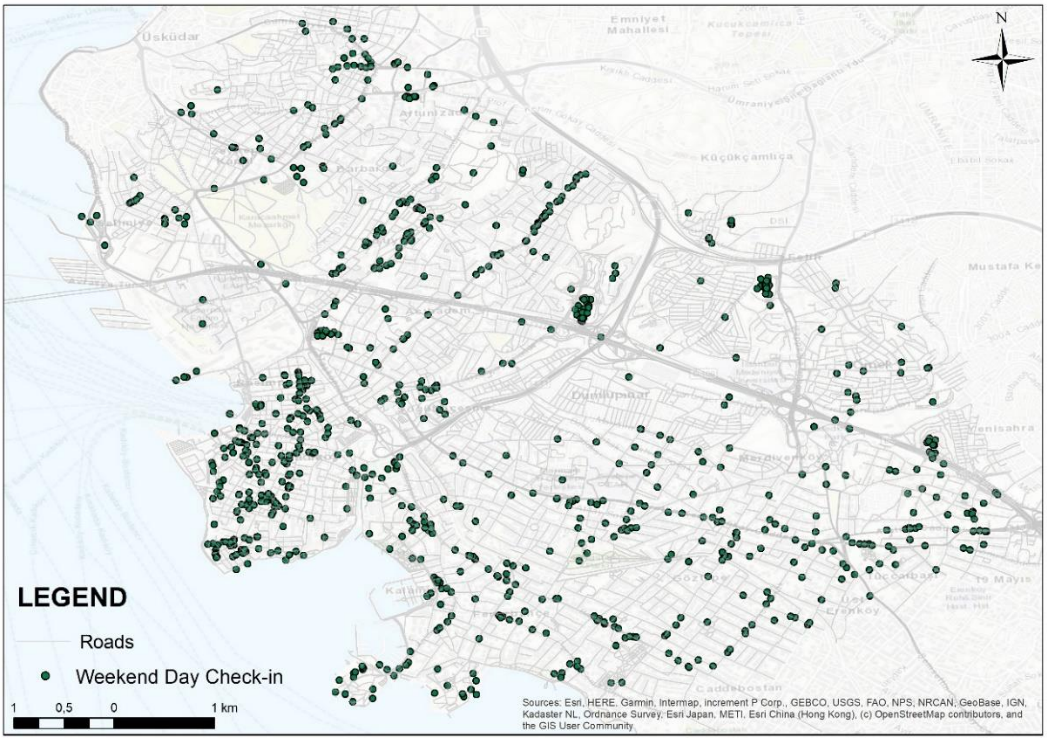

Figure 3.10 Check-in locations of weekend day venues

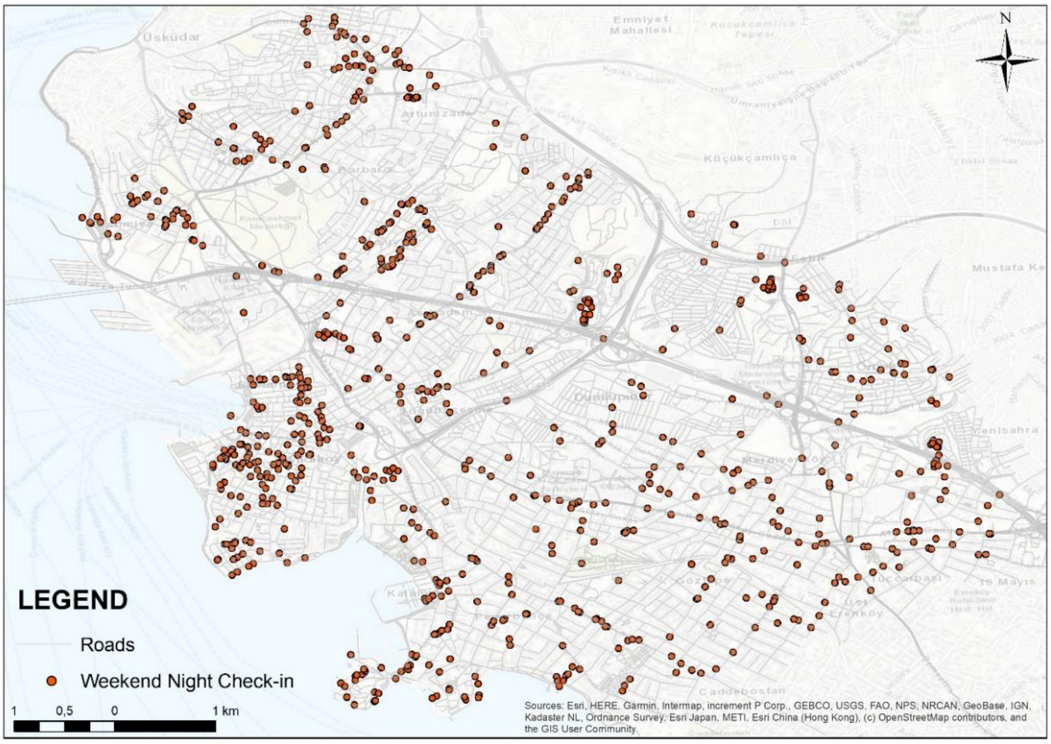

Figure 3.11 Check-in locations of weekend night venues

3.2.2 Bus Transportation Data

According to the 2019 Istanbul Transportation Report, bus transport has the largest share in public transportation (Figure 3.12). Therefore, bus stations were selected to present availability of public transportation in this study.

The bus transportation data was collected from OpenStreetMap database. The variables included in this dataset are bus stop locations and bus routes. In total 141 bus stops points and 2040283 meters bus route lengths were obtained (Figure 3.13).

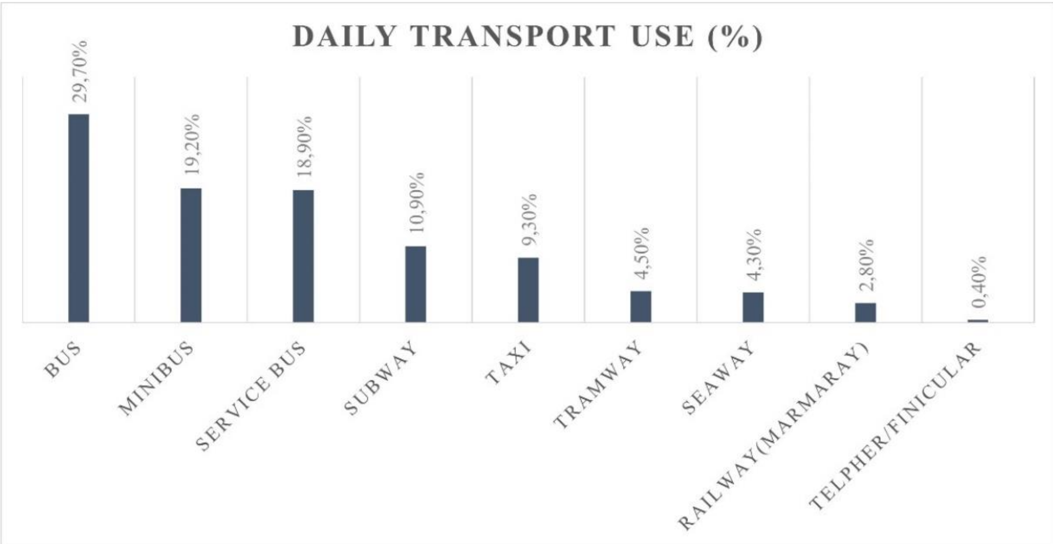

Figure 3.12 Istanbul daily transport use (%)

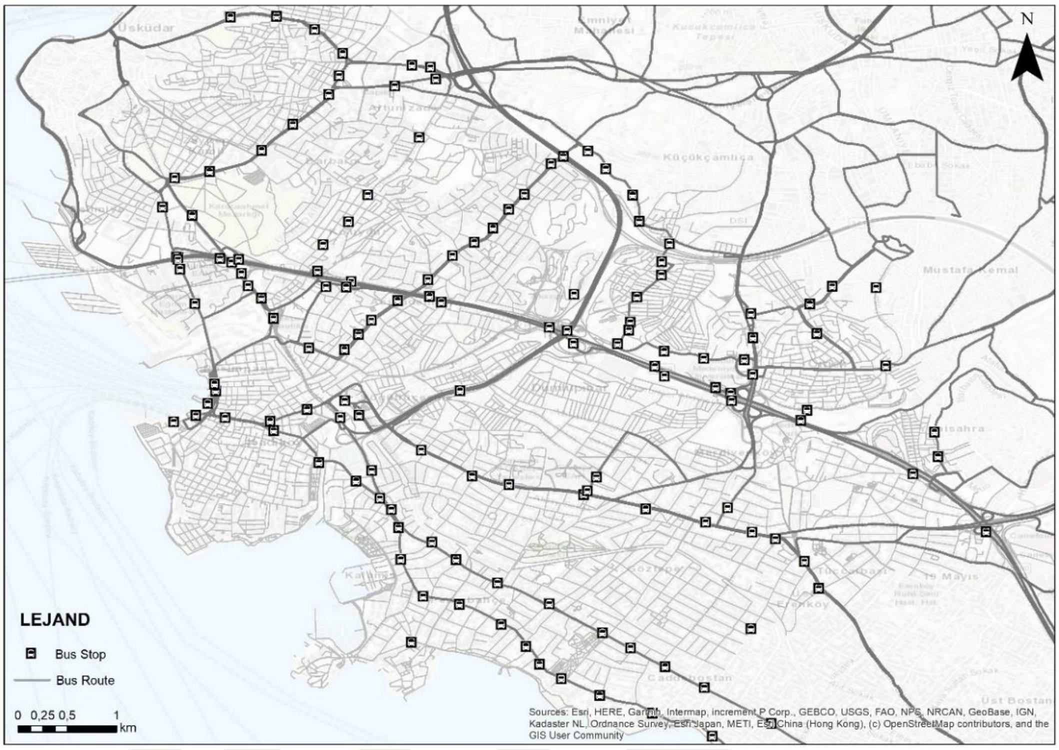

Figure 3.13 Kadikoy bus stations

3.3 Spatial Descriptive Statistics

The mean center is the average X and Y coordinates for a series of points on a map. Mean centers can be calculated with projected geographic data. The mean center is a simple and widely spatial statistics technique used to measure the center of the spatial distribution of point features (Cubukcu, 2021) (Figure 3.14).

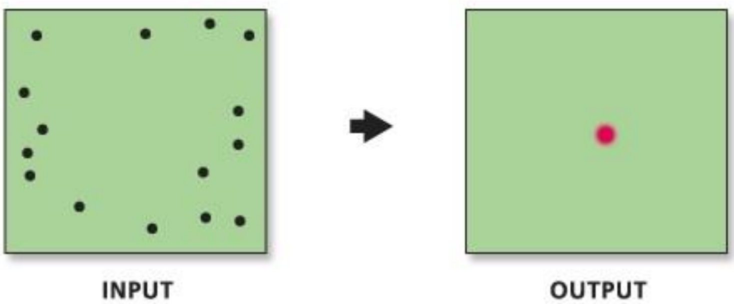

Figure 3.14 Illustration of mean center (Esri, 2009)

There are two very common measures of the spatial dispersion for point data features: (1) standard distance and (2) standard deviational ellipse. The standard deviation ellipse is superior since it indicates direction. The standard deviation ellipse contains approximately 68% of the spatial observations when normal distribution over space. Therefore, it is a strong spatial distribution measure. When calculating standard deviational ellipse for determining the spatial distribution, mean center, deviation from the x-axis, deviation from the y-axis, and angle of deviation the y-axis are calculated (Cubukcu, 2021; Li et al., 2017) (Figure 3.15).

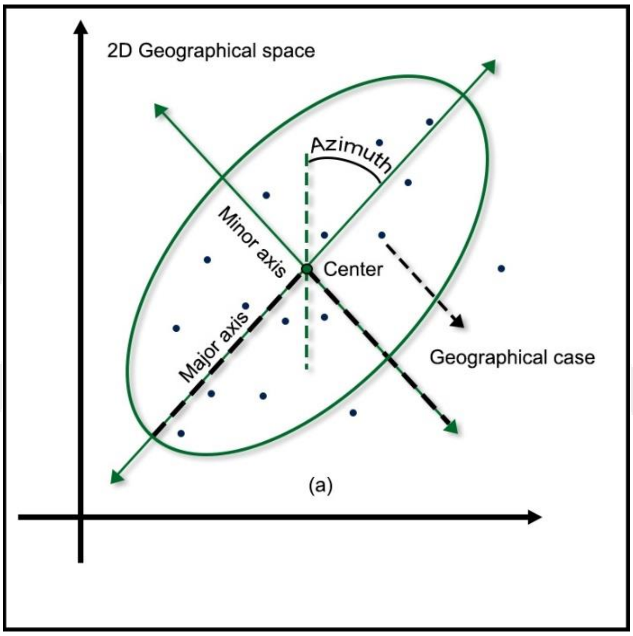

Figure 3.15 Basic elements of standard deviational ellipse (adopted from Li et al., 2017)

Mean centers and standard deviational ellipses were calculated in ArcGIS 10.3. The results of these calculations are shown in Table 3.5. The mean centers and the standard deviational ellipses are shown in Figures 3.16, 3.17, 3.18 and 3.19.

According to the results, the mean center and the direction and size of standard deviational ellipse for weekday night points data are quite different from the others. For the weekday night, mean center of these points is located about 450 meters north of the other mean centers. The mean center of the weekday night venues is located on the north. On the other hand, the mean centers of the weekday day, weekend day and weekend night venues are very close to each other (Figure 3.20).

Table 3.5 Spatial descriptive statistics of Foursquare data

	Mean	**Center**	**Standard**	**Deviational**	**Ellipse**	**Points**	**Area (ha)**
	Y Coord.	**X Coord.**	**Y Std. Dist.**	**X Std. Dist.**	**Rotation**	**n**	
Weekday Day	40.9926	29.0460	0.019927	0.028841	113.762271	896	1683
Weekday Night	40.9971	29.0443	0.01681	0.03082	110.200591	92	1517
Weekend Day	40.9923	29.0454	0.019439	0.028135	109.916399	843	1600
Weekend Night	40.9935	29.0457	0.019909	0.029405	113.891052	785	1713

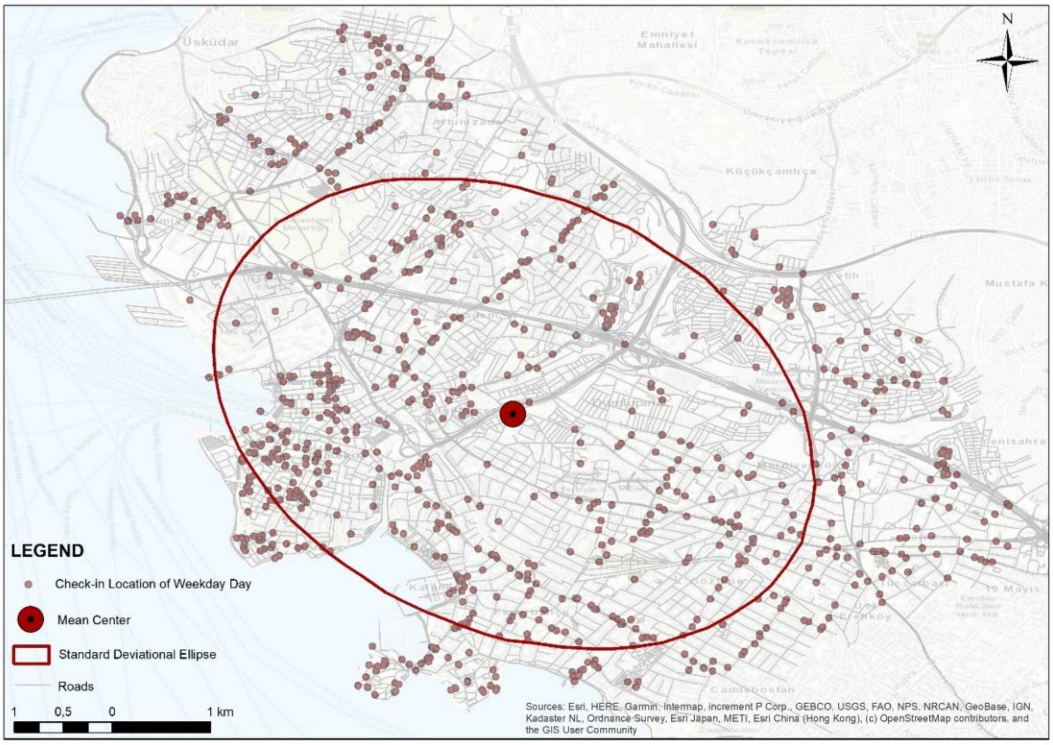

Figure 3.16 Mean center and standard deviational ellipse of weekday day

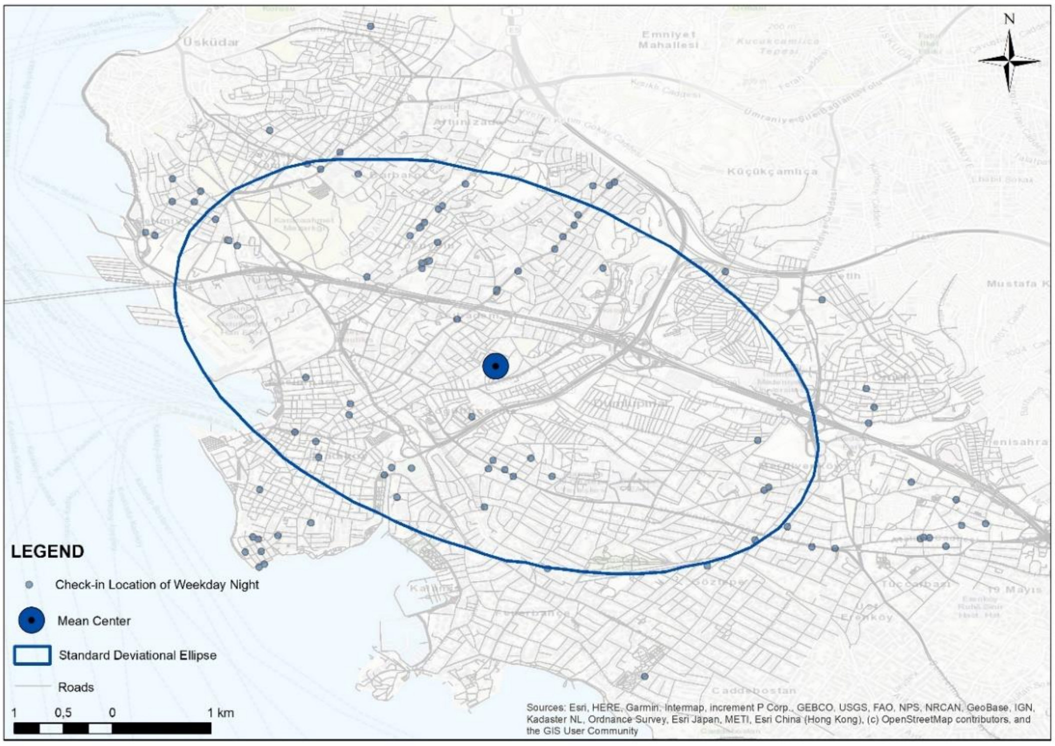

Figure 3.17 Mean center and standard deviational ellipse of weekday night

Figure 3.18 Mean center and standard deviational ellipse of weekend day

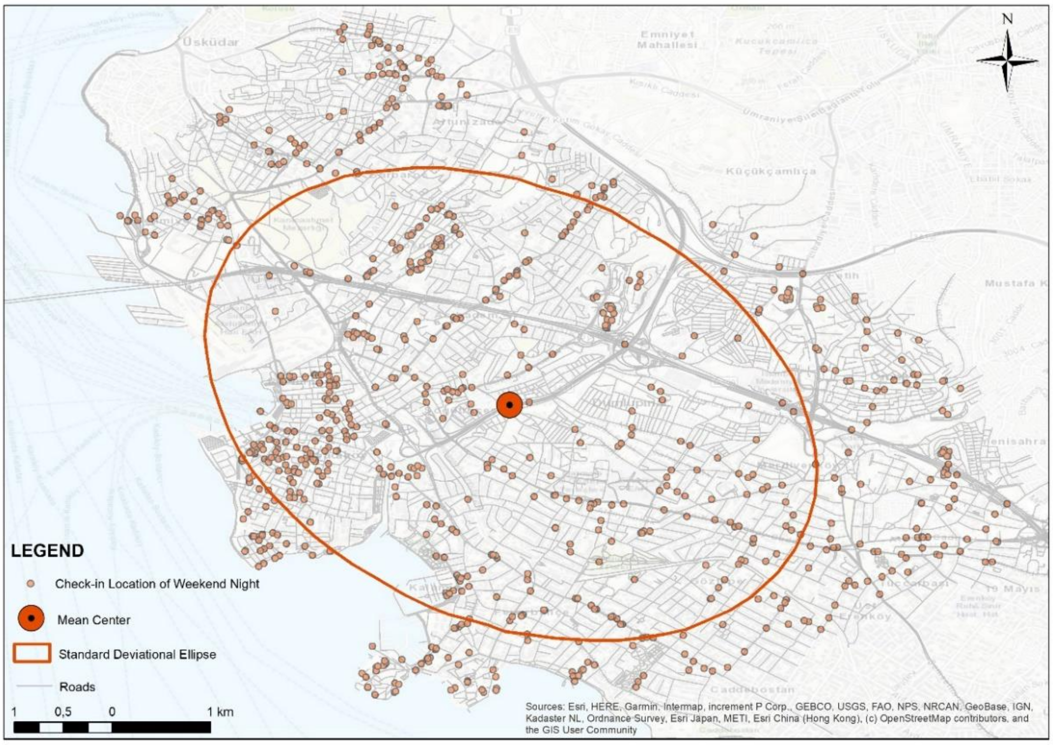

Figure 3.19 Mean center and standard deviational ellipse of weekend night

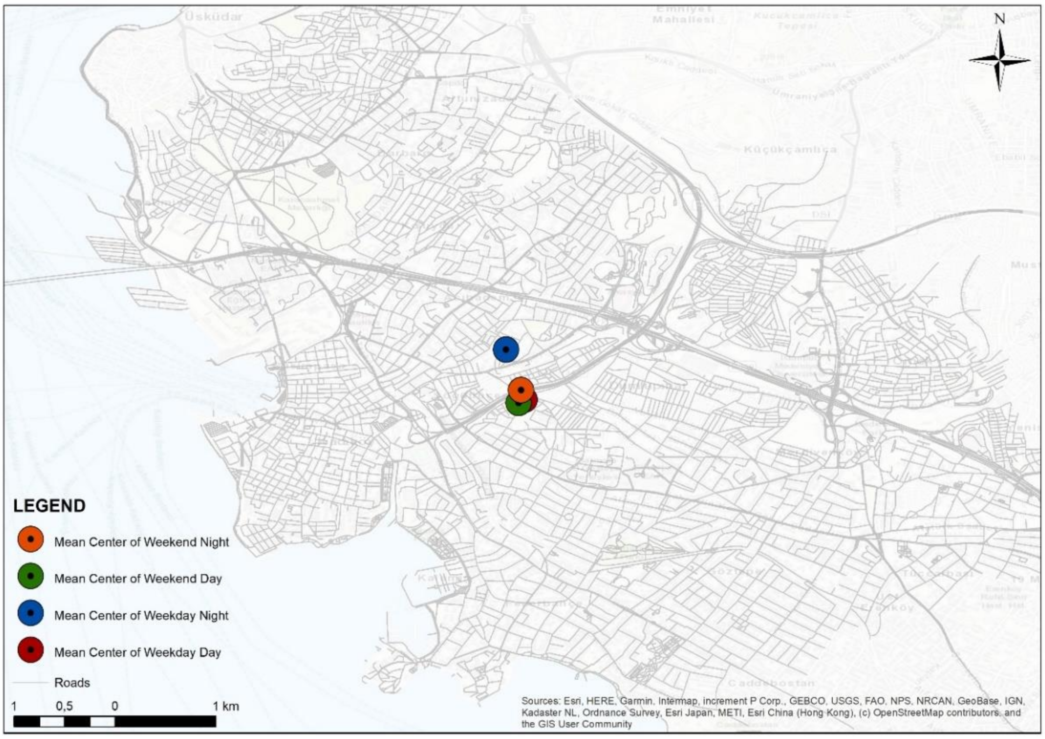

Figure 3.20 Mean center of dataset

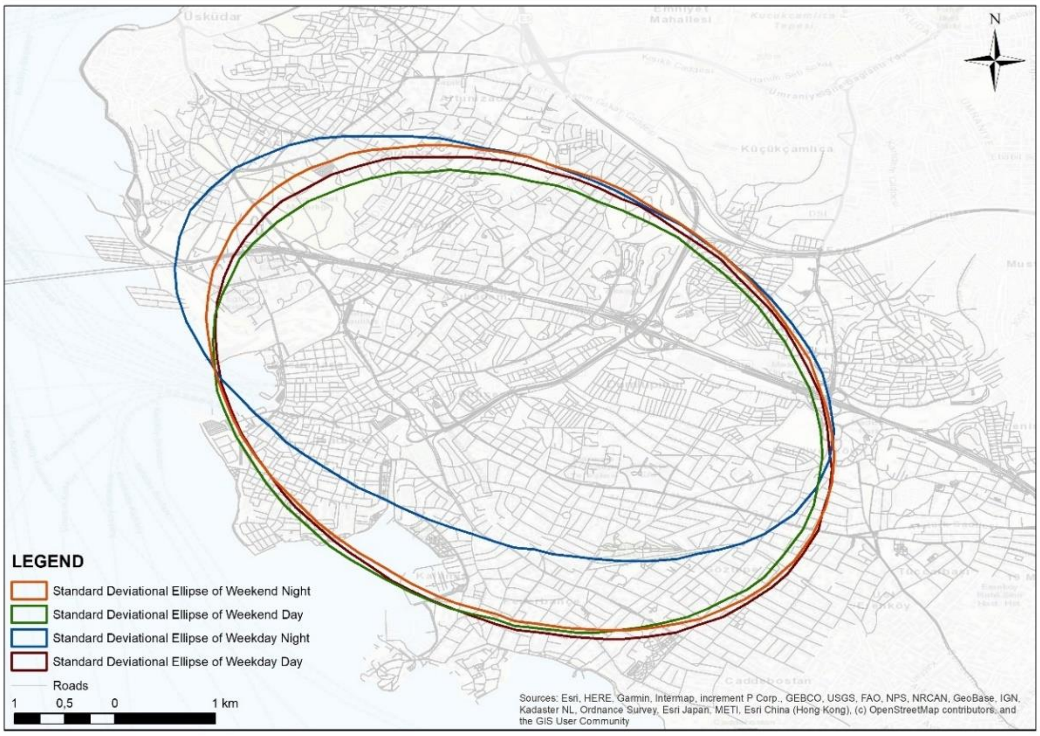

Figure 3.21 Standard deviational ellipse of dataset

The standard deviational ellipse of the weekday day, weekend day and weekend night venues are similar in size and orientation while the standard deviational ellipse of the weekday night venues differs from the others. The standard deviational ellipse of the weekday night venues is located on the north in contrast to other standard deviational ellipses locations (Figure 3.21). However, the standard deviational ellipse of venues at different times is not different.

CHAPTER FOUR
ANALYSIS AND RESULTS

In this section, three different analyses are conducted. The first is Kernel density used to generalize at different hours of weekday and weekend. The second is quadrat analysis for weekdays and weekends and days and nights to understand whether point distributions are significantly different or not. The last analysis is the closest facility, which finds the closest path from Foursquare venues to the bus stops and to understand the differences in accessibility on different day and at different hours.

4.1 Density Analysis

Kernel Density is a spatial analyst technique of GIS. Kernel Density calculates a magnitude-per-unit area from point features using a kernel function to fit smoothly surface to each point. GIS-based Kernel Density Estimation (KDE) is calculated using a radius input through which the various density levels (Figure 4.1). The radius is either manually or automatically defined (Bonnier, Finné & Weiberg, 2019).

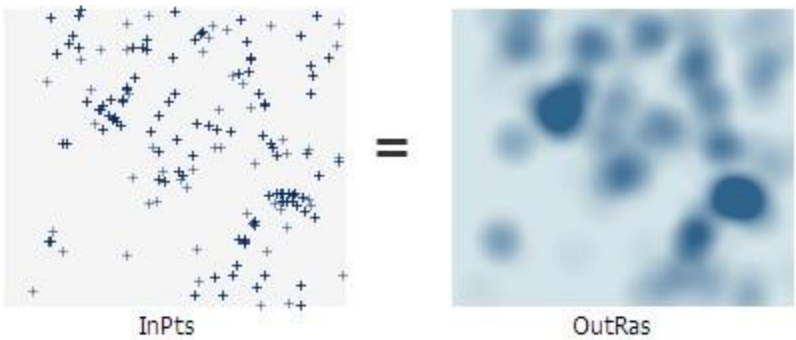

Figure 4.1 Illustration of kernel density (Esri,2009)

4.1.1 Density Analysis of Weekdays and Weekends Check-in Venues

In this chapter, kernel density is conducted for weekday and weekend check-in venues (Figure 4.2 and 4.3). Weekday check-in venues consist of Monday, Tuesday, Wednesday, Thursday while weekend check-in venues consist of Friday, Saturday and Sunday.

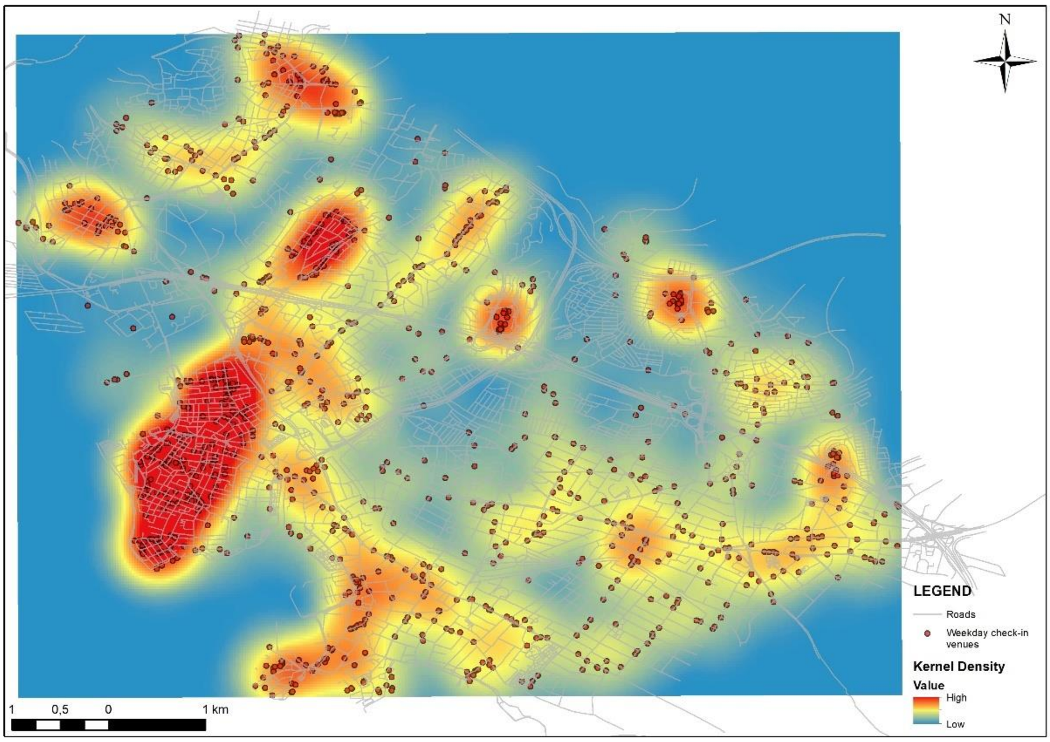

Figure 4.2 Kernel density of weekday check-in venues

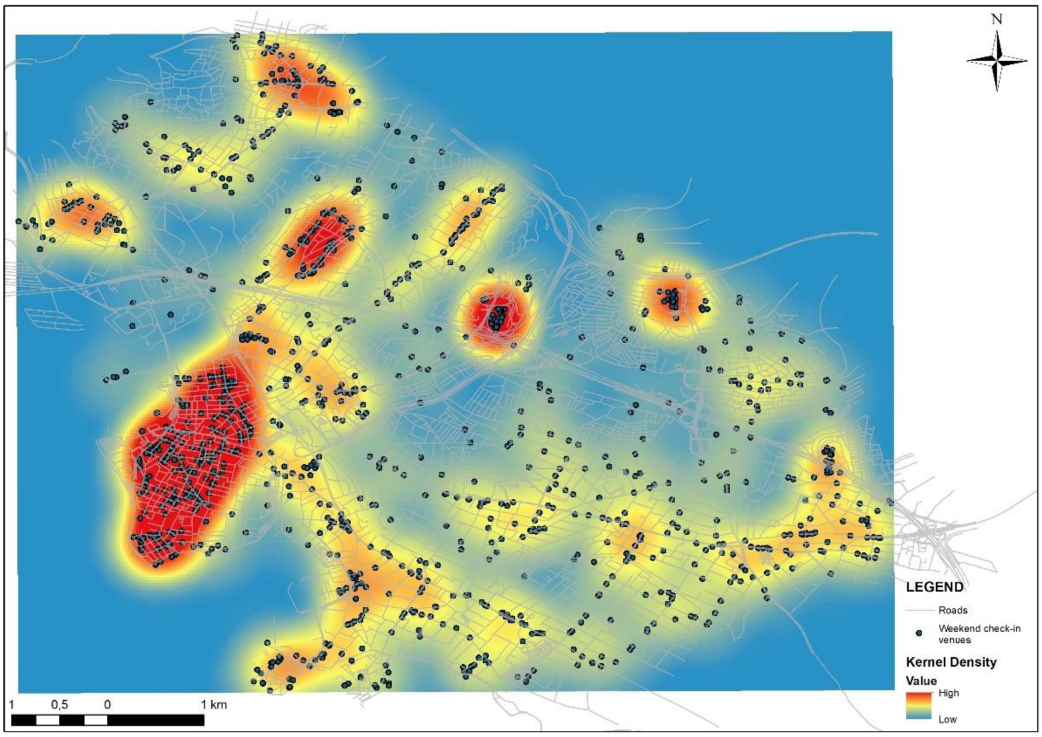

Figure 4.3 Kernel density of weekend check-in venues

The check-in venue may have been both weekdays and weekends. Thus, the results show that the density of weekday and weekend check-in venues is not very different from each other. The centre and seaside of Kadikoy have a high density on weekdays and weekends. Furthermore, the north of the district has a high density both weekdays and weekends.

4.1.2 Density Analysis of Weekdays and Weekends Check-in Times

In this chapter, kernel density analysis is conducted for weekday and weekend regarding check-in hours. Kernel density of Foursquare venues are based on weekday index and weekend index fields. These index values are obtained in Python according to the days and hours. Firstly, the index calculator is calculated to the Python code and determined nightlife index parameter to understand check-in time for this district. The code following:

```
def index_calculator(self):

        time_list = NightlifeIndex.time_list(self)

        dict = {'6:00:00': 7, '7:00:00': 5, '8:00:00': 3, '9:00:00': 2, '10:00:00': 1, '11:00:00': 2, '12:00:00': 2, '13:00:00': 2, '14:00:00': 3, '15:00:00': 3, '16:00:00': 3, '17:00:00': 4, '18:00:00': 4, '19:00:00': 5, '20:00:00': 6, '21:00:00': 7, '22:00:00': 7, '23:00:00': 9, '0:00:00': 9, '1:00:00': 10, '2:00:00': 10, '3:00:00': 10, '4:00:00': 9, '5:00:00': 8}

        index = 0

        var= 0

        index_list = []

        x = 0

        while x < len(time_list):

            index_values = dict[time_list[x]]

            index_list.append(index_values)

            x = x+1

            var = np.var(index_list, axis=0)

            index = statistics.median_grouped(index_list)

        return round(var), index.
```

Then, each day is divided into two parts according to the check-in hours. The index values are calculated to the check-in hours. The code following:

```
mondayIndex = (NightlifeIndex(monday_1).index_calculator()[1] + NightlifeIndex(monday_2).index_calculator()[1])/2
tuesdayIndex = (NightlifeIndex(tuesday_1).index_calculator()[1] + NightlifeIndex(tuesday_2).index_calculator()[1])/2
wednesdayIndex = (NightlifeIndex(wednesday_1).index_calculator()[1] + NightlifeIndex(wednesday_2).index_calculator()[1])/2
thursdayIndex = (NightlifeIndex(thursday_1).index_calculator()[1] + NightlifeIndex(thursday_2).index_calculator()[1])/2
fridayIndex = (NightlifeIndex(friday_1).index_calculator()[1] + NightlifeIndex(friday_2).index_calculator()[1])/2
saturdayIndex = (NightlifeIndex(saturday_1).index_calculator()[1] + NightlifeIndex(saturday_2).index_calculator()[1])/2
sundayIndex = (NightlifeIndex(sunday_1).index_calculator()[1] + NightlifeIndex(sunday_2).index_calculator()[1])/2
```

Lastly, index value of weekday and weekend is calculated to the hours and days. The code following:

```
weekday_index = round ((mondayIndex + tuesdayIndex + wednesdayIndex + thursdayIndex)/4)
weekend_index = round ((fridayIndex + saturdayIndex + sundayIndex) / 3).
```

After calculating index values according to this Python code, each check-in venue has check-in hours on days and index values on weekdays and weekends. The sample check-in venue is presented in Table 4.1.

Table 4.1 Sample of check-in venue

Name	Veis Rumeli Dondurması
Location	
Monday_1	Null
Monday_2	Null
Tuesday_1	13:00-01:00
Tuesday_2	Null
Wednesday_1	13:00-18:00
Wednesday_2	20:00-01:00
Thursday_1	Null
Thursday_2	Null
Friday_1	15:00-02:00
Friday_2	Null
Saturday_1	14:00-00:00
Saturday_2	Null
Sunday_1	12:00-13:00
Sunday_2	15:00-00:00
Weekday index	2
Weekend index	4

According to the weekday and weekend index parameters, index 1 and 2 mean check-in at daytime, while index 3,4 and 5 mean check-in later in the day. The results are shown Figure 4.4 and Figure 4.5.

Canepa (2007) suggested a walking distance of 400 m for buses and 800 m for rail transport based on observations. The radius for kernel density is then accepted 500 m in this study. Cell size is defined as a 50.

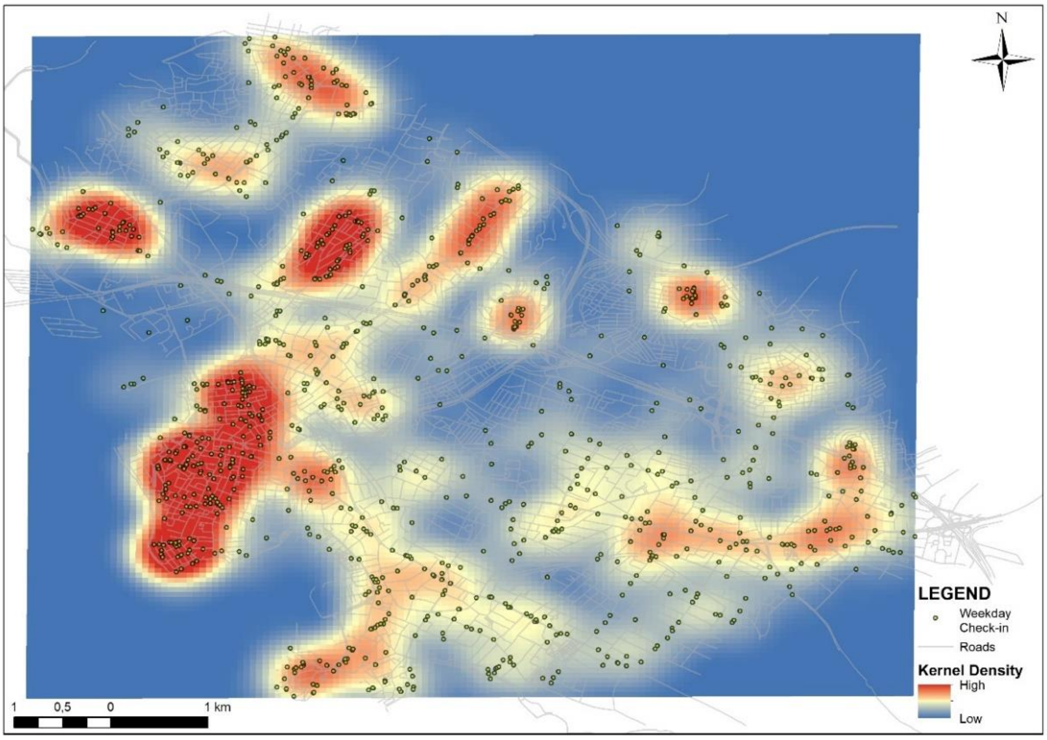

Figure 4.4 Kernel density of weekdays check-in times

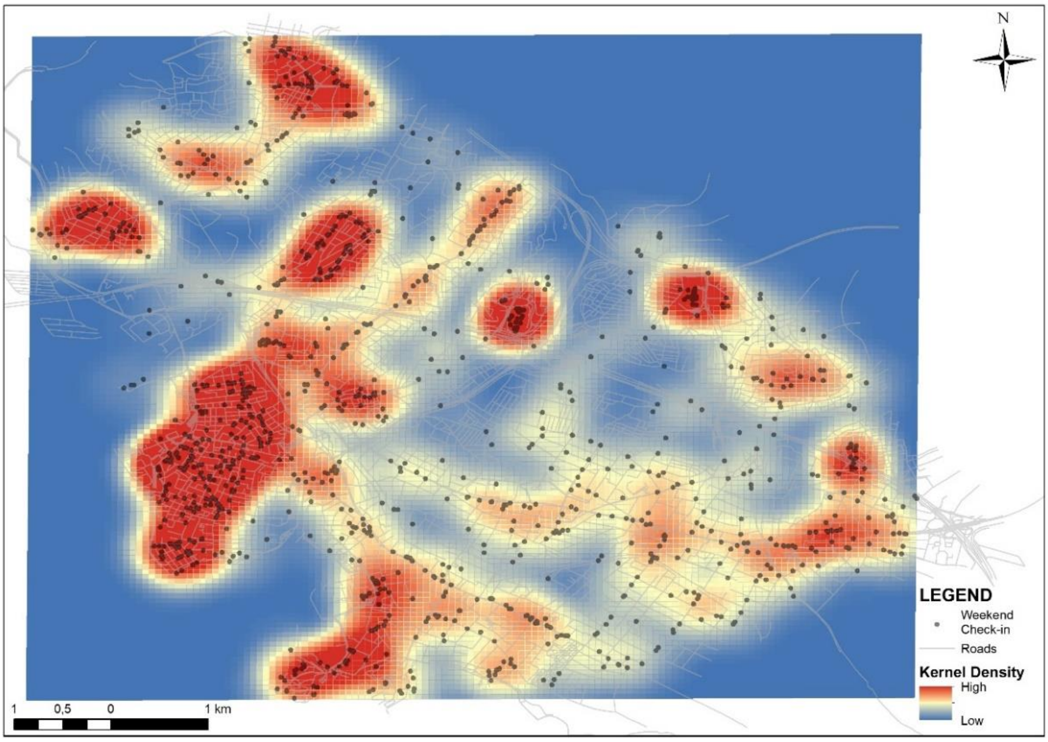

Figure 4.5 Kernel density of weekends check-in times

As a result, the density of weekday and weekend check-in venues is not very different from each other. Especially, the centre of Kadikoy and seaside have a high density on weekdays and weekends.

The density of check-in time appears to be higher on weekends. Moreover, weekend check-in venues densify in the seaside and north of the study area. However, higher densities are observed both on weekdays and weekends in the centre of the Kadikoy district.

4.2 Quadrat Analysis

In this chapter, quadrat analysis is calculated for weekday and weekend daytime and nighttime hours and to understand whether these point data differ significantly or not.

Quadrat Analysis is one of the point pattern techniques that explain how to point data is distributed over space. The study area is divided into equal quadrats and compared according to the point count in each quadrat (Cubukcu,2021) (Figure 4.6).

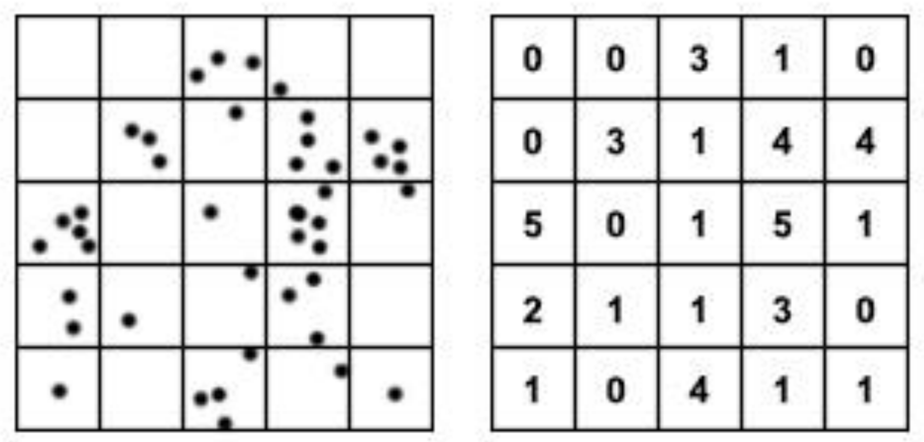

Figure 4.6 Quadrat distribution and count in each quadrat

First, the quadrat area is calculated, then one edge of the quadrat square is calculated.

$$K = \frac{2 \times A}{n} \tag{4.1}$$

$$k = \sqrt{K} = \sqrt{\frac{2 \times A}{n}} \tag{4.2}$$

Where A is the study area, n is the number of points and k is the edge side length.

Then the width and length of the study area is divided into quadrat edge length to find the integer numbers of rows (rk) and columns(ck) and the frequency distribution table is prepared according to the count of points in each quadrat (Cubukcu,2021).

$$rk = \frac{lenght\ of\ area}{k} \tag{4.3}$$

$$ck = \frac{width\ of\ area}{k} \tag{4.4}$$

The number of quadrats*(m*) is calculated by multiplying the number of rows and columns.

$$m = rk \times ck \tag{4.5}$$

After finding the number of rows and columns, the study area is divided into quadrats. The counts in each quadrat are the frequency and these frequency numbers are added to Microsoft Excel to calculate cumulative frequency and cumulative frequency probabilities. Cumulative frequency is found by adding preceding frequencies for the count of points in each quadrat, while cumulative frequency probability is found cumulative frequency divides into total quadrat count (Cubukcu, 2021). These values are calculated in Excel.

After finding the cumulative frequency probabilities for the day (P_o) and the night (P_h) it is calculated Kolmogorov - Smirnov z-statistics(K-S_z). The K-S_z is calculated using the absolute maximum value of the differences of the compared day and night cumulative frequency probabilities (Cubukcu, 2021).

$$K - S_z = \sqrt{\frac{mo \times mh}{mo + mh}} \times \max|P_o - P_h| \tag{4.6}$$

mo=quadrat count of the day mh=quadrat count of the night

The statistical significance of the result is tested with the hypothesis test:

Null hypothesis (H_0): The two spatial distributions examined are same.

Alternative hypothesis (H_A): The two spatial distributions examined are different.

When the statistical significancy level α is 0.05, K-$S_{z\alpha}$ is 1.36 and if |K-S_z| ≥K-$S_{z\alpha}$ null hypothesis can be rejected.

Quadrat analysis is applied to points of day and night on weekdays and weekends in Kadikoy district to see point distribution. When calculating the area of the study district was used Calculate Geometry in ArcGIS 10.3 and area is found as 30 km^2.

4.2.1 Quadrat Analysis of Day and Night on Weekends

For the weekend day, the number of points is 843, and the area 30 km^2.

$$k = \sqrt{\frac{2 \times 30}{843}} \cong 0.265 \tag{4.7}$$

$$rk = \frac{6}{0.265} \cong 23 \tag{4.8}$$

$$ck = \frac{5}{0.265} \cong 19 \tag{4.9}$$

For the weekend night, the number of points is 785, and the area 30 km^2.

$$k = \sqrt{\frac{2 \times 30}{785}} \cong 0.275 \tag{4.10}$$

$$rk = \frac{6}{0.275} \cong 22 \tag{4.11}$$

$$ck = \frac{5}{0.275} \cong 18 \tag{4.12}$$

The count of quadrats is 437 for the weekend day(*mo*) and 396 for the weekend night(*mh*) (Figure 4.7 and 4.8). The result of Kolmogorov - Smirnov z-statistics is presented Table 4.2, 4.3 and 4.4.

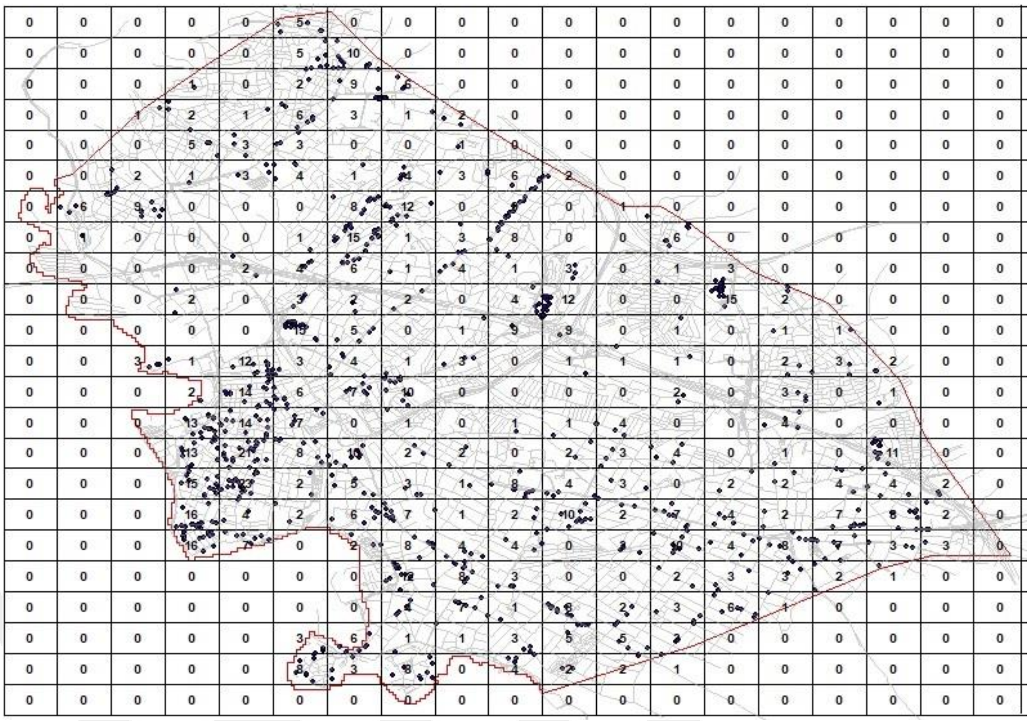

Figure 4.7 Count in each quadrat for weekend days

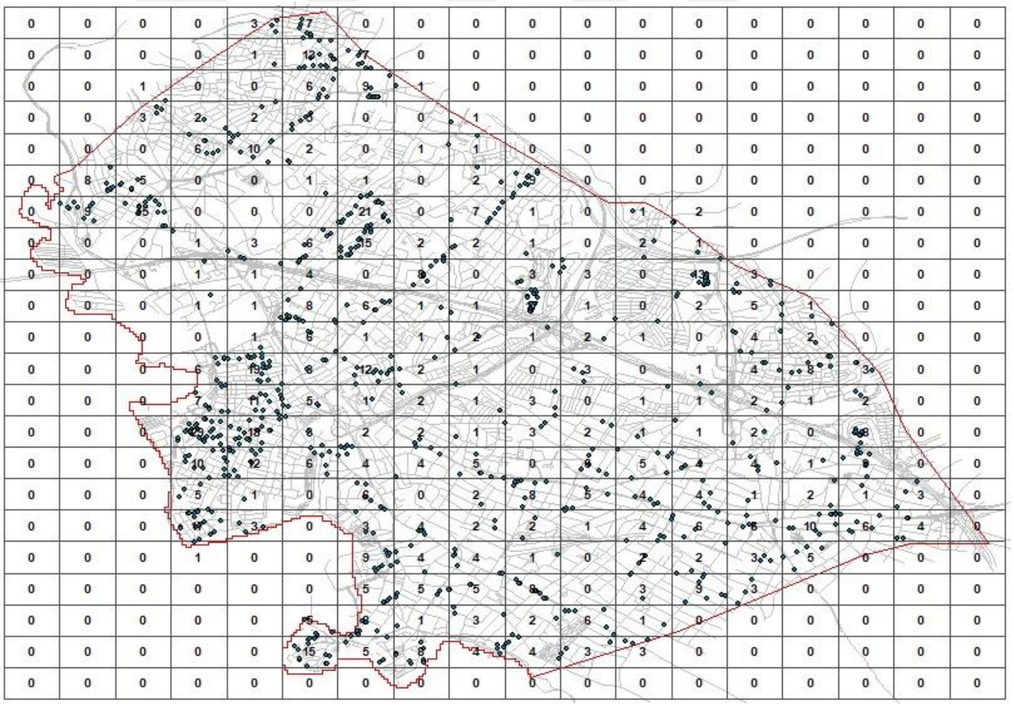

Figure 4.8 Count in each quadrat for weekend nights

Table 4.2 The result of quadrat analysis for the weekend day

Point in quadrat (weekend day)	**Frequency (weekend day)**	**Cumulative Frequency (weekend day)**	**Cumulative Frequency Probability (weekend day) (P_o)**
0	259	259	0.5926
1	36	295	0.6750
2	32	327	0.7482
3	28	355	0.8123
4	19	374	0.8558
5	7	381	0.8718
6	10	391	0.8947
7	8	399	0.9130
8	11	410	0.9382
9	5	415	0.9496
10	5	420	0.9610
11	1	421	0.9633
12	4	425	0.9725
13	2	427	0.9771
14	2	429	0.9816
15	4	433	0.9908
16	2	435	0.9954
17	0	435	0.9954
18	0	435	0.9954
19	0	435	0.9954
20	0	435	0.9954
21	1	436	0.9977
22	0	436	0.9977
23	0	437	1
24	0	437	1
25	0	437	1
26	0	437	1
27	0	437	1
28	0	437	1
29	0	437	1
30	0	437	1
31	0	437	1
32	0	437	1
…	…	…	…
843	0	437	1

Table 4.3 The result of quadrat analysis for the weekend night

Point in quadrat (weekend night)	Frequency (weekend night)	Cumulative Frequency (weekend night)	Cumulative Frequency Probability (weekend night) (P_h)
0	224	224	0.5656
1	45	269	0.6792
2	27	296	0.7474
3	21	317	0.8005
4	16	333	0.8409
5	14	347	0.8762
6	13	360	0.9090
7	4	364	0.9191
8	9	373	0.9419
9	6	379	0.9570
10	3	382	0.9646
11	1	383	0.9671
12	2	385	0.9722
13	2	387	0.9772
14	0	387	0.9772
15	3	390	0.9848
16	0	390	0.9848
17	2	392	0.9898
18	1	393	0.9924
19	1	394	0.9949
20	0	394	0.9949
21	1	395	0.9974
22	0	395	0.9974
23	0	395	0.9974
24	0	395	0.9974
25	0	395	0.9974
26	0	395	0.9974
27	0	395	0.9974
28	0	395	0.9974
29	1	396	1
30	0	396	1
31 32 …	0 0 …	396 396 …	1 1 …
785	0	396	1

Table 4.4 The result of $|P_o - P_h|$

Cumulative Frequency Probability (weekend day) (P_o)	**Cumulative Frequency Probability (weekend night) (P_h)**	**$\|P_o - P_h\|$**
0.5926	0.5656	0.0270
0.6750	0.6792	|-0.0042|
0.7482	0.7474	0.0008
0.8123	0.8005	0.0118
0.8558	0.8409	0.0149
0.8718	0.8762	|-0.0044|
0.8947	0.9090	|-0.0143|
0.9130	0.9191	|-0.0061|
0.9382	0.9419	|-0.0037|
0.9496	0.9570	|-0.0074|
0.9610	0.9646	|-0.0035|
0.9633	0.9671	|-0.0037|
0.9725	0.9722	0.0003
0.9771	0.9772	|-0.0001|
0.9816	0.9772	0.0044
0.9908	0.9848	0.0059
0.9954	0.9848	0.0105
0.9954	0.9898	0.0055
0.9954	0.9924	0.0029
0.9954	0.9949	0.0004
0.9954	0.9949	0.0004
0.9977	0.9974	0.0002
0.9977	0.9974	0.0002
1	0.9974	0.002
1	0.9974	0.002
1	0.9974	0.002
1	0.9974	0.002
1	0.9974	0.002
1	0.9974	0.002
1	1	0
1	1	0
1 1 …	1 1 …	0 0 …
1	1	0
$\max\|P_0 - P_h\|$		0.027

The result of max $|P_o - P_h|$ is 0.027.

$$K - S_z = \sqrt{\frac{437 \times 396}{437 + 396}} \times 0.027 \tag{4.13}$$

$$K - S_z = 0.389 \tag{4.14}$$

When α is 0.05 $K\text{-}S_{z\alpha}$ is 1.36 and the result is 0.389 then the $|K\text{-}S_z| \geq K\text{-}S_{z\alpha}$ condition is not fulfilled, the null hypothesis can't be rejected. The two spatial distributions examined are the same. The statistically significant results reveal that the patterns observed on weekend day and weekend night are not different.

4.2.2 Quadrat Analysis of Day and Night on Weekdays

For the weekday day, the number of points is 896, and the area 30 km^2.

$$k = \sqrt{\frac{2 \times 30}{896}} \cong 0.257 \tag{4.15}$$

$$rk = \frac{6}{0.257} \cong 23 \tag{4.16}$$

$$ck = \frac{5}{0.257} \cong 19 \tag{4.17}$$

For the weekday night, the number of points is 92, and the area 30 km^2.

$$k = \sqrt{\frac{2 \times 30}{92}} \cong 0.804 \qquad (4.18)$$

$$rk = \frac{6}{0.804} \cong 7 \qquad (4.19)$$

$$ck = \frac{5}{0.804} \cong 6 \qquad (4.20)$$

The count of quadrat is 437 for the weekend day(*mo*) and 42 for the weekend night(*mh*) (Figure 4.9 and 4.10). The result of Kolmogorov - Smirnov z-statistics is presented Table 4.5, 4.6 and 4.7.

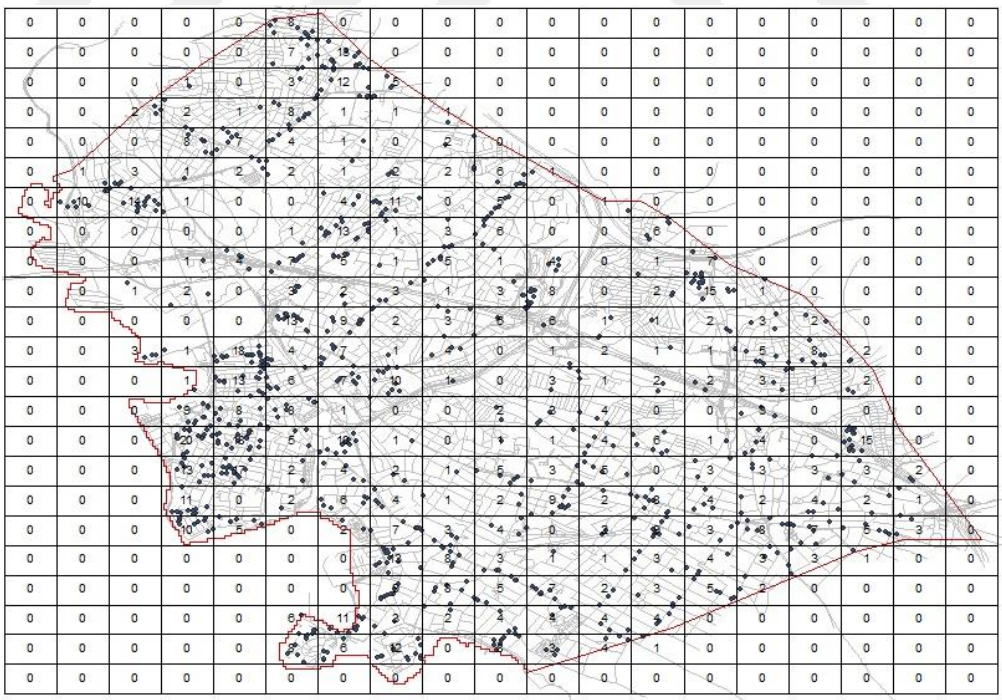

Figure 4.9 Count in each quadrat for weekday days

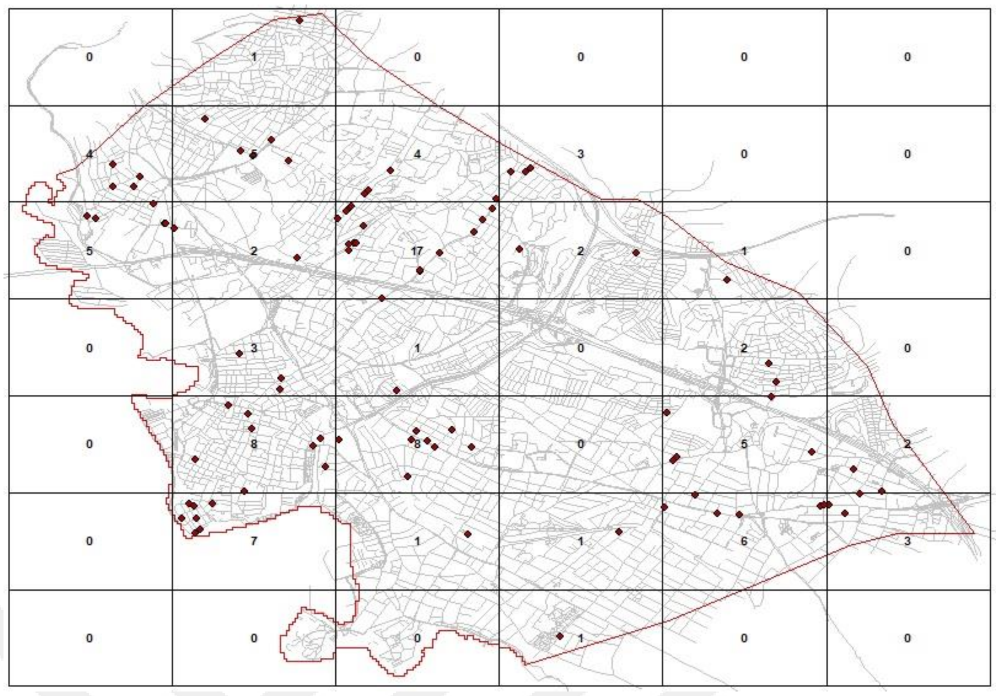

Figure 4.10 Count in each quadrat for weekday nights

Table 4.5 The result of quadrat analysis for the weekday day

Point in quadrat (weekday day)	**Frequency (weekday day)**	**Cumulative Frequency (weekday day)**	**Cumulative Frequency Probability (weekday day) (P_o)**
0	242	242	0.5537
1	44	286	0.6544
2	32	318	0.7276
3	28	346	0.7917
4	20	366	0.8375
5	12	378	0.8649
6	10	388	0.8878
7	9	397	0.9084
8	13	410	0.9382
9	5	415	0.9496
10	4	419	0.9588
11	3	422	0.9656
12	2	424	0.9702
13	6	430	0.9839
14	1	431	0.9862
15	2	433	0.9908
16	0	433	0.9908
17	1	434	0.9931
18	2	436	0.9977
19	0	436	0.9977
20	1	437	1
21	1	437	1
22	0	437	1
23	0	437	1
24	0	437	1
25	0	437	1
26	0	437	1
27	0	437	1
28	0	437	1
29	0	437	1
30	0	437	1
31 32 …	0 0 …	437 437 …	1 1 …
896	0	437	1

Table 4.6 The result of quadrat analysis for the weekday night

Point in quadrat (weekday night)	**Frequency (weekday night)**	**Cumulative Frequency (weekday night)**	**Cumulative Frequency Probability (weekday night) (P_h)**
0	19	19	0.4523
1	6	25	0.5952
2	4	29	0.6904
3	3	32	0.7619
4	2	34	0.8095
5	3	37	0.8809
6	1	38	0.9047
7	1	39	0.9285
8	2	41	0.9761
9	0	41	0.9761
10	0	41	0.9761
11	0	41	0.9761
12	0	41	0.9761
13	0	41	0.9761
14	0	41	0.9761
15	0	41	0.9761
16	0	41	0.9761
17	1	42	1
18	0	42	1
19	0	42	1
20	0	42	1
21	0	42	1
22	0	42	1
23	0	42	1
24	0	42	1
25	0	42	1
26	0	42	1
27	0	42	1
28	0	42	1
29	0	42	1
30	0	42	1
31 32 …	0 0 …	42 42 …	1 1 …
92	0	42	1

Table 4.7 The result of $|P_o-P_h|$

Cumulative Frequency Probability (weekday day) (P_o)	**Cumulative Frequency Probability (weekday night) (P_h)**	**$\|P_o-P_h\|$**
0.5537	0.4523	0.0270
0.6544	0.5952	|-0.0042|
0.7276	0.6904	0.0008
0.7917	0.7619	0.0118
0.8375	0.8095	0.0149
0.8649	0.8809	|-0.0044|
0.8878	0.9047	|-0.0143|
0.9084	0.9285	|-0.0061|
0.9382	0.9761	|-0.0037|
0.9496	0.9761	|-0.0074|
0.9588	0.9761	|-0.0035|
0.9656	0.9761	|-0.0037|
0.9702	0.9761	0.0003
0.9839	0.9761	|-0.0001|
0.9862	0.9761	0.0044
0.9908	0.9761	0.0059
0.9908	0.9761	0.0105
0.9931	1	0.0055
0.9977	1	0.0029
0.9977	1	0.0004
1	1	0.0004
1	1	0.0002
1	1	0.0002
1	1	0.002
1	1	0.002
1	1	0.002
1	1	0.002
1	1	0.002
1	1	0.002
1	1	0
1	1	0
1 1 …	1 1 …	0 0 …
1	1	0
max$\|P_0-P_h\|$		0.101

The result of max $|P_o-P_h|$ is 0.101.

$$K - S_z = \sqrt{\frac{437 \times 42}{437 + 42}} \times 0.101 \tag{4.21}$$

$$K - S_z = 0.625 \tag{4.22}$$

When α is 0.05 $K\text{-}S_{z\alpha}$ is 1.36 and the result is 0.625 then the $|K\text{-}S_z| \geq K\text{-}S_{z\alpha}$ condition is not fulfilled, the null hypothesis can not be rejected. The two spatial distributions examined are same.

Quadrat Analysis shows that the same check-in patterns are observed in weekday days and weekday nights in the study area. The statistically significant results reveal that the patterns observed on weekday days and weekday nights are the same. Moreover, the effective use of nightlife venues is favorable for the city at different hours and different days.

4.3 Network Analysis

According to Fischer (2006), the network data model is the most popular GIS environment. The model is based on the basic vectors of GIS databases, the node (a zero-dimensional entity) and the arc (a one-dimensional entity). Moreover, GIS represent a network model as consist of arch with nodes and arc intersections.

A network system consists of edges (lines) and connecting junctions (points) (Figure 4.11). Furthermore, the road network also system consists of these elements. Road networks are useful for urban area studies which urban sprawl in developing and developed areas (Ahmadzai, Rao & Ulfat, 2019).

Figure 4.11 Edges and junctions of network system

Closest Facility Analysis is used in this study. The Closest Facility Analysis is one of the Network Analysis tools in ArcGIS software (Figure 4.12). The closest facility analysis finds the measure of traveling for pedestrians or vehicles between incidents and facilities and determines which are nearest to one other. This network analysis extension makes it easy to set the analysis parameters for the closet facilities analysis, such as travel time, travel cost and the directions of travel (from incident to the facility or from the facility to the incident) (Ahmed et al., 2017).

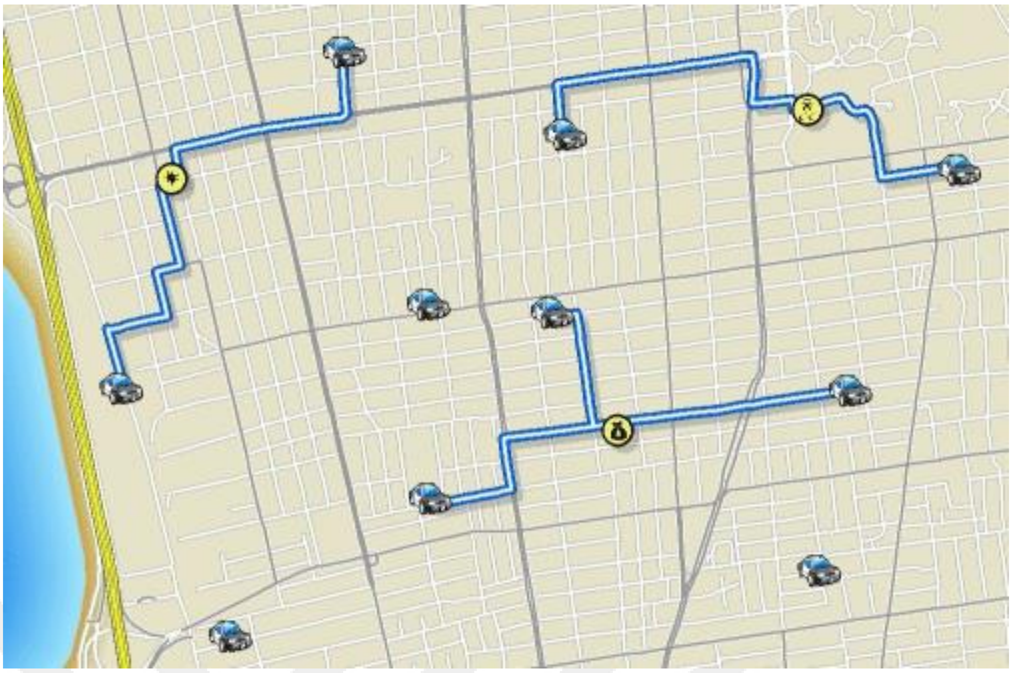

Figure 4.12 The closest facility illustration (Esri, 2009)

The Independent sample T-test is used to compare the walking meter lengths to bus stops for the day and the night on weekday and weekend to check if there were any significant differences. The Statistical Package for Social Science (SPSS) was employed to analyze this data statistically. According to the calculated t-statistic, the statistical significance of the result is tested with the hypothesis test.

Null hypothesis (H_0): The two samples were chosen randomly from the same population and, the mean of these two populations is the same.

Alternative hypothesis (H_A): The two samples were chosen randomly from the different population and, the mean of these two populations is the different.

4.3.1 The Closest Facility Analysis of Day and Night of Weekend

This section proposed the closest facility analysis to measure the distance from venues to bus stops for the weekend day and night. Walking distances were calculated in ArcGIS 10.3 (Figure 4.13 and 4.14). Descriptive statistics values of total distance presented in Table 4.8. Then, Independent T-test was calculated in SPSS to compare the walking distance and presented in Table 4.9.

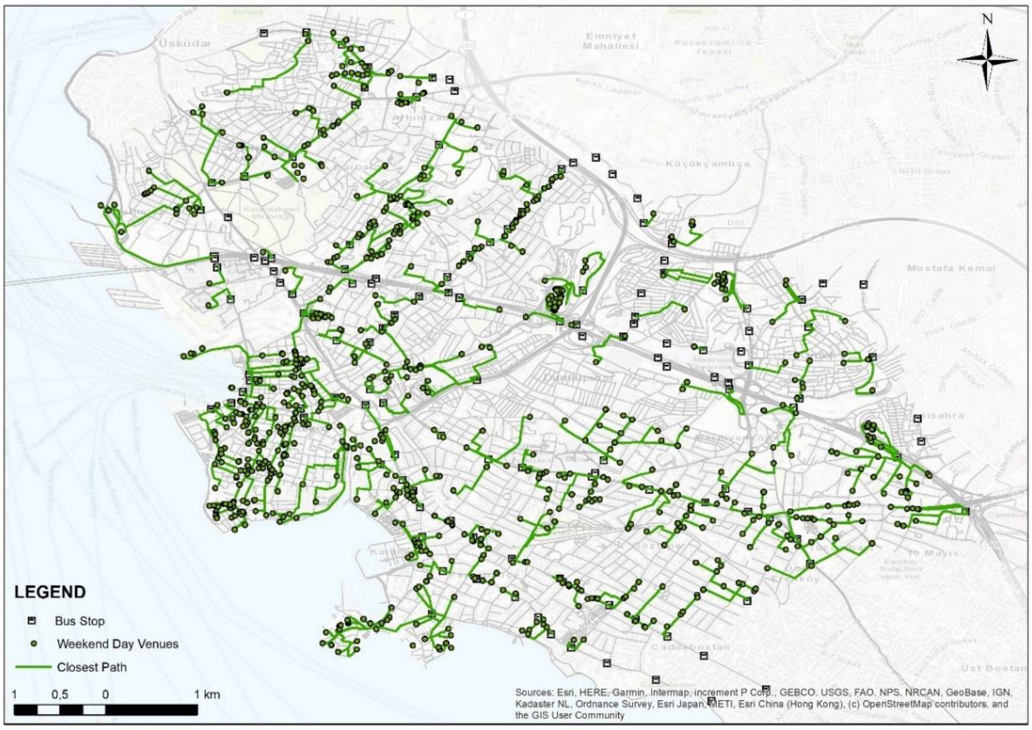

Figure 4.13 The closest path from venues to bus stops on weekend day

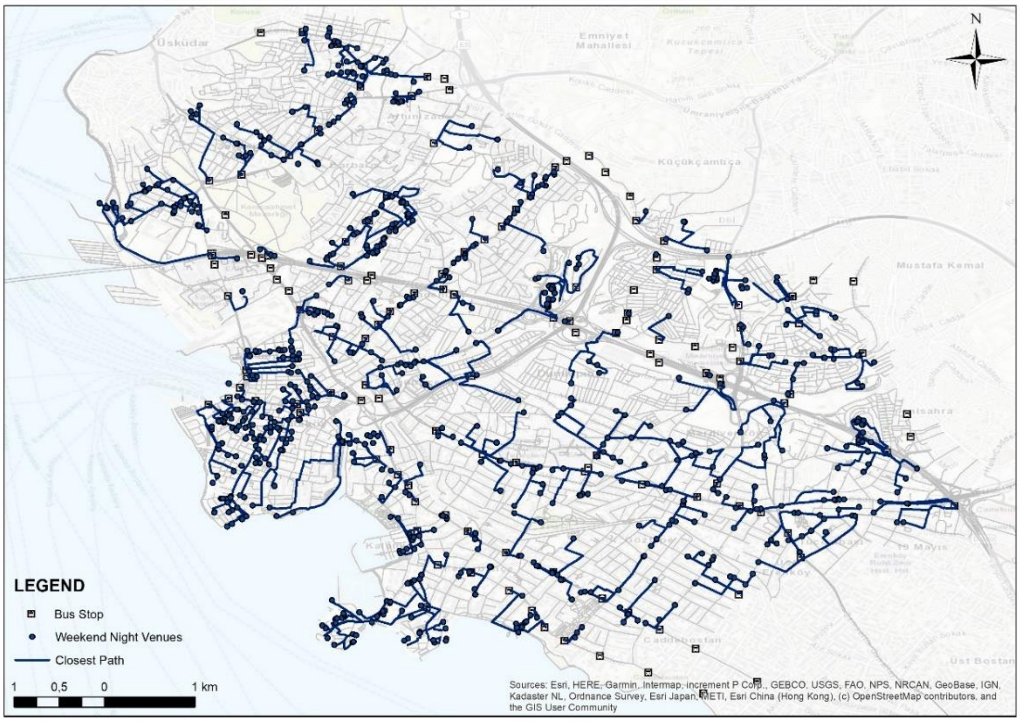

Figure 4.14 The closest path from venues to bus stops on weekend night

Table 4.8 Descriptive statistics for distances to bus stops(m) on weekends

	Type	N	Mean	Std.Deviation	Std.Error Mean
Total Distance	Weekend Day	839		312.207	10.778
	Weekend Night	783	400.207	295.008	10.542

Table 4.9 Independent samples test for distances to bus stops on weekends

		F	Sig.	t	df
Total Distance	**Equal variances assumed**	1.748	0.186	0.758	1620
	Equal variances not assumed			0.759	1619.749

When α is 0.05 and df is 1620 t_α is 1.962 and the t-statistics is 0.758 then the $|t| \geq t_\alpha$ condition is not fulfilled, then the null hypothesis can not be rejected. The two samples are chosen randomly from the same population and, the means of these two populations are the same.

The mean of the total distance of weekend day and night is not different. The Independent samples test demonstrated that observation of walking distance meters from the Foursquare venues to the bus stops are the same at different times on weekends.

4.3.2 The Closest Facility Analysis of Day and Night of Weekday

This section presents the closest facility analysis to measure the distance from venues to bus stops for the weekday days and nights. Walking distances are calculated in ArcGIS 10.3 and illustrated in Figure 4.15 and 4.16. In Table 4.10 and Table 4.11, descriptive statistics values of total distance and Independent T-test results are presented.

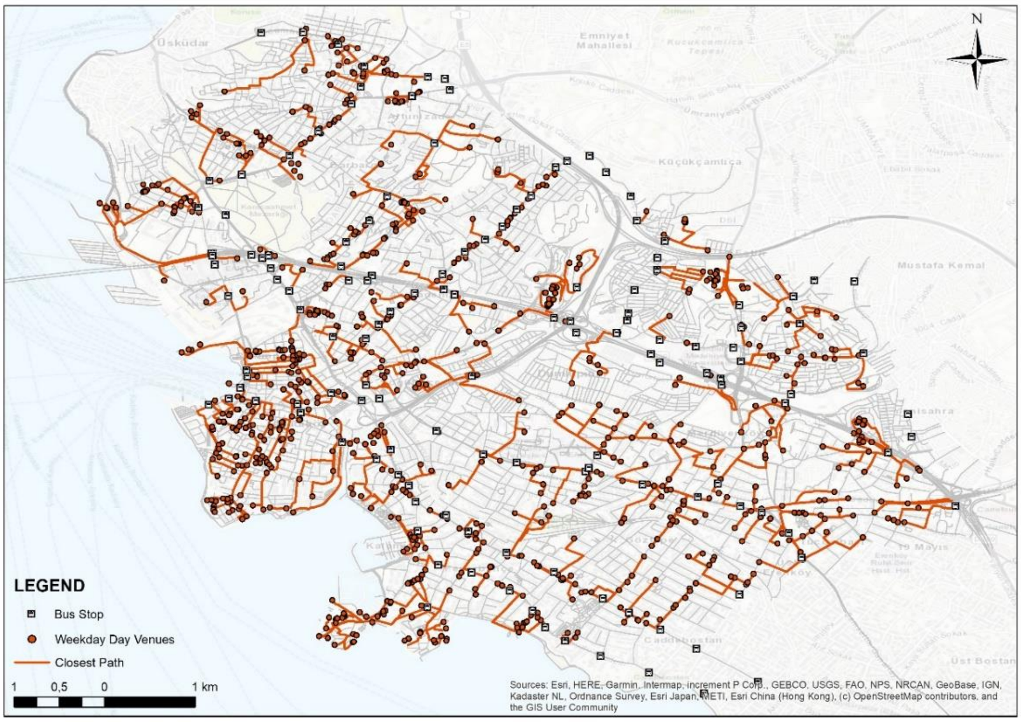

Figure 4.15 The closest path from venues to bus stops on weekday day

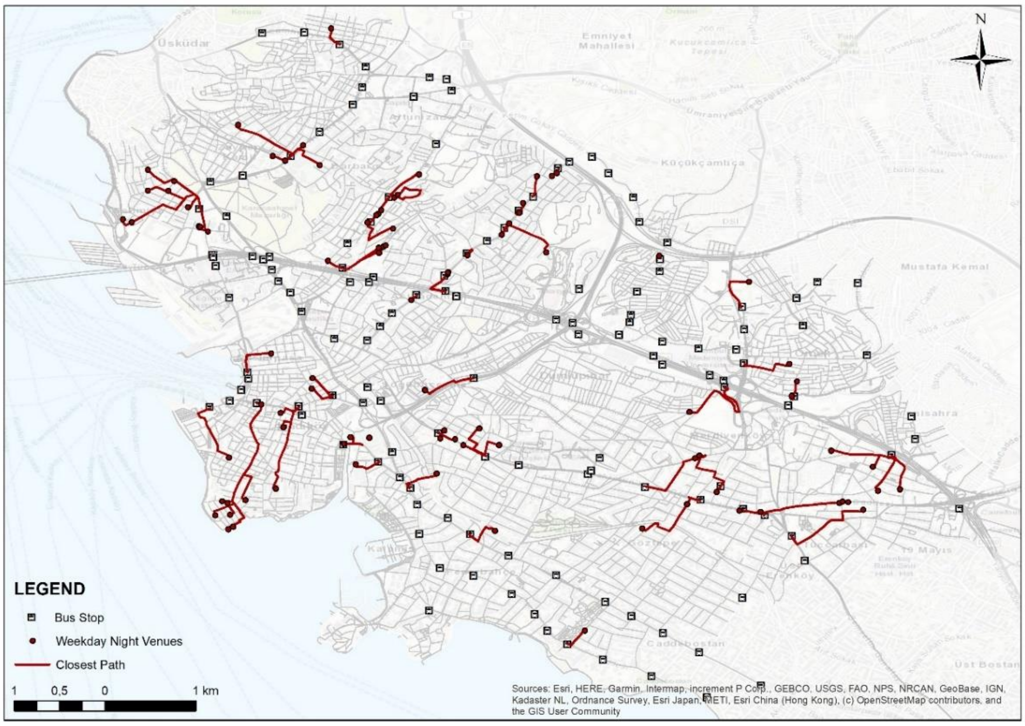

Figure 4.16 The closest path from venues to bus stops on weekday night

Table 4.10 Descriptive statistics for distances to bus stops(m) on weekdays

	Type	N	Mean	Std.Deviation	Std.Error Mean
Total Distance	Weekday Day	892	403.667	291.039	9.744
	Weekday Night	74	449.861	401.037	46.619

Table 4.11 Independent samples test for distances to bus stops on weekdays

		F	Sig.	t	df
Total Distance	**Equal variances assumed**	12.992	0.000	-1.270	964
	Equal variances not assumed			-0.970	79.506

When α is 0.05 and df is 964 t_α is 1.962 and the t-statistics is -1.270 then the $|t| \geq t_\alpha$ condition is not fulfilled, then the Null Hypothesis can not be rejected. The two samples are chosen randomly from the same population and, the means of these two populations are the same.

The mean of the total distance of weekday day and night is not different. The Independent samples test demonstrated that observation of walking distance meters from the Foursquare venues to the bus stops are the same at different times on weekdays. When considering with quadrat analysis results, the same observation of walking distance meters means the same human behavior at different times. Furthermore, the effective use of nightlife venues is crucial for the city, then observation of the same patterns is favorable on day and night.

CHAPTER FIVE
CONCLUSION

This study primarily examined the spatial behavior of people at different hours and different days in the city. Furthermore, the deal with relationship between spatial behavior and accessibility to public transportation is assessed.

Previous studies revealed land use, tourist behavior and user's preference using various social media data (Frias-martinez et al., 2012; García-Palomares et al., 2017; Rossi et al., 2018;Salas-Olmedo & Quezada, 2017). Moreover, some studies focused on the spatial distribution of venues using check-in data and aimed to understand which activity observed more at what time of the day(Hasan et al., 2013; Hong, 2015). There have been different studies of measuring accessibility. Location-based data contribute to public transport choice as a new aspect and aim to understand travel behavior in the city (Rybarczyk et al., 2018). Many researchers focused on walkability at the different destinations to understand walking accessibility. Literature of walkability revealed that these studies associated with the socio-economic characters and spatial structure (Gao et al., 2020; Sarker et al., 2019).

According to the spatial descriptive statistics results, the mean center and the direction of the standard deviational ellipse for weekday night points data are quite different from the weekday day, weekend day and weekend night distributions. The mean center of the weekday night venues is located on the north and the mean centers of the weekday day, weekend day and weekend night venues are very close to each other. Weekday night venues close to transportation routes while weekday day, weekend day and weekend night venues close to the coastal region. These results also highlighted the direction of the standard deviational ellipse of weekday night venues differs from others. The direction of the standard deviational ellipse of weekday day, weekend day and weekend night venues is towards to the coast of the study area. Because the coastal region has a lot of parks and more attractive places than others.

Among other studies, this research suggests that not only examination of spatial distribution at the different times in the city but the measuring of the accessibility as well. This study used three significant analyses; kernel density analysis, quadrat analysis and network analysis.

The first part of this study is kernel density analysis calculated for weekday and weekend regarding check-in hours. The density of the Foursquare venues appears to be higher on weekends. Especially, density of check-in venues is high at the seaside and north of the case study area on weekends. Furthermore, it has a high density both on weekdays and on weekends in the centre of the Kadikoy district.

The second analysis of this study is quadrat analysis and the statistical significance of the result is tested with the hypothesis test. The statistically significant result revealed that the patterns observed at different periods are not different. The check-in patterns are observed the same both on weekday days and weekday nights and weekend days and weekend nights. In conclusion, this research demonstrated that the effective use of nightlife venues is favorable for the city and observed the same pattern at different hours and different days.

Closest facility analysis is used in this study to understand accessibility measure differences between weekdays and weekends and days and nights. The closest path from the check-in venues to the bus stops is calculated in ArcGIS. Independent samples test is applied to compare the means of the total distance to public transport stops at different times in the study area. The Independent Samples Test showed that the mean for walking distance meters from the Foursquare venues to the bus stops are the same at different times. The same pattern is observed in accessibility measure on weekdays and weekend and on days and nights. These findings indicate that relationship between accessibility to public transport and spatial behavior.

There are some limitations to this study. First, the dataset consists of Foursquare check-in data and this application users. Due to including only Foursquare users, there is no evidence of other users' preferences and their behavior. Second, the spatial distribution of Foursquare check-in data is highly homogeneous in the study area. Therefore, human spatial behavior may differ in non-homogeneous areas.

However, due to the widespread use of social media application in recent years these study findings contribute to literature about human behavior at different times. In addition to spatial behavior, day time and night time experience of venue users help to improve various public transport accessibility. Moreover, applying the closest path from these venues can contribute to human walking behavior for future studies. For future research, it will be meaningful to investigate different urban areas and other public transportation modes.

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