

Article

Location-Based Analyses for Electronic Monitoring of Parolees

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Abstract: This study analyses the spatio-temporal pattern of parolees using electronic monitoring, where the developed spatial framework supports the Environmental Criminology concepts such as crime patterns or crime attractive locations. A grid-based solution for spatio-temporal analyses is introduced to ensure the anonymity of the parolees. In order to test these developed concepts, the Istanbul Metropolitan Area was selected as the pilot study area. Following the developed concepts of the Crime Pattern Theory, a spatial framework was designed. A novel grid-based weighted algorithm for the most attractive areas was generated via spatial point-of-interest data and a conducted survey among police officers. The designed framework and the spatio-temporal analyses were carried out for 77 parolees using geostatistical methods. The major findings of the study are (a) 24-hour trajectories of each parolee was monitored; (b) the most attractive grids within the city were defined; and (c) for each parolee, the entrance time to the grid and the time spent within that grid were reported and analyzed. This study is a preliminary study for spatio-temporal detection of parolees' trajectories, where location-based analyses serve well. This study aims to aid decision-makers to better monitor the parolees and justify the benefits of surveillance.

Keywords: electronic monitoring; spatial; temporal; geographic information systems (GIS); R programming; Istanbul

1. Introduction

The concept of electronic monitoring of parolees has emerged by integrating technology to probation applications. By definition, parole “refers to criminal offenders who are conditionally released from prison to serve the remaining portion of their sentence in the community” [1], where the probation is a period when a criminal must behave well and not commit any more crimes to avoid being sent back to prison. It is the method used for monitoring the convicted prisoners or detainees due to prosecution or suspicion of offence. The monitoring process could easily benefit from information technologies, namely location-based services and spatial data analyses, where such applications could highly benefit from mature geospatial surveys. The use of electronic monitoring systems enables the spatial and temporal monitoring of the perpetrators of crime; besides, it intersects with the place (or situation) and the offender dimensions of the four basic dimensions of the crime [2]. Hence, environmental criminology, where the problem has a spatial nature, examines the crime phenomenon in terms of the “where” and “when” questions. Researchers and decision-makers in environmental criminology perform spatial and temporal analyses to determine the criminal patterns and make conceptions regarding the crime itself [3]; however, the full benefits of location-based analyses have yet to be discovered.

Geometry Theory of Crime [4,5] and Crime Pattern Theory [6], which are among the theories of Environmental Criminology, describe how criminals are affected by daily mobility and routine movements. According to these theories, potential criminals begin to notice opportunities to commit crimes during their daily routine activities. The specific areas that can lay the ground for the crime formation are hotspots where the crime is often committed and people bearing different types of crime are gathered [7,8]. All routine activities that take place form an environmental backcloth with the combination of different social, economic, political, and physical dimensions [9]. In this respect, the areas where they go home, to school, to work, or for entertainment, i.e., routine activities, are called the activity space, while the awareness space begins to emerge by becoming familiar with all the environmental factors within the activity space. There are nodes, pathways, and edges in routine activities and awareness space [5].

Brantingham and Brantingham [10] have suggested that some of the places in the activity nodes, pathways, nodes, and edges encourage more crime to occur compared to other places, calling them “crime generators and crime attractors”. Crime generators are defined as areas where human density is too high, where crime formation becomes inevitable due to confusion and intensity. Crime attractors are places that attract crime and the criminal, and lay the ground for crime formation. Examples of places that produce and attract crime include schools, fast-food restaurants, shopping malls, bars, etc. [10–12]. Location information must be obtained to perform the analysis of the places designated as crime generators and attractors. Such information is currently available as a point-of-interest (POI) in open source spatial databases. Furthermore, perpetrators move within a certain pattern [9]. Furthermore, the spatio-temporal patterns are local and depending upon the social characteristics of the society. Environmental criminology is interested in spatio-temporal analyses to better understand and prevent the risk of crime. However, studies on parolees data using electronic monitoring systems are quite rare [13]. Hence, the full potential of geospatial data acquisition and analysis has yet to be explored.

This study aims to illustrate the potential of spatial information science within environmental criminology, via spatio-temporal analyses such as the frequency and pattern of movement of electronically monitored parolees. This initial study for Istanbul includes generating the crime attractors and generators places that are defined as “the most attractive areas”, where data of 77 Global Navigation Satellite System (GNSS) surveilled parolees were analyzed spatio-temporally. The number of the study sample size is a significant number according to information sensitivity in environmental criminology. The methodology included a survey among selected police officers of Istanbul, where the aim was to identify crime attractive areas. Furthermore, the study area needed to be generalized to keep the parolee’s data anonymous. For this purpose, 1 km × 1 km grids were generated. A primary reason for selecting this resolution was to secure privacy. Additionally, there was a concern that if the smaller or larger resolution had been chosen, there might have been some difficulties for point-of-interest data representation. A higher resolution could be determined for congested cities such as Istanbul, but a 1 km × 1 km resolution was chosen so that such analyses could be used in non-congested cities and rural areas. Such grid-based methods have been used to identify and determine patterns for sequences of such point data [14,15].

Analyses were performed with the help of the spatial database and open-source statistical package R. This enables the discovery of the frequency of parolees in the grids representing the most attractive areas. This study is one of the early studies conducted on the people who had previously committed a crime, and aimed to test the environmental criminology theories valid in Turkey. The methodology applied in this research, as well as the results and findings obtained from the methodologies used, is believed to contribute to the development of knowledge about electronic monitoring and environmental criminology.

2. Data and Methodology Used

This section introduces the study area and the data of the parolees within the spatial framework.

With 15 million inhabitants, Istanbul is the most populous city in Turkey and Europe. Considering that Turkey's population is 80 million, Istanbul hosts almost one-fifth of the country's population even though it is not the capital of the country. It has 39 districts, and the Istanbul Strait connects Asia to Europe. This historic city, currently considered as the cultural and economic center of the country, was founded a long time ago and it spreads over 5343 km² [16].

According to the police and gendarmerie statistics, 383,750 incidents occurred in 2016 and 445,408 incidents occurred in 2017 in Istanbul Province [17]. The most important reasons for the selection of Istanbul as the study area are because it has the highest population density and the highest number of electronic monitoring possibilities by GNSS.

Electronic monitoring, which began in 1964 at Harvard University [18], had not been used by judicial authorities to track criminals until 1983. In 1983, Jack Love, the judge of Albuquerque in New Mexico, U.S., sentenced three criminals to house control under an electronic monitoring order [19,20]. Today, electronic monitoring systems are widely used in many countries [21,22]. The studies carried out by Işık [23] in Turkey, Hucklesby and his colleagues [24,25] in Europe, Renzema [26] in the USA and Di Tella and his colleague [27] in Argentina on usage rates by countries were some of the studies carried out on this subject since 1983.

In electronic monitoring systems, the active GNSS systems, which are among the operating principles of electronic monitoring, are designed to continuously receive and send signals of the location and time information of the monitored person. Today, GNSS (such as GPS, Galileo, BeiDou, and GLONASS) systems are extensively used due to technological developments [28]. Electronic monitoring systems communicate with monitoring centers through software. GNSS Electronic monitoring systems use global navigation satellite systems with geographical information systems that store and manage spatial data [29] by using advanced data mining techniques [13]. GNSS electronic monitoring system data can be used for the detection of behavior patterns [30,31]. In this study, data obtained from GNSS-supported active electronic monitoring systems were applied. Thus, highly valuable spatial data of people who have previously committed a crime and are now electrically monitored were used in the analysis.

In Turkey, electronic monitoring is carried out by the Department of Probation under the General Directorate of Prisons and Detention in the Ministry of Justice. This system in Turkey is applied for the fulfilment of some judicial supervision measures imposed in place of detention before the verdict, the fulfilment of some optional punishment imposed in place of imprisonment after the verdict, and for the supervision and monitoring of released criminals within the society and following their conditional release from the prison. According to data released in 2017 [32], electronic monitoring has begun in 2012 in Turkey, and has been applied to 27,313 cases until April 19, 2017. Of the total electronic monitoring cases, only 1785 cases were monitored using GNSS tracking systems. There are no home detention and victimized unit cases that were monitored by using the same system. In addition, there was no data and document on how many parolees commit crimes after being released in Turkey.

In this study, the selected cases covered 77 people; 5 of them were female and 72 were male. The total number of records of electronic monitoring data was 1,919,587 within Istanbul. The average number of records for all parolees was 26,288. The data was collected between the years 2014 and 2017. According to the records, parolees were labelled as follows: 37 persons (48%) for sex crimes, 14 persons for assault (18%), 14 persons for theft (18%), and 12 persons for murder (16%). Hence, no specific groups were therefore targeted. This is the full dataset within the Ministry of Justice GNSS tracking system. The system was initialized in 2014, where all records were retrieved until 2017. The original data obtained from the Ministry of Justice included 124 parolees. To obtain better analysis results, 2 parolees tracked in less than 7 days and 45 of the parolees that belonged to any of the crime group that has less than 10 people have been eliminated.

Point-of-interest (POI) data was retrieved from the OpenStreetMap (OSM) [33] website. This information was used to determine the locations for crime generators and attractors in environmental criminal theories. Accordingly, POIs representing bars, night clubs, pubs, ATM's, banks, stadiums,

sports centers, gyms, playgrounds, airports, coach stations, terminals, hotels, motels, hostels, guesthouses, universities, schools, colleges, hospitals, cafes, beverages, grocery stores, car parks, courthouses, shopping malls, dormitories, public buildings, bus stations, railway stations, ferries, terminals, picnic sites, campsites, toilets, department stores, supermarkets, restaurants, fast-food outlets, graveyards, kindergartens, sanctuaries, museums, cinemas, and theatres were selected. The number of POIs was 32,901. In the study, the coordinates and usage of the POIs were used as the main data to calculate the most attractive areas, which were generally evaluated as sources for the crime. In the study, the breakdown of POIs according to location types was as follows: 3490 restaurants, 2829 bus stops, 2577 cafes, 2375 pitches, and 2199 supermarkets.

The attractive locations for criminals may be assessed in environmental criminology theories with the local characteristics in different societies. In this study, a survey was conducted through Google Forms [34] to measure the probability of a crime occurring in places that may be attractive to the criminals. This survey was conducted with 51 policemen who were selected among those that were considered to be more in contact and familiar with crime and the criminal. In the questionnaire, the 5-point Likert scale was used to measure the likelihood of all types of crime occurring in POIs. Scoring of the locations in the range of 1 (strongly disagree) to 5 (strongly agree) was requested from the respondents.

2.1. Methodology Used

The framework for the analysis and data processing was determined and shown in Figure 1. Along with the framework, some steps were identified as the explanatory data analysis (EDA) of the data [35–37]. The most important part was the spatio-temporal analysis of the data to be analyzed through geographic information systems and R programming because of its spatial nature. Due to the sensitivity of the data, information on parolees should be kept anonymous and the study area needs to be generalized. Thus, 1 km × 1 km grids were generated, and the survey subsequently carried out. Tools used for the required analysis were as follows: the open-source PostgreSQL geographic database, ESRI ArcGIS Software [38], and R: A Language and Environment for Statistical Computing [39], for data mining with the spatio-temporal analysis methods.

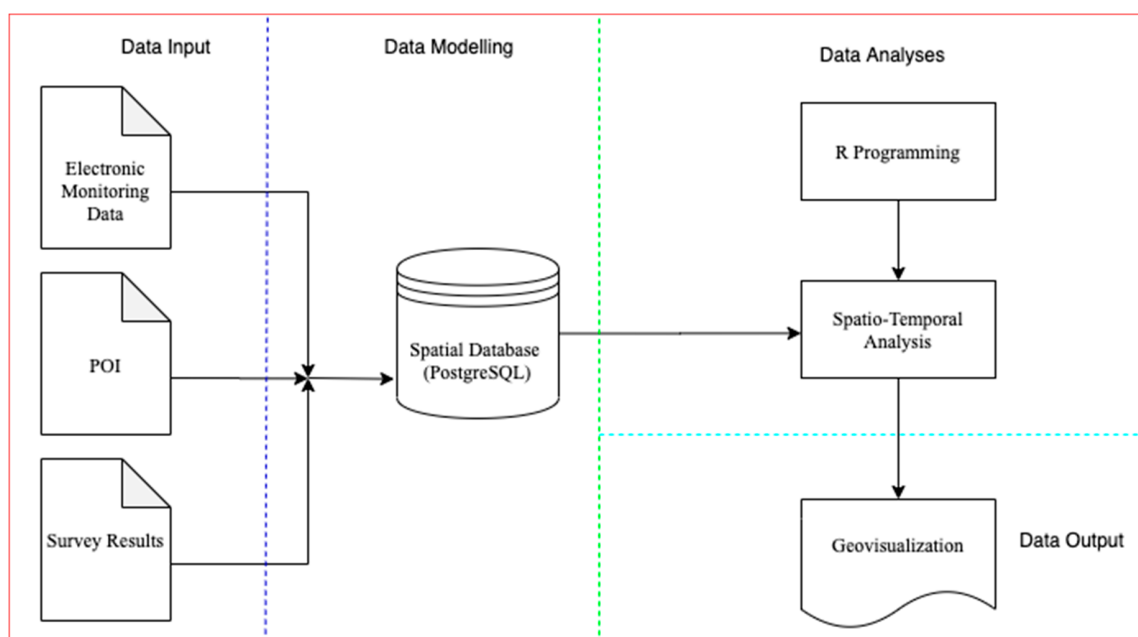


Figure 1. A framework of the methodology used.

The framework was divided into three main categories, namely, data input, data analysis, and data output. They are presented in Figure 1, and explained below.

2.1.1. Data Input

The data input category consists of the collection of data. In this study, the electronic monitoring data of the parolees who had previously committed crimes in Istanbul, have probation and electronic monitoring decisions with GNSS, and also the POI data of Istanbul were used. Data on electronic monitoring were obtained by special permission taken from the Department of Probation of the General Directorate of Prisons and Detention Centers of the Ministry of Justice of Turkey. The Ministry of Justice of Turkey has provided electronic monitoring data anonymously within the scope of the personal data security. The data included spatial information, such as "ID, latitude, longitude, and time", as well as demographic information, such as "probation name, article type, crime type, gender, and age". In the data received, the number of parolees who were electronically monitored with GNSS was 77. The first data date from the received data was 16 February, 2014, and the last data date was 20 February, 2017. The temporal sampling of the parolees was one minute. The total number of records received was 1,919,587, this after eliminating the data belonging to those areas outside the provincial borders of Istanbul. The duration of the monitoring of people who were being electronically monitored varied. This process changed according to the decision made by the Department of Probation.

While the abovementioned processes were progressing, a survey study was designed and implemented apart from these procedures.

2.1.2. Data Modelling

After the data input category, the first step in the data modelling category was the transfer of the electronic monitoring data and POI data to the geographic information systems software with the geographic database created in PostgreSQL. The POI data and then the electronic monitoring data were transferred from the geographical database to the GIS environment. In OSM, most of the POI were stored as an areal (polygon) object. Hence, such data were transformed into points and merged into the GIS environment.

2.1.3. Data Analysis

At this stage, after converting all the different spatial data into nodal data, grids were created to provide better representation of these data that has been analyzed. These grids both make the analysis more understandable and help to settle ethical concerns about the privacy of individuals. For this reason, 1 km × 1 km grids were created to cover the city of Istanbul in the GIS environment. Furthermore, these 1 km² grids have been evaluated as an adequate spatial resolution to conduct similar spatial algorithms. After the grids were created, the numbers of POIs falling into each grid were counted. These grids were formed independently. Based on the survey results of these grids, the most intense ones were selected.

In the survey study, it was aimed to learn the crime rate coefficients of the participants by taking into account the POI information obtained from OSM. Therefore, because of the multiplication of coefficients gathered from the survey study with the number of POIs in each grid, the total score was calculated. This score has been used to determine the attractiveness level of the grids. For instance, when all of the police officers gave 5 points for nightclubs, each nightclub was multiplied by 5 points. In case of two nightclubs in one grid, 10 points from the nightclubs were added to the total score. An example of the total score calculation is shown in Figure 2.

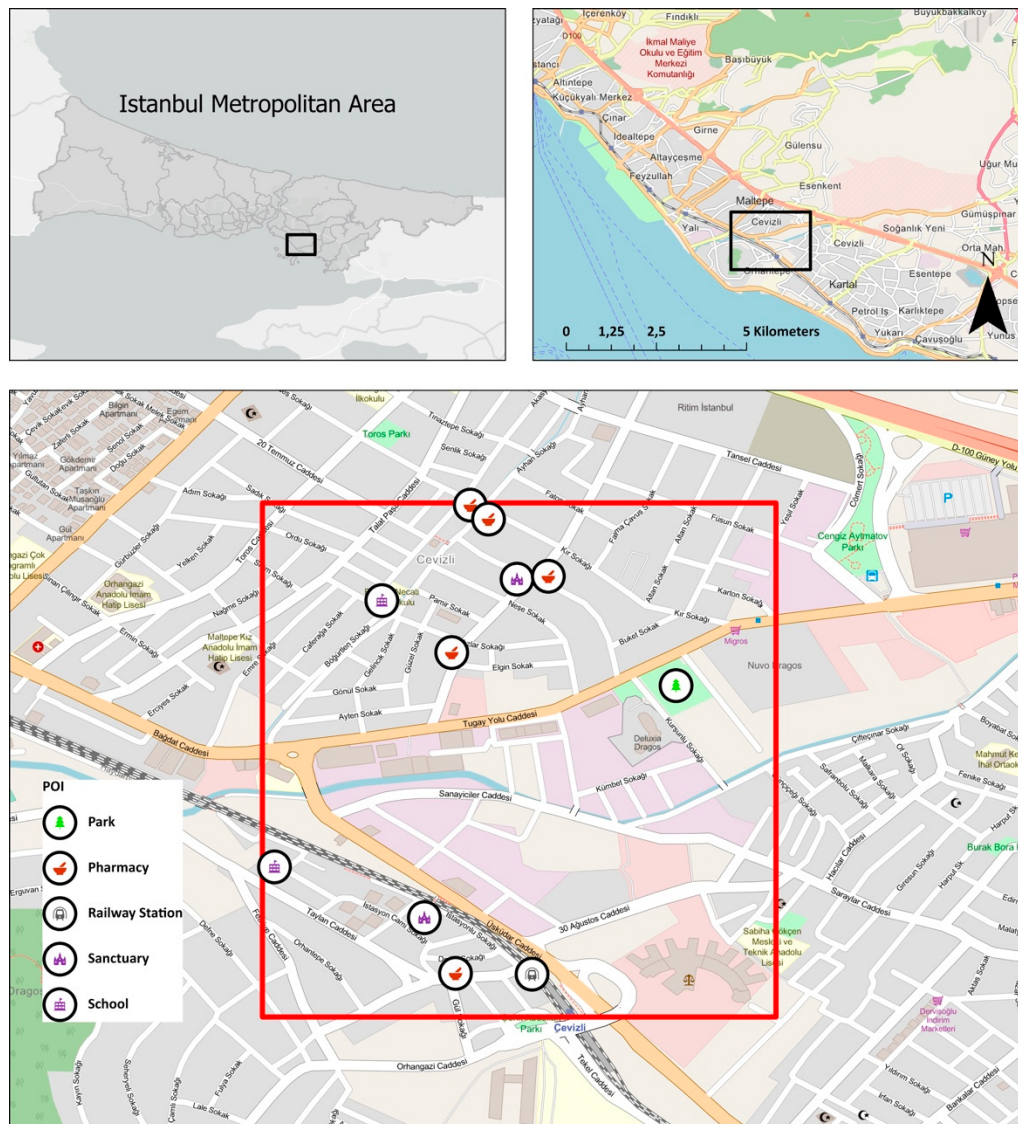


Figure 2. Example of the total score calculation.

Total Score: Score to be used to determine the most attractive areas:

a, b, c, ... z: Crime attractor and crime generator places

$I_1, I_2, I_3, \dots, I_n$: As a result of the survey, the related crime type of the crime incidence;

$$\text{Total Score} = (a \times I_1) + (b \times I_2) + (c \times I_3) + \dots + (z \times I_n) \quad (1)$$

As can be seen in Figure 2, there existed 1 park, 5 pharmacies, 1 railway station, 2 sanctuaries, and 2 schools that can be defined as places that attracted crime within the $1 \times 1 \text{ km}^2$ grid drawn with a red frame. The coefficients were calculated with the Equation (1), and they were assumed to be values given in Equation (2).

$$\text{Total Score} = (1 \text{ park} \times 2.71) + (5 \text{ pharmacy} \times 3.08) + (1 \text{ railway station} \times 2.75) + (2 \text{ sanctuary} \times 2.2) + (2 \text{ school} \times 3.18) = 31.62 \quad (2)$$

The map of Istanbul, which was obtained as a result of the calculations in the relevant example shown in Figure 2, was subjected to the necessary symbology and visualization procedures. In these

symbolology processes, visualization was based on the impression method [40] that depended on the standard deviation, used in density surface maps related to crime analysis.

All data sets obtained with GIS and the geographic database were transferred to the R programming environment. The “arctgisbinding” package [41] was used in the transfer process. Data discovery was performed with packages such as “tidyverse” [42] and “ggplot” [43] to be further used in the R programming environment. Another package used for spatio-temporal analysis in the R programming environment was “recurse” [44]. With the “recurse” package, it was possible to calculate the number of repeated entry times in certain areas and the time spent in the specified areas. The “sp” package [45,46] was used for spatial operations in the R programming environment. In this way, the calculation of the staying times in the grids with the repeated entry times to the most attractive areas was performed.

2.1.4. Data Output

Following the completion of the data analysis process in the GIS and R programming environments, the process of obtaining the results of these analyses started. In the output phase, tables and other outputs were obtained with the help of maps in the GIS and R programming environments.

3. Results and Discussion

Before conducting the spatial analysis, electronic monitoring data retrieved from the authorities were explored in detail.

According to the type of crimes, the average, minimum, and maximum ages were descriptively analyzed, and the obtained results achieved are shown in Figure 3.

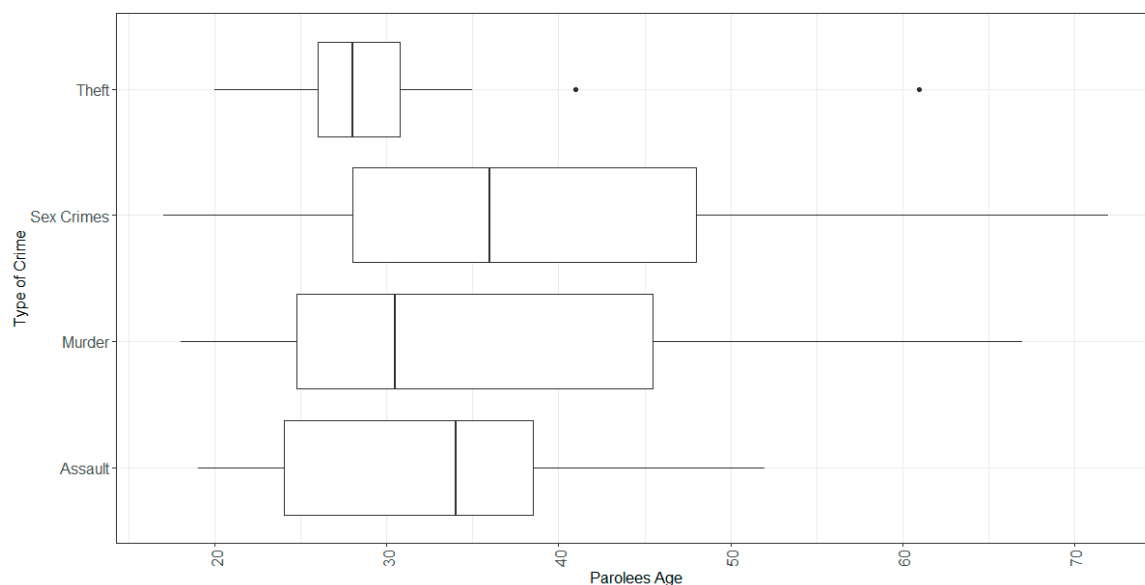


Figure 3. Age distribution of parolees according to crime types.

According to the dataset of the parolees, the average monitoring day per person was 66 days, where the highest and lowest number of monitoring days were 9 and 122, respectively. The records of the parolees according to the type of crimes and their total numbers are provided in Table 1. Most of the data were collected from people who committed sex crimes; secondly, assault; thirdly, murder; and fourthly, theft.

Table 1. The mean and total amount of recorded points data by type of crime.

Type of Crime	Average Number of Data per Person	Total Number of Recorded Point Data
Sex Crimes	31,523	1,166,333
Assault	23,559	329,821
Murder	22,030	264,355
Theft	18,834	263,674

Various spatial analyses have been conducted with this information, where some of them are provided in Figure 4. The initial analysis was to detect the activity pattern of parolees within the city. The activity patterns of parolees belonging to the four types of crimes were mapped between 10 a.m. and 8 p.m. The basis of this time selection was the assumption that this time interval presented the busiest hours of routine everyday activities. There were also possibilities of crime being committed outside the selected hours. Nevertheless, we focused on the range of hours where mobility was most intense, and where the majority of the circulation occurred.

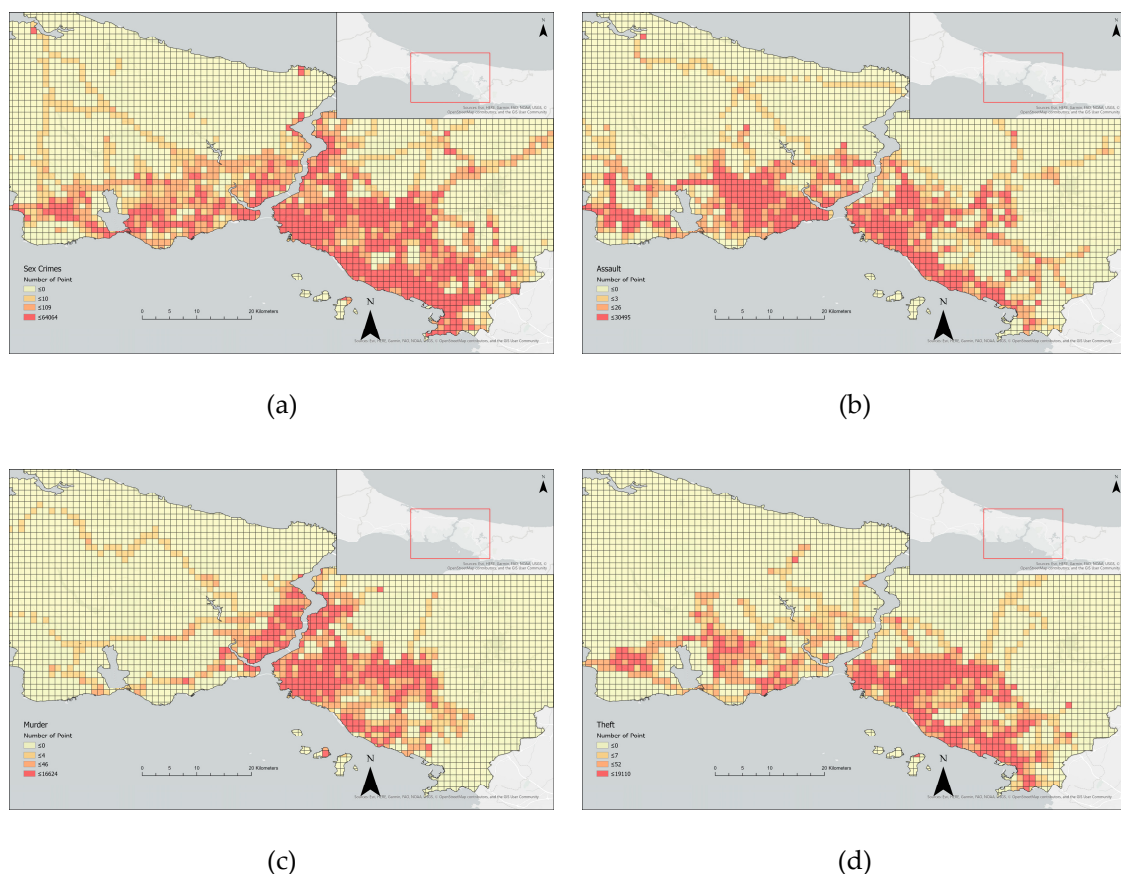


Figure 4. GNSS records of parolees registered in the grid within the hours between 10 a.m. and 8 p.m. (a) Sex crimes parolees; (b) assault parolees; (c) murder parolees; (d) theft parolees.

Hotspot analysis was also carried out as another spatial analysis. A total of 141 cells were determined as a hotspot with the confidence of 90% and above. The result of the hotspot analysis (Getis-Ord Gi*) of the parolees between 10 a.m. and 8 p.m. is shown in Figure 5. In this part of the study, only hotspots were considered. Thus, the cold spots obtained from the analysis have been excluded. The 1 km x 1 km grids were applied to generalize the detailed location information.

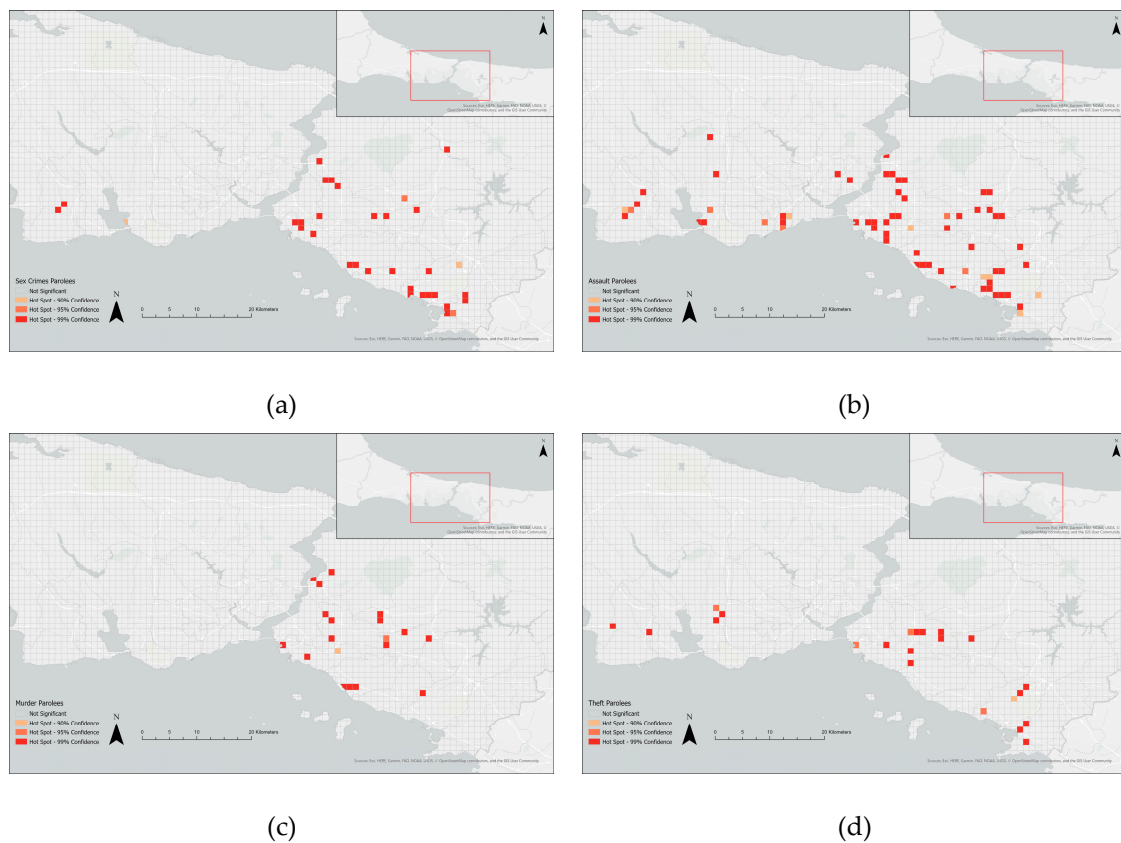


Figure 5. Hotspot analysis of parolees registered in the grid within the hours between 10 a.m. and 8 p.m. for different types of crime: (a) Sex crimes parolees; (b) assault parolees; (c) murder parolees; (d) theft parolees.

As a result of the survey, the crime attractiveness per location was assessed. Participants were asked to rate POIs concerning crime attractiveness, where a scale between 1 and 5 was used. Within the scale, 5 was the most attractive, whereas 1 was the least attractive. The results of the survey are illustrated in Table 2. According to the survey, the riskiest places were bars, nightclubs, and pubs. In line with the previous studies, this result showed that these places could play a significant role in the formation of the crime [47–50]. The second category were universities, while the third and fourth were cafes, as well as ATM's and banks, respectively, which are usually crowded. In contrast to the studies in which restaurants and public buildings were frequently considered crime attracting and crime generating places [51–54], these places were almost half more reliable than bars and nightclubs according to respondents.

Table 2. Crime attractiveness per location types according to the survey results.

Place Name	N ¹	Mean	SD ²
Bars. Night Clubs. Pubs	51	4.65	0.59
Universities	51	3.61	1.00
Cafes	51	3.49	1.07
ATM's and Banks	51	3.29	1.20
Stadiums. Sports Centers. Gyms. Playgrounds	51	3.29	1.10
Hotels. Motels. Hostels. Guesthouses	51	3.24	1.01
Beverages. Grocery Stores	51	3.22	1.22
Airports. Coach Stations. Terminals.	51	3.19	0.98

Table 2. Cont.

Place Name	N ¹	Mean	SD ²
Schools. Colleges	51	3.18	1.01
Shopping Malls	51	3.10	1.08
Hospitals. Pharmacies	51	3.08	1.16
Car Parks	51	2.86	1.36
Bus Stations. Railway Stations. Ferry. Terminals	51	2.75	0.93
Dormitories	51	2.75	1.13
Courthouses	51	2.73	1.15
Parks. Picnic Sites. Camp Sites	51	2.71	1.24
Public Buildings	51	2.61	1.10
Restaurants. Fast Foods	51	2.59	1.13
Department Stores. Supermarkets	51	2.55	1.21
Toilets	51	2.47	1.30
Sanctuary	51	2.20	1.10
Graveyards	51	2.06	1.06
Kindergarten	51	1.90	0.92
Museums. Cinemas. Theatres	51	1.82	0.99

¹ Number of participants; ² Standard deviation.

The visualization of crime attractiveness grids by total scores is shown in Figure 6.

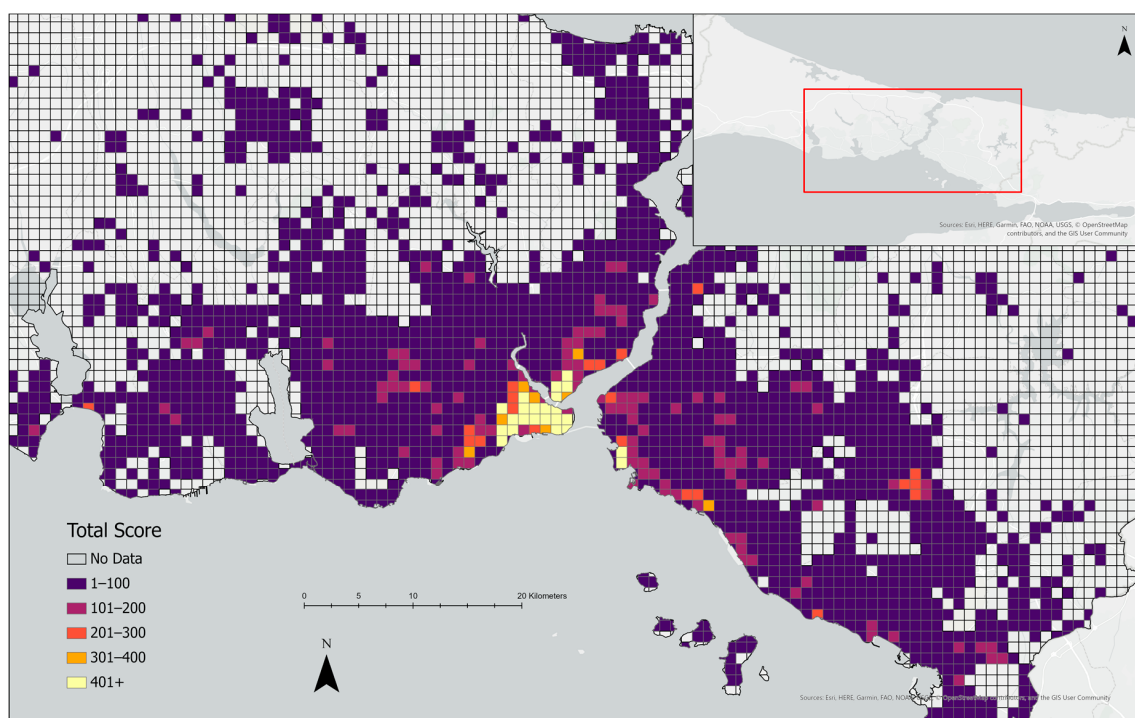


Figure 6. Crime attractiveness according to the survey.

According to the survey conducted in this study, certain areas and environmental factors were considered as influential in the formation of criminals and the crime, but they were preventable and designable. The study showed that there was a greater intensification in some of the grids that were 1 km × 1 km in size, which were sufficient to reveal the patterns of the criminals in the intensified cells. There were 23 different cells higher than 400 points according to the weight of the total score.

After this stage, these 23 cells were used in all analyses in the R programming environment. A total of 54 of the 77 parolees have entered 2044 different times into these grids. The results of the analysis of

how long the parolees spent time in the 23 cells, which were the most attractive areas, are shown in Figure 7. Those who committed sex crimes accounted for 52% of the total time spent inside the most attractive areas. It was observed that sex crimes parolees tended to go to the most attractive areas further than other types of crime parolees in the used dataset. Of those who committed murder, less than 30% spent their time inside the most attractive areas.

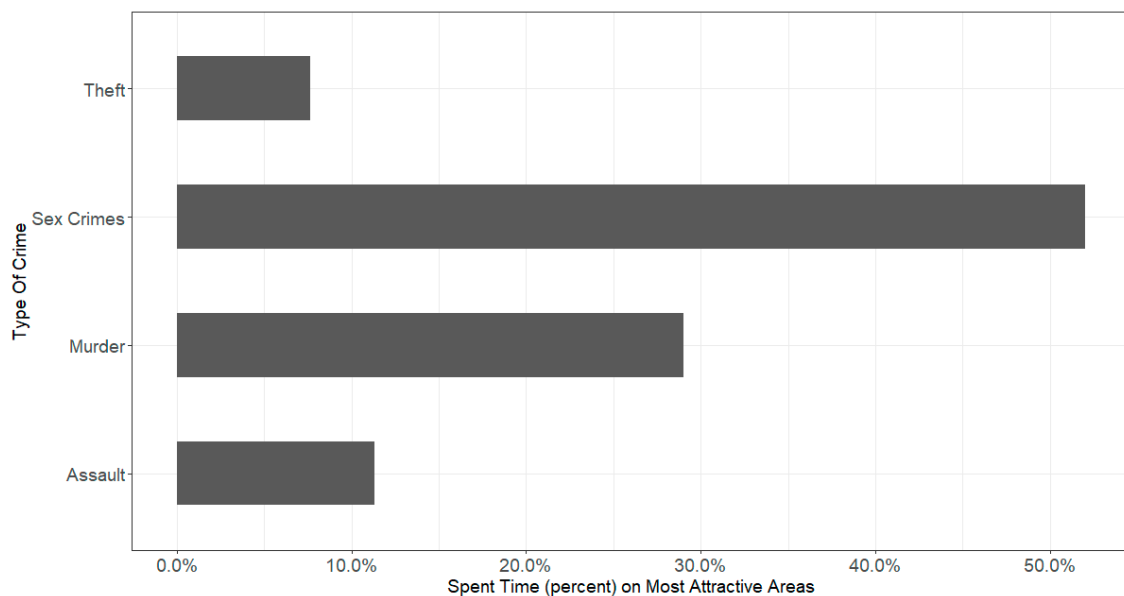


Figure 7. The time spent in most attractive areas by crime types.

The time spent in each cell according to the type of crime is shown in Figure 8. In 19 of the 23 cells, parolees spent less than the mean of the time spent, and in 4 cells they spent more time. The parolees who committed sex crimes were seen especially in grids 7, 10, 11, and 18. As illustrated, people who committed murder were concentrated in the 7th grid.

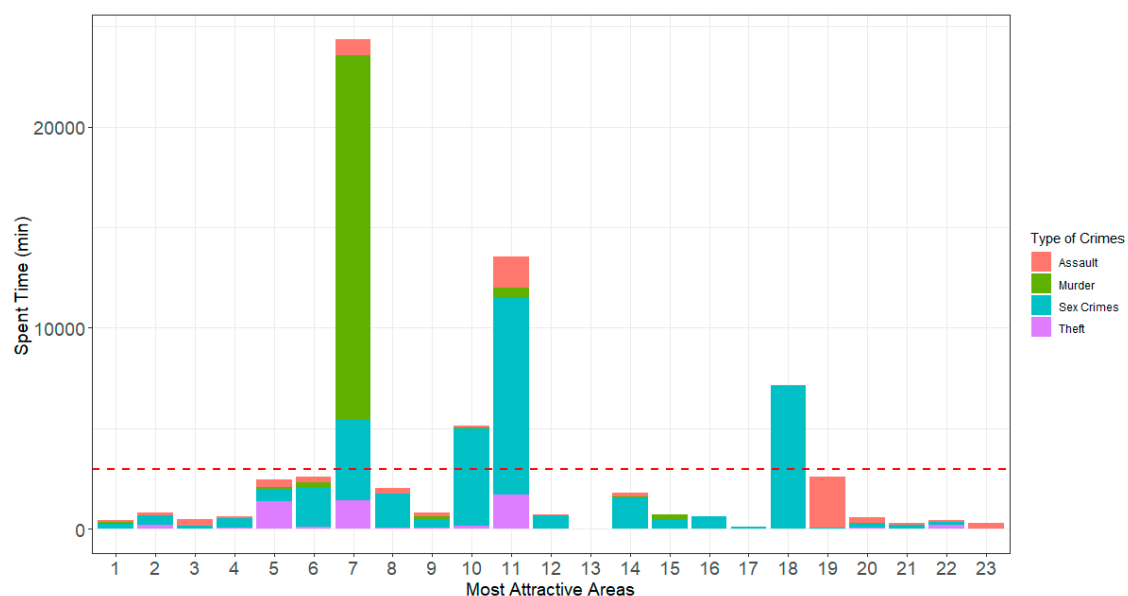


Figure 8. Time spent by crime types in the most attractive areas.

The result of the analysis of the time spent by the parolees who had electronic monitoring and the time passed after they have entered are shown in Figure 9. In this analysis, the lower limit was

determined as 1 min and the upper limit was determined as 1440 min. In this way, short stays were excluded. The red line in the figure shows the mean of the time spent by entrance time. It was also noticed that those who committed sex crimes entered the attractive areas at 11:00 a.m. and have spent more time there. However, those who entered at 10.00 a.m. have spent comparatively less time.

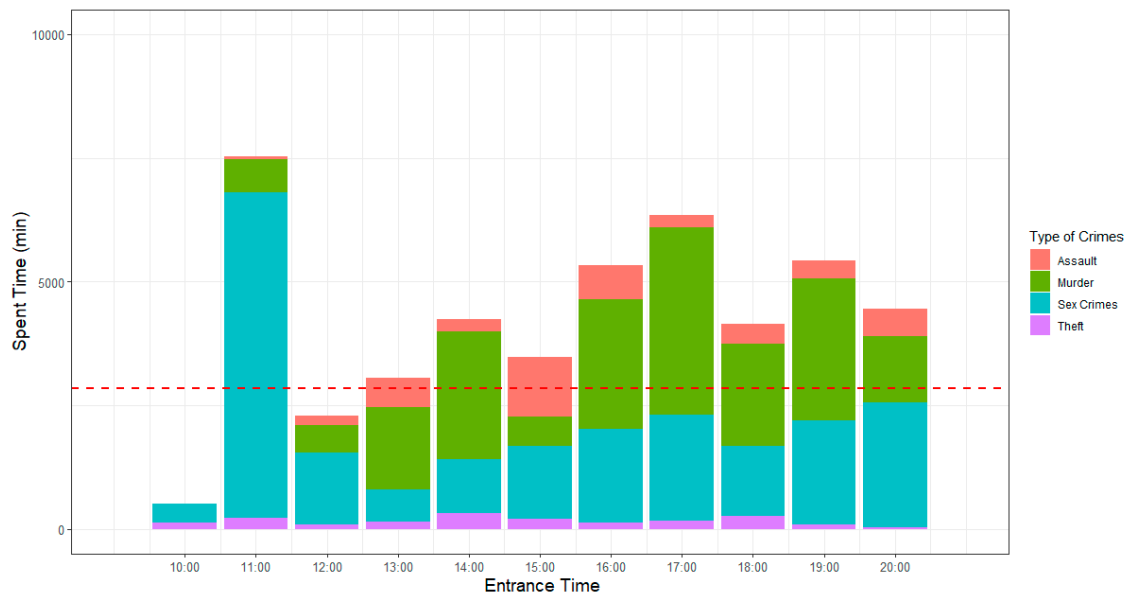


Figure 9. Entrance time and duration in the most attractive areas per category.

One of the major findings, namely, varying opportunities depending upon the crime type, is also fully in line with another study on electronic monitoring (Rossmo et al. [13]). Accordingly, some types of crime need longer periods of planning than others. Another major finding, detection of hotspots via clustering analyses, has also contributed to revealing the spatial patterns of crime. Hence, a similar small number of studies regarding the spatial patterns of crime is supported. Such studies generally focused on identifying concentrations of crime events and the prediction of crime locations. For example, Chainey et al. [55] have examined hotspot methods, including grids, to predict the spatial patterns of crime, where the crime location data was utilized. In this study, the hotspot method (Getis-Ord Gi*) was used to determine the highest values in the implemented grids, where the information was retrieved from the GNNS-based electronic monitoring of parolees. Furthermore, this spatial analysis incorporates POI and GNSS data, where, due to the sensitivity of data, a spatial gridding approach is utilized. Via the followed approach, the duration of staying in a specific type of location could be measured.

This study also used a wide variety of geo-statistical methods to analyze this interesting and unique data set for Turkey. However, several others could not be applied at this stage due to the limitations of the current dataset.

4. Conclusions

In this study, the added value of spatio-temporal analyses to environmental criminology was explored. It is possible to analyze and visualize the data of parolees and their places with the help of spatio-temporal analyses techniques and algorithms. Various categories of crime were investigated, where the major finding was that parolees tend to go to certain areas that are defined as the most attractive area. The spatial analyses assisted to understand crime and criminal behavior. It was also noticed that if those who committed crimes enter the attractive areas at certain times, they spent more time there. It is possible to evaluate that most attractive areas are places that are probably also important for parolees. It is observed that the most attractive areas in Istanbul are concentrated in the city center. This confirms that the places in which crime attractors and crime generators are located is the most

densely populated areas of the city. Similar valuable information can be presented to decision-makers by the collection of more spatial and temporal information on the subject through having a higher number of parolees with electronic monitoring, thus improving the spatio-temporal analyses.

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References

1. BJS What is the difference between probation and parole? Available online: <https://www.bjs.gov/index.cfm?ty=qa&iid=324> (accessed on 1 March 2020).
2. Andresen, M.A. The place of environmental criminology within criminological thought. In *Classics in environmental criminology*; CRC Press: Boca Raton, FL, USA, 2016; pp. 21–44.
3. Wortley, R.; Townsley, M. *Environmental criminology and crime analysis*, 2nd ed.; Routledge: Abingdon, UK, 2016; ISBN 9781317487104.
4. Brantingham, P.L.; Brantingham, P.J. Notes on the Geometry of Crime. In *Environmental Criminology*; Brantingham, P.J., Brantingham, P.L., Eds.; Sage Publications: Beverly Hills, CA, USA, 1981; pp. 27–53.
5. Brantingham, P.L.; Brantingham, P.J. Nodes, paths and edges: Considerations on the complexity of crime and the physical environment. *J. Environ. Psychol.* **1993**, *13*, 3–28. [\[CrossRef\]](#)
6. Brantingham, P.L.; Brantingham, P.J. Environment, routine and situation: Toward a pattern theory of crime. *Adv. Criminol. Theory* **1993**, *5*, 259–294.
7. Block, R.L.; Block, C.R. Space, place and crime: Hot spot areas and hot places of liquor-related crime. *Crime Place* **1995**, *4*, 145–184.
8. Eck, J.; Chainey, S.; Cameron, J.; Wilson, R. *Mapping Crime: Understanding Hotspots*; National Institute of Justice (NIJ): Washington, DC, USA, 2005.
9. Brantingham, P.J.; Brantingham, P.L.; Andresen, M.A. The geometry of crime and crime pattern theory. *Environ. Criminol. Crime Anal.* **2017**, 98–115.
10. Brantingham, P.; Brantingham, P. Criminality of place. *Eur. J. Crim. Policy Res.* **1995**, *3*, 5–26. [\[CrossRef\]](#)
11. Groff, E.; Weisburd, D.; Morris, N.A. Where the action is at places: Examining spatio-temporal patterns of juvenile crime at places using trajectory analysis and GIS. In *Putting Crime in Its Place*; Springer: Berlin, Germany, 2009; pp. 61–86.
12. Song, G.; Bernasco, W.; Liu, L.; Xiao, L.; Zhou, S.; Liao, W. Crime Feeds on Legal Activities: Daily Mobility Flows Help to Explain Thieves' Target Location Choices. *J. Quant. Criminol.* **2019**, 1–24. [\[CrossRef\]](#)
13. Rossmo, D.K.; Lu, Y.; Fang, T. Spatial-Temporal Crime Paths. In *Patterns, Prevention, and Geometry of Crime*; Andresen, M.A., Kinney, J.B., Eds.; Routledge: London, UK, 2012; pp. 16–42.
14. Mariescu-Istodor, R.; Fränti, P. Grid-Based Method for GPS Route Analysis for Retrieval. *ACM Trans. Spat. Algorithms Syst.* **2017**, *3*. [\[CrossRef\]](#)
15. Zhang, D.; Li, N.; Zhou, Z.-H.; Chen, C.; Sun, L.; Li, S. iBAT: Detecting anomalous taxi trajectories from GPS traces. In Proceedings of the 13th International Conference on Ubiquitous Computing, Beijing, China, 17–21 September 2011.
16. Şengör, A.M.C.; Kindap, T. The Geology and Geomorphology of İstanbul. In *Landscapes and Landforms of Turkey*; Springer: Berlin, Germany, 2019; pp. 249–263.

17. Anadolu Agency Istanbul's 2-Year Crime Statistics (2016–2017). Available online: <https://www.aa.com.tr/tr/turkiye/istanbulun-2-yillik-suc-istatistigi/1092162> (accessed on 3 April 2019).
18. Schwitzgebel, R.; Schwitzgebel, R.; Pahnke, W.N.; Hurd, W.S. A program of research in behavioral electronics. *Behav. Sci.* **1964**, *9*, 233–238. [CrossRef]
19. Burrell, W.D.; Gable, R.S. From BF Skinner to Spiderman to Martha Stewart: The past, present and future of electronic monitoring of offenders. *J. Offender Rehabil.* **2008**, *46*, 101–118. [CrossRef]
20. Gable, R.S. The ankle bracelet is history: An informal review of the birth and death of a monitoring technology. *J. Offender Monit.* **2015**, *27*, 4–8.
21. Nellis, M.; Beyens, K.; Kaminski, D. *Electronically Monitored Punishment: International and Critical Perspectives*; Willan: San Francisco, CA, USA, 2013; ISBN 1136242783.
22. Pinto, S.; Nellis, M. 7th European electronic monitoring conference survey of electronic monitoring: Analysis of questionnaires. In Proceedings of the 7th European Electronic Monitoring Conference, Evora, Portugal, 5–7 May 2011; pp. 5–7.
23. Işık, E. *Türkiye’de Denetimli Serbestlik Uygulamaları. Türkiye’de Denetimli Serbestlik 10. Yıl Uluslararası Yaklaşımlar Sempozyumu 2015*; Atalay Matbaacılık Ltd.: Ankara, Turkey, 2015; pp. 3–7.
24. Hucklesby, A. Understanding Offenders’ Compliance: A Case Study of Electronically Monitored Curfew Orders. *J. Law Soc.* **2009**, *36*, 248–271. [CrossRef]
25. Hucklesby, A.; Beyens, K.; Boone, M.; Dunkel, F.; McIvor, G.; Graham, H. *Creativity and Effectiveness in the Use of Electronic Monitoring: A Case Study of Five Jurisdictions*; University of Leeds and Criminal Justice Programme of the European Commission: Leeds, UK, 2016.
26. Renzema, M. Evaluative research on electronic monitoring. In *Electronically monitored punishment: International and critical perspectives*; Routledge: London, UK, 2013; pp. 247–270.
27. Di Tella, R.; Schargrodsky, E. Criminal recidivism after prison and electronic monitoring. *J. Polit. Econ.* **2013**, *121*, 28–73. [CrossRef]
28. Haverkamp, R. Electronic Monitoring. In *Encyclopedia of Criminology and Criminal Justice*; Bruinsma, G., Weisburd, D., Eds.; Springer: New York, NY, USA, 2014; pp. 1329–1338. ISBN 978-1-4614-5690-2.
29. Bıçakçı, Y.S.; Seker, D.Z. Elektronik İzleme Teknolojisi ve Türkiye’de Uygulanması. In *Türkiye’de Denetimli Serbestlik 10. Yıl Uluslararası Yaklaşımlar Sempozyumu*; Özyörük, D., Ed.; T.C. Adalet Bakanlığı: İstanbul, Türkiye, 2015; pp. 214–218.
30. Wang, Y.; Qin, K.; Chen, Y.; Zhao, P. Detecting anomalous trajectories and behavior patterns using hierarchical clustering from taxi GPS data. *ISPRS Int. J. Geo-Inf.* **2018**, *7*, 25. [CrossRef]
31. Duncan, M.J.; Mummery, W.K. GIS or GPS? A comparison of two methods for assessing route taken during active transport. *Am. J. Prev. Med.* **2007**, *33*, 51–53. [CrossRef]
32. DS Data of Electronic Monitoring. In Proceedings of the National Electronic Monitoring Conference, İzmir, Turkey, 20–21 April 2017.
33. OpenStreetMap OpenStreetMap. Available online: <http://download.geofabrik.de/europe/turkey.html> (accessed on 20 January 2020).
34. Google Forms “Suç Üreten ve Suça Çeken Yerlere İlişkin Anket (in Turkish)”. Available online: <https://forms.gle/w6oCFiuSUGsLk2Vq9> (accessed on 5 October 2019).
35. Fayyad, U.; Piatetsky-Shapiro, G.; Smyth, P. From Data Mining to Knowledge Discovery in Databases. *AI Mag.* **1996**, *17*, 37.
36. Han, J.; Pei, J.; Kamber, M. *Data mining: Concepts and Techniques*; Elsevier: Amsterdam, The Netherlands, 2011; ISBN 0123814804.
37. Miller, H.J.; Han, J. *Geographic data mining and knowledge discovery*; CRC Press: Boca Raton, FL, USA, 2009; ISBN 1420073982.
38. ESRI ArcGIS Pro: Release 2.3.1 2019. Available online: <https://community.esri.com/docs/DOC-13013-arcgis-pro-roadmap-february-2019> (accessed on 23 April 2020).
39. R Core Team. *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2019.
40. Gorr, W.L.; Kurland, K.S. *GIS Tutorial for Crime Analysis*; Esri Press: Redlands, CA, USA, 2012; ISBN 158948214X.
41. ESRI arcgisbinding: Bindings for ArcGIS 2018. Available online: <https://community.esri.com/thread/213764-r-arcgis-bridge-v101229-r-studio-r-v350> (accessed on 23 April 2020).

42. Wickham, H. tidyverse: Easily Install and Load the “Tidyverse” 2017. Available online: <https://tidyverse.org/> (accessed on 23 April 2020).
43. Wickham, H. *ggplot2: Elegant Graphics for Data Analysis*; Springer: New York, NY, USA, 2016; ISBN 978-3-319-24277-4.
44. Bracis, C.; Bildstein, K.L.; Mueller, T. Revisitation analysis uncovers spatio-temporal patterns in animal movement data. *Ecography (Cop.)* **2018**, *41*, 1801–1811. [[CrossRef](#)]
45. Bivand, R.S.; Pebesma, E.; Gomez-Rubio, V. *Applied spatial data analysis with {R}*, 2nd ed.; Springer: New York, NY, USA, 2013.
46. Pebesma, E.J.; Bivand, R.S. Classes and methods for spatial data in {R}. *R News* **2005**, *5*, 9–13.
47. Bernasco, W.; Block, R. Robberies in Chicago: A block-level analysis of the influence of crime generators, crime attractors, and offender anchor points. *J. Res. Crime Delinq.* **2011**, *48*, 33–57. [[CrossRef](#)]
48. Groff, E.R.; Lockwood, B. Criminogenic facilities and crime across street segments in Philadelphia: Uncovering evidence about the spatial extent of facility influence. *J. Res. Crime Delinq.* **2014**, *51*, 277–314. [[CrossRef](#)]
49. Ratcliffe, J.H. The spatial extent of criminogenic places: A changepoint regression of violence around bars. *Geogr. Anal.* **2012**, *44*, 302–320. [[CrossRef](#)]
50. Roncek, D.W.; Maier, P.A. Bars, blocks, and crimes revisited: Linking the theory of routine activities to the empiricism of “hot spots”. *Criminology* **1991**, *29*, 725–753. [[CrossRef](#)]
51. Eck, J.E.; Clarke, R.V.; Guerette, R.T. Risky facilities: Crime concentration in homogeneous sets of establishments and facilities. *Crime Prev. Stud.* **2007**, *21*, 225.
52. Kinney, J.B.; Brantingham, P.L.; Wuschke, K.; Kirk, M.G.; Brantingham, P.J. Crime attractors, generators and detractors: Land use and urban crime opportunities. *Built Environ.* **2008**, *34*, 62–74. [[CrossRef](#)]
53. Santos, R.B. *Crime Analysis with Crime Mapping*; Sage Publications: Thousand Oaks, CA, USA, 2016; ISBN 1506331025.
54. Sherman, L.W. Hot spots of crime and criminal careers of places. *Crime Place* **1995**, *4*, 35–52.
55. Chainey, S.; Thompson, L.; Uhlig, S. The utility of hotspot mapping for predicting spatial patterns of crime. *Secur. J.* **2008**, *21*, 4–28. [[CrossRef](#)]



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