

Urban Planning with Mobile data

التخطيط الحضري باستخدام بيانات الهاتف المحمول

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Abstract

Urban green space is closely related to the quality of life of residents. Researchers and academic scholars from various institutes have also pointed out the important role that urban green space can play in the interaction between human and the environment. Most of the methods for urban green space planning take into consideration neither take in the number of users, nor the area and service capacity of green spaces. To address such problems an optimized 2SFCA method to study public facility planning from both the supply and demand sides was put forward in 2014. In the application of the 2SFCA method, some key data inputs include the number of urban residents that a public facility serves, and also the accurate spatial distribution of urban residents where considered. Traditionally, these data are acquired through social surveys and lack timeliness and precision. In recent years, with the rapid development of computer and information technology, it has become possible to use mobile devices, such as cell phones and various location-based services (LBS) provided by APPs installed on smart devices have become a source of urban data with high availability and practical value. In this study, facilitated by mobile phone location data, more specific features of the spatial distribution of urban residents are identified. Further, population distribution in relation to traffic analysis zones is mapped. On this basis, the two-step floating catchment area method (2SFCA) is adopted in combination with urban green space planning to evaluate the per capita area of green space and its accessibility in practice. Subsequently, classification of per capita area and spatial distribution of green spaces within the study area are obtained; thus, urban districts currently with low accessibility to green areas are identified and can be deemed as key areas for the planning of green areas in the future. The study concludes that mobile phone data can be used to more accurately map the spatial distribution of residents; while, the 2SFCA offers a more comprehensive quantitative measuring of the supply and demand of green spaces. The two combined can be used as an important basis for decision-making in the planning of urban green spaces. Since urban green space can be regarded as a kind of public facility, the methodology of the present study is also believed to be applicable in studies of other types of urban facilities

ملخص البحث

يرتبط الفضاء الأخضر الحضري ارتباطًا وثيقًا بجودة حياة السكان. كما أشار الباحثون والباحثون الأكاديميون من مختلف المعاهد إلى الدور الهام الذي يمكن أن يلعبه الفضاء الأخضر الحضري في التفاعل بين الإنسان والبيئة. إن معظم طرق تخطيط المساحات الخضراء الحضرية تأخذ بعين الاعتبار عدم أخذها في عدد المستخدمين ، ولا المساحة ومساحة الخدمة للمساحات الخضراء. ولمعالجة هذه المشاكل ، طُرح أسلوب مُحسَّن لـ SFCA 2لدراسة. تخطيط المرافق العامة من جانبي العرض والطلب في عام 2014. وفي تطبيق طريقة SFCA 2، تشمل بعض مدخلات البيانات الرئيسية عدد سكان الحضر الذين يخدمهم مرفق عام ، وكذلك التوزيع المكاني الدقيق لسكان الحضر حيث تم النظر فيه. تقليديا ، يتم الحصول على هذه البيانات من خلال الاستقصاءات الاجتماعية ونقصها في الوقت المناسب والدقة. في السنوات الأخيرة ، مع التطور السريع للكمبيوتر وتكنولوجيا المعلومات ، أصبح من الممكن استخدام الأجهزة المحمولة ، مثل الهواتف المحمولة والخدمات القائمة على المواقع المختلفة (LBS) التي توفر ها التطبيقات المثبتة على الأجهزة الذكية أصبحت مصدرا للبيانات الحضرية مع توافر عالية وقيمة عملية. في هذه الدراسة ، التي تسهلها بيانات موقع الهاتف المحمول ، يتم تحديد خصائص أكثر تحديدًا للتوزيع المكاني لسكان الحضر. وعلاوة على ذلك ، يتم تعيين توزيع السكان فيما يتعلق مناطق تحليل حركة المرور. على هذا الأساس ، تم اعتماد طريقة منطقة التجميع العائمة ذات الخطوتين (2SFCA) بالتزامن مع تخطيط المساحات الخضراء في المناطق الحضرية لتقييم مساحة الفرد من المساحات الخضراء وسهولة الوصول إليها من الناحية العملية. بعد ذلك ، يتم الحصول على تصنيف مساحة الفرد والتوزيع المكاني للمساحات الخضراء داخل منطقة الدراسة ؛ وبالتالي ، يتم تحديد المناطق الحضرية التي تتمتع حاليا بإمكانية الوصول المنخفضة إلى المناطق الخضراء ويمكن اعتبارها مناطق رئيسية لتخطيط المناطق الخضراء في المستقبل. وخلصت الدراسة إلى أن بيانات الهاتف المحمول يمكن استخدامها لتحديد خريطة التوزيع المكاني للسكان بدقة أكبر ؛ في حين تقدم SFCA 2 قياسًا كميًا أكثر شمولًا للعرض والطلب في المساحات الخضراء. يمكن استخدام الاثنين مجتمعين كأساس مهم لاتخاذ القرار في تخطيط المساحات الخضراء الحضرية. بما أنه يمكن اعتبار المساحة الخضراء الحضرية كنوع من المرافق العامة ، يُعتقد أيضًا أن منهجية الدر اسة الحالية قابلة للتطبيق في در اسات لأنواع أخرى من المر افق الحضرية

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1. Introduction

Urban green spaces form an extremely crucial part of any urban ecosystem. It is very well known that most liveable and attractive cities around the globe like central park in New York, Millennium Park in Chicago, Trafalgar Square in London, Hosier Lane in Melbourne and many more are known for their green spaces and its impact on integration with local culture, societal development and neighbourhood building process. Not only cultural impacts but green spaces also provide preservation of natural environment, smooth flowing of ecosystem cycle, recreational spaces and much more. In today's time where concept of Smart Cities and sustainability is in much hype, continuing to value and preserve urban green spaces will play a vital role on the outcome of various strategies local government bodies are willing to implement in their respective cities or countries. At the same time urban green spaces will also continue to prove a major challenge particularly in developing nations where there is always space, resources and development limitations.

Researchers and academic scholars from various institutes have also pointed out the important role that urban green space can play in the interaction between human and the environment (Kabisch, Qureshi & Haase, 2015). Green spaces are key elements of urban landscape and urban sustainability (Rojas et al., 2016). Scholars have affirmed the values of urban green spaces in terms of health (Maas et al., 2006), economic (Saz Salazar & Menéndez, 2007), social, and climatic benefits (Lafortezza et al., 2009). Recent studies have also showed that access to green spaces can also help in reducing health issues, improve one's wellbeing, remedy for depression and also reduces various other physiological indicators. With the continued increase of urbanization, it is projected that 90% of the world's population will be living in cities by the end of the 21st century (Economic, U.N.D.O. 2018). Therefore, the reasonable planning of green spaces will have a direct bearing on the quality of life of urban residents (Szulczewska et al., 2014). Talking about Dubai, Dubai Municipality with their vision of "Dubai 2020" have also projected a total of 12,200 hectors of urban green spaces through landscaping and horticulture activities. The Director General of Dubai Municipality Haussain Nasser Lootah, from time to time has emphasised on importance of urban green spaces in existing and future development of Dubai and has also citied that the total green spaces in Dubai has increased by over four million square meters in last 3 years. Furthermore, he also said that "The UAE currently stipulates that nearly 25 per cent of the project development area must be set aside for landscaping, in addition to various emirates across the country focusing on building new parks and landscaped zones. Statistics from Dubai Municipality highlight this trend. Over the last 30 years in Dubai alone, the number of landscaping projects completed per year has risen by over 600 per cent." (Khaleej Times)

In today's time of digitalisation and with maturity of technologies like Geographical Information System (GIS) and Remote Sensing (RS), planning process for urban green spaces have been much simplified. The spatial analysis component of GIS can facilitate the evaluation of urban green space system from multiple perspectives, such as accessibility, disaster prevention and risk control, and attractiveness, out of which, accessibility is regarded as one of the most important criteria (Coles & Caserio, 2015) However, most accessibility evaluations are based on simple buffer analysis of green

spaces or network analysis of roads. Most of these methods take into consideration neither the number of users, nor the area and service capacity of green spaces (Germann-Chiari & Seeland, 2004). To address such problems, (Wang Fahui et al.) put forward an optimized 2SFCA method to study public facility planning from both the supply and demand sides (Wang, 2014). Since green space can be deemed as a kind of public facility, goods, or service, the approach is also applicable for the planning of urban green spaces. In the application of the 2SFCA method, some key data inputs include the number of urban residents that a public facility serves, and also the accurate spatial distribution of urban residents. Traditionally, these data are acquired through social surveys and lack timeliness and precision. In recent years, with the rapid development of computer and information technology, it has become possible to use urban big data to analyse spatial behaviours of urban residents and the mechanism behind urban functioning. According to official reports released by the Ministry of Industry and Information Technology, the number of mobile phone (cell phone) users in China has reached 1,306,000,000 by December 2015, which means that every 100 persons own 95.5 cell phones on average. At present, mobile devices, such as cell phones and various location-based services (LBS) provided by APPs installed on smart devices have become a source of urban data with high availability and practical value. In fact, mobile phone data have been used to study the behaviour of urban residents since an early time, from the temporal and spatial analysis of human behaviours based on a small sample group of 30 people by (Ahas & Mark, 2005) and also studies that cover large numbers of residents in Milan and Rome (Reades et al., 2007). These studies advanced not only in terms of data size but also in visualization and representation. In recent years, mobile data have been used to identify the commuting of residents, and further the functional zones of the city (Pei et al., 2014).

In general, various studies have proven that mobile phone data, can, to a certain extent, reflect the temporal and spatial distribution of urban residents and their movement trajectory, which in turn, makes it possible to acquire data of urban residents' distribution with high precision. In my present studies here I have compared the traditional population estimation with the new method of using the mobile data to get the deviation from the accurate figures.

2. Literature Review

As mentioned before many researchers and subject scholars have made good contribution in research and development of using mobile for planning of green spaces. Since the present thesis also deals with using LBS technology for planning of Urban Green Spaces reviews of literatures from various scholars where studied. The major reason for literature review was to find gaps and to know where this present thesis can fill the gaps in enriching planning process for urban green spaces and micro green spaces using mobile technology. This Micro green space is a one of the available green space and further can be considered one of the public facilities or more commonly public goods as well as services (Wu, H. et al). Currently, the trend is toward making the urban planning using inventory planning as opposite to previous incremental planning as used before, nowadays less government are creating the public spaces on a highly dense location. And from here the need for micro green space as it is small as well as flexible. Those can be even distributed in the city without looking into the other land resources. Additionally, in terms of accessibility those spaces are often used by

public. In this study, the authors built a model for the population distribution using the data from mobile operators. This also discussed the issue of accessibility based on the existing green spaces.

The work flow used by this study is shown in Figure 1. As per this figure the main stages of the model are making the population distribution then using the 25FCA by GIS the accessibility for the green spaces had been calculated.



The equation used by this tool is as follows:

$$A_{i} = \sum_{j \in (d_{ij} \le d_{0})} R_{j} = \sum_{j \in (d_{ij} \le d_{0})} \frac{S_{j}}{\sum_{j \in (d_{ij} \le d_{0})} P_{k}}$$

Where S = Supply

P = Demand

R = Ratio between actual capacity and the population served by this area

J = public facility as a centre point

A = Accessibility

I = location where we are calculating the accessibility

After studying 25FCA and their implication in GIS (Wu.H et al) demonstrated the importance of valid data along with quantitative analysis as this will improve the analysis and can help the urban planners in getting more accurate results. In the present study, one of the limitations the calculation of the catchment area related to the green space based on the centroid range method. This study was takenforward and it presented many of the ways such that the CDRs of the telecom network can be utilized for providing key information for the city dynamics in order to be used by urban planners. The dataset used in this research is 2 months for the cellular traffic for Morristown, New Jersey (NJ), city in US with around 20,000 residents (Beckar et al). The approach was discussed through tabulation, analysis using statistics, and finally visualization.

The places where the people live is one of the main information to be used by urban planners. Worker people are using their mobiles between 8 am - 6 pm as those are considered the business hours. More specifically, a worker needs to satisfy two conditions. At least 4 calls/messages for each week in the business hours, as this activity involves. Also minimum of 2 unique days for each week to have those calls/SMS transactions. To validate the derived results, authors compared them with the publicly available US Population data. Specifically, the 2000 Census Transportation Planning Package in which information about people places of their residence as well as work. Then mapping the census data to the ZIP codes under study. Authors showed the possibility of identifying the patterns in the human activity related to different city parts by analysing the phone usage for the antenna coverage areas. By studying the associated patterns. This will allow government officials for building the model to show the flow for the people by parts of the city and with relation to the time. This will in turn help them to detect the anomalies for example a dangerous crowding near the concert. Those patterns are called the life beat for the city. To perform the analysis for the CDR data with reference to the antennas in parallel, authors developed an interesting visual way to represent the multivariate in the data.

To counter traffic data generated from antennas related to mobile network a real time mode to monitor the population density for the urban area in the city, assuming that activity intensity of the cell (the area covered around the antenna) has a direct relation to the presence of the mobile users was made. This technique had been tested against the metropolitan area for the city of Milan in Italy. Results were shown as a group of maps illustrating the people use of the urban space along the time (Examples are monitoring the 24 hours for the working day; comparing the working days with nonworking ones i.e. Saturday as well Sunday; observing the special events examples of such is a soccer match running on the stadium). So, the method showed visualization in terms of social dynamics as run on the built-up areas and this in turn showed the spatial zoning according to the time use for the urban functions. This makes the relationship for the human ecosystem engineering framework for the objective of providing the theoretical approach in order to investigate the effect of urban structure on the distribution of people, and this is in turn showed the integration of spatial as well as the temporal aspects of the human being. Once tested, the authors discussed several applications to use this technique for the sake of improving the efficiency related to the management of the urban systems as well as the planning for their use by monitoring the dynamics of human beings. The Data of the mobile phone related antennas named as intensity related to the cell-phone of the user's activity) had been transmitted to be used by researchers from the national mobile telecommunications authority and was aggregated as well as anonymous in form. The Data calculation was performed after relating the x and y location of the cell phone related antennas, and each antenna had an identifier as ID number as well as the geographical coordinates and for the area under study 232 antennas was the total number of antennas on this area and the activity was recorded for specific antenna in a period of 24 hours. By plotting that information in the diagram as well as maps authors arrived into conclusion that the social activity of the mobile users is considerably high within the day and start to decrease over the night and this can be translated further into the conclusion that in this city the activity goes during the morning hours and start to decrease at night. In another project authors used cell phone technology so that the urban planners can take benefits from its live data.

In addition to that, this research was built on the readily available data that had been gathered by the telecom companies. The most interesting and promising followed step could be to run the ad hoc experiments partnering with the mobile phone operator. The researchers are currently busy working for tracing in terms of urban movements for the paging related to handsets. The whole research was done in an aggregated format, so that individual privacy had been taken into account, with resolution in the hundreds of meters. (Doyle et al) used the telephony data obtained from the mobile operator in order to visualize the people regional flows within Ireland. Besides, using the modified technique for Markov chains in order to rank the most significant regions that interest the mobile subscribers had been investigated. Methodology has been presented that demonstrates the use of ranking for significant regions to the interest for estimating the population in the national level and the results obtained shows a strong correlation when compared to the census data. Both voices calls as well as the SMS related data had been spitted into an originating in addition to the terminating files, on the other side the logs related to the data contain the information on the sessions for mobile Internet.



The data used from Republic of Ireland and it represents the call detailed records (CDR) from the Meteor that is a mobile operator for the purpose of visualizing the flows in the regional level for the people within Ireland. By using the data related to CDR this not only helped in estimating the identification of active mobile regions that has an interesting flow as well as estimating for the density. There are several potential applications with practical importance such as forecasting the utility load as well as the providing a dynamic service related to transportation as such services needs the feed/source related to the human daily activity, for both real time as well as archived or historical side, for predicting the demands on the human-related service. The high correlation on the results that had been estimated by the Central Statistics Office on Ireland and those census data confirms the effectiveness related to the Markov chain for fixed row on the vector analysis in order to approximate the population density and

their proportions. While the estimation of the population using the mobile data techniques will not give a fine-grained result when compared to the census, the fluctuations in population will be monitored in small temporal resolutions as well as with lower cost. Each way of estimating the density for population as discussed during the research came with several advantages in addition to disadvantages. Although estimating which was derived from subscribers taking into consideration the maximum weighting method will give a more accurate result, calculating the individual vector will take more computational power as intensive when compared to single based calculation needed for aggregating the vector approach.

Besides, the approach based on aggregated data is preserving the privacy, since the calculations are performed based on all subscriber data and not for individual subscriber related to the regions for interest. (Soto, Frías-Martínez) in their studies presented a technique by which automatic land use classification is achieved using cell phone network generated information. The approach at the beginning aggregate the data generated by the antennas over the cellular network and thereafter identify the best distribution in in order to find the patterns on the data for the purpose of discovering the citizen's use for the different regions in the city. This technique had been validated using the collected records from the cellular network on the city of Madrid. The approach in this research is based on data mining for solving the problem of classifying and identifying the land use. When comparing this approach with the traditional approaches where questionnaires were distributed this approach provide a costeffective solution and also it adds the capability for the tracing the use of land and its evolution with reference to the time and focusing the study for a specific social background examples of such is tourists as well as socio-economic. Here we need to mention that the approach used by this research will not cancel the approaches based on traditional urban analysis and it will enhance them. The plan in future is to find alternative sources for the information in order to improve the validation as well as to construct some additional classifiers in order to detect the land use. Here the approach followed by this research as to define first the BTS activity, as well as the extension of its coverage; this can be defined by knowing the number for the calls managed with the specific BTS with reference to the time.

This activity had been represented by a matrix Vn with several parameters as the BTS identifier, time in terms of days, time in terms of minutes and finally the number of calls. The signature Xn related to the BTS can be defined with several aggregations for the associated information in the activity matrix Vn. The aggregations presented here are total aggregation; weekday as well as weekend related aggregation and finally the daily aggregation. The total aggregation will define the signature related to specific BTS and this in turn can be defined as the average of the activities as collected the specific time slot on all the days. The fact here is that human dynamics will vary between the weekdays as well as the weekend days, and in turn translating those differences into the BTSs use. By aggregating the weekday-weekend in terms of calling activities as collected and reported for a specific time slot taking into consideration both different types for the day's weekdays as defined to be from Monday till Fridays well as weekend days as defined by Saturday as well as Sunday. And thereafter the final signature can be represented by concatenating the two components. Finally, by performing the aggregation on the daily level as this can be defined by extending the aggregation performed for the weekday-weekend, and hence each day for each week will have its own component. And be considering all the days of the week.

All related signatures had been normalized before the identifying the land uses. The results where graphically presented three examples of each one of the aggregation types mentioned above. With the first figure showing total aggregation and this in turn present a peak around the 12 AM as well as a peak around the 7PM. But the peak recorded on 12AM have a smaller when compared to the one identified at 7PM and here this indicate that the worker's residential location as coming back home. In one another studies the authors proposed in this paper that using the accumulative signal strength as received (RSSI) to study the whole transmissions of the cellular phones for the areas can give valuable information with independent results. The process of detecting the areas with high density over the data set with RSSI temporal had been demonstrated. Thereafter, many of the future applications applying those methods had been discussed and this will complement the traditional analysis, in order to represent the intensity for both urban as well as local activities related to time/space factors. By measuring the localized accumulative signal strength as emitted by the mobile devices with the help of RSSI sensors. Using the captured data will help in extracting the dynamic behavioural patterns with reference to the human activity, this can be an alternative way to Erlang metric method as described before. With use of the captured sensing parameters, this method provides a lot of advantages when compared to the network metric usage related data as follows:

• Data can be captured without mobile operator's cooperation

• This method works regardless of the modulation type used as GSM as well as the 3G protocols

• This data can provider a finer result for both location as well as temporal resolution and hence more accurate and quick.

On the other hand, sensing the strength of the signal or performing the so called RSSI method with single source in mind has several limitations and one of them is the spatial accuracy. Such issues on the accuracy can be solved by using some techniques that are utilised on the researches for cognitive radio. As a first method is to weight the points associated with RSSI both in terms of spatial as well as temporal form specific sensor with some points coming from radios near the geographical area, and in this way, accuracy can be enhanced. Secondly, by performing the modelling process for an environment that has accurate models this will for sure help in quantifying the existing data as well as giving insight into their behaviour. Thirdly, running the calibration process taking into consideration the coverage of each base station will have a direct impact on reducing the effects resulted from the variation on power transmission for the mobile devices. As a last point to mention, the location of the sampling topology related to the sensor network will play an important role to determine the performance, more specifically where the heights of the sensor are used as a variable parameter, and accordingly methods to insure the uniformity related to the topology will be used. An issue may happen when associating the activity related to RSSI to ratio of the mobile device, or on other words the distinguishing between a user generated RSSI signal on the coverage of the sensor and other users far away. Having a high dense network topology will insure that the readings associated to the spectral energy from a specific sensor is localised with some limitations. The solutions for such problem are available and one of them is to localize the activity related to the process of sensor identification. And in this method the sensor node having the highest value related to the RSSI is assumed to have the coordinate for the associated activity. Accordingly, this will reduce the special resolution and thus resulted into an advanced technique for combining the information related to the multi-sensor to locate the mobile devices more accurate and this will be a more suitable method.

By monitoring the accumulative signal strength as received from the mobile phone can help a lot on knowing the information related to the usage of the mobile and can be used in turn in geographical mapping. Several advantages as well as disadvantages for this method. However, with being able to capture a lot of activities associated with the mobile device and without the involvement of the mobile operators as well as without the intruding on the general public privacy, the flexibility associated with this method outweighs all the difficulties in order to provide a reliable collection. The method suggested here can complement other traditional techniques for mapping the mobile usage. So, in brief, if available the mobile usage data can help on the level of city for example and the RSSI data can help on the level of building etc. Zuo, X. and Zhang, Y. in their research aimed to explore the use of mobile phone data for detecting the hot spots in the urban areas and accordingly understand the urban system.

As a new method for enhancing and better understanding the urban system for the cities can be achieved by analysing the traffic data as by cell phone and with relation to the communication activity. The results for those experiments showed the possibility of exploring the urban system by using the methods showed in the above figure and based on the cell phone traffic data. The cell phone data is currently providing the researchers and urban planners with a new way in order to view and model the structure as well as the dynamics related to the urban system. And with the use of some proposed methods, the algorithm suggested in this paper can detect the spatiotemporal hotspots and find them timely. By visualizing the traffic data as generated by cell phone, the dynamic structure related to the Kunming is well known. By running the detection algorithm, some of the resulted hotspots can give us more information about popular places or events, and those are of interest for some of the people. The living pattern in the urban areas can be revealed by the hotspots detected above. In this research, the efficiency related to the proposed methods had not been taken into account. Also, the analysis performed here deals with the activity related to cell phones, and on the future, this can be related to the people living activity. In addition to that, and in the algorithm for the hotspot detection, the number related to the hotspots can be regarded as an input parameter. There are other clustering algorithms that can be used for auto detection of the number related to the clusters, but this proposed method is more flexible more flexible. Future researches can focus on the study of real time related hotspot. Another application of this algorithm is in case of emergencies for events running on the city. Also, smart card data had been used to investigate the patterns related to human mobility. By using the extensive smart card records and resolving the results in both time as well as space, the mean spatial as well as temporal mobility patterns had been studied with reference to larger scales and this in turn reveal the regular behaviour of those patterns. Also travel behaviour had been investigated in terms of patterns at individual level accordingly this showed that the mobility patterns are regular and also gave the hot spots. Decision support related to the transport planning in addition to the management can take benefit from the analytical methodologies for spatially as well as temporally quantifying, visualizing, and examining the urban mobility patterns as developed by this paper. The datasets being used by this research for describing the patterns associated with the urban mobility includes both bus as well as subway transport services. As per the survey conducted by a private company the percentage of people using smart card is 55% for bus trip and 61% for subway passenger's trip. The

smart card data being used in this research covers the transit records for one month as December 2008 of about 5 million smart card users. Daily there is a total of 1.5 million transit records coming from the passengers with smart cards. The smart card data include below information:

- Temporal patterns related to the public transit users
- Spatiotemporal patterns related to the subway users
- Daily check-in as well as check-out for different stops in the subway route
- Spatiotemporal patterns for both day and night peak related hours

Based on those information decisions can be taken toward changing the transportation management. This had been done in order not to allow the data resulted from the analysis to be sparse if individual coordinates of attendees had been considered. Instead, useful patterns can be found by aggregating the data. For the bias removal attendees who live in the same area for the event had been removed otherwise it will not be easy to distinguish between both the event and home. For the events under study, authors maintained as separate analysis result that contains those correspond to the pattern distribution related to the attendee origin, and this had been evaluated at different levels as zip code

Area and the average size for such area is 4:5km2. An example of this is to show that the number of attendees is 96 and this corresponds to 20% for population as this related to the Shakespeare's \Comedy of Errors" at the Boston Common and in turn to show the number for the people as comes from different zip code.

The main objective here is for testing whether two events with same type will show same patterns. In turn, if we have the pattern distribution, the event type can be predicted. This goal was met by running several tests for the 8 models related to the prediction, then the accuracy had been measured with respect to the fraction of the correct event types as identified. As prerequisites to the training phase, the events distribution had been analysed in order to get baseline for the classifier. In principle this leads to knowing the resulted accuracy for the certain classifier which selects in random manner specific 5 type related to the event or in general selects the same type related to the event, and in turn using the same for comparing to improve the quality of the analysis. On average the baseline contributes to 23.34% with respect to the random classification. On the other hand, by choosing a classifier the event that corresponds to the highest probability will have an accuracy of 35%. Here there where two limitations. The location data is not continuously provided but is available only when users are active (call, SMS, data connection). Secondly, we assign origins to users' home locations regardless of where their trips start. This does not hinder our analysis because we are interested in characterizing the taste of the local communities. Further studies considering larger datasets of events and cell-phone users should be performed to obtain more statistically significant results.

To overcome disadvantages from above literature reviews, in this study, facilitated by mobile phone location data, more specific features of the spatial distribution of urban residents are identified. Further, population distribution in relation to traffic analysis zones is mapped. On this basis, the two-step floating catchment area method (2SFCA) is adopted so that mobile phone data can be used to more accurately map the spatial distribution of residents; while, the 2SFCA offers a more comprehensive quantitative measuring of the supply and demand of green spaces. The two combined can be used as an important basis for decision-making in the planning of urban green spaces.

3. Dataset

3.1 Traffic data

This data is related to two months of collection namely November, 2013 as well as December 2013 this covered both Milan city in addition to Trentino Province. Those two areas had been selected since Milan is considered as the main industrial in addition to commercial, as well as financial centre with reference to Italy. The population of this city is about 1.3 million. On the other hand, Trentino is considered as an autonomous related province with reference to Italy, and this is located in the northern of the country. The area covered here is 6,000 km2, and the total population is about 0.5 million.

- 1. Square id: This is related to the Milano GRID shapefile and it stored numeric values.
- 2. Time interval: and by adding the 10 minutes we can obtain the end of the time. And this stored numeric value.
- 3. Country code: the country code and stored numeric values.
- 4. SMS in: Received SMS for Square under study and it stored numeric values.
- 5. SMS out: Sent SMS related to the Square under study and it stored numeric values.
- 6. Call in: Received calls with relation to the Square under study, and this stored numeric values.
- 7. Call out: Issued calls related to the Square under study, and it stored numeric values.
- 8. Internet traffic: Performed internet transactions within the Square and it stored numeric values.

Important notes

- 1. The traffic files have csv extension.
- 2. If the activity is not recorded with relation to the specific field and the value will be missing for the related file. An example of this is that no SMS sent then the record will look like the below:

s \t i \t c \t \t SMSout \t Callin \t Callout \t Internettraffic

Where: $\ \ t$ is tab character

Moreover, if no traffic is recorded for a specific time, square and country code then the record look like the below

s \t i \t c \t \t \t \t \t \t

and this will not be stored as part of the dataset

3.2 Spatial Data

3.2.1 Grid

Some of the datasets are spatially aggregated using a regular grid overlaid on the territory. The Grid dataset [Data Citation 2: Harvard Data verse http://dx.doi.org/10.7910/dvn/QJWLFU,Data Citation 3: Harvard Data verse http://dx.doi.org/10.7910/dvn/FZRVSX] provides the geographical reference of each square which composes the grid in the reference system: WGS 84—EPSG:4326.

- square id: identification string of a given square of the Milan or Trentino GRID;
- Time Interval: The cell geometry expressed as geoJSON and projected in WGS84 (EPSG: 4326).

3.2.2 Milano grid Enrich Layer

This layer includes the population for each square and those details had been extracted from ArcGIS Online using the enrich tool on ArcPro

4. Methodology

4.1 Analysis for specific parks

In order to understand the patterns on the usage of the parks, two main parks had been selected for further analysis

The associated cells related to telecom traffic had been extracted from by overlying the parks layer with the cell layer and run an intersect operation.

1. The traffic data had been filtered on the bases of extracted cells as per the below workbench (Sample had been generated):



Figure 1 : Extract the traffic cells for to the sample park

2. In order to perform the BIG data analysis, and as ESRI limited to point features then we need to convert the polygons into points for further analysis on the GeoAnalytics extension and below is the procedure to Find the centroid of the cell

Calculate Geometry						
Property: X Coordinate of Centroid						
Coordinate System						
○ Use coordinate system of the <u>d</u> ata source:						
GCS: V	/GS 1984					
Use coordinate system of the data frame: PCS: WGS 1984 Web Mercator Auxiliary Sphere						
<u>U</u> nits:	Decimal Degrees v					
Calculate selected records only About calculating geometry OK Cancel						

Figure 2 : Find the centroid of the cell

3. Convert from EPOCH to the standard date/time

=TEXT ((C4 / 86400000) + 25569 + TIME (4, 0, and 0),"dd/mm/yyyy HH:MM: ss")

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	225	⊂Output			00			col0	
		00			col1			result	
		COIL			col2			col1	
012		012			col3			col2	
ml4		COI3			col4			col3	
015		014			col5			col4	
col6					col6			col5	
col7					col7			· col6	
)	result			_result			col7	
			1	(▷ <rejected></rejected>		•		

Figure 3 Workbench to convert the time field

4. Adding the location details to the rows:



Figure 4 Location Details

Full ETL model



Figure 5 Workbench created for the full transformation

4.1.1 Results

By running the Heat map analysis along with time factor in mind:

For Park 1:

@1/1/2014 12 PM



Figure 6 Heat Map at 12 PM

@ 1/1/2014 8 PM



Figure 7 Heat Map at 8 PM

From the above figures we can see a concentration of people on the North East area of the park

For Park 2:



Figure 8 Heat Map for Park 2



Figure 9 Heat Map at 12 PM



Figure 10 Heat Map at 8 PM



Figure 11 Park 1 at different time over the day



Figure 12 Park 2 at different time over the day



Figure 13 Park 1 at different time over another day



Figure 14 Park 2 at different time over another day



Figure 15 Park 1 at different time over another day

4.2 Analysis for the whole data using the Two-step Floating Catchment Method and mobile data

4.2.1 Introduction

Two-step Floating Catchment Method or 2SFCA as abbreviated is considered a popular method for measuring the accessibility in general and for public facilities specifically

This method had been created by both Luo as well as Wang during the 2003 and the main objective was to measure the accessibility for health care related facilities and those can be found in detail on this link <u>http://doi.org/10.1068/b29120</u>. The 2SFCA method has several improvements. And with this in mind this had formed the family of Floating Catchment Area Methods. Details about those methods can be found on the article authored by Vo, Plachkinova, and Bhaskar as published on 2015. The Article name is Assessing Healthcare Accessibility Algorithms: A Comprehensive Investigation of Two-Step Floating Catchment Methodologies Family. And this had been published as a Proceedings for the Americas Conference related to the Information Systems.

In brief technically speaking the 2SFCA includes two major steps and each of those steps is creating a coverage area named catchment. The resulted two catchments are laid on top of each other, or in brief 'floating'. And the end result is a spatial accessibility model. Going deeper into this method and for calculating the needed result this had been achieved by following the below steps:

"Step 1: With the default 30 minute for driving time (first catchment) from the park facility, get the total population such that citizens can reach during the drive time, after that compute the park-to-population ratio. In the case related to individual parks, the parks ratio is 1 relative to the sum of population reached to this park.

Step 2: With the 30 minutes for driving time (second catchment) from the centre of population area, calculate again the park-to-population ratio for the individual park that resides on the drive time. Calculate the accessibility index using the sum of all park-to-population ratios.

4.2.2 Perform the first step

Since our first caveat is that the park capacity is 300, we should have this information in our Parks Feature Class.

1. Adding the capacity field into the parks FCL

As per the below figure:

	🎟 natural_Study ×									
Fie	Field: 🛱 Add 🙀 Delete 🛱 Calculate 🛛 Selection: 🤀 Zoom To 🖶 Switch 📄 Clear 💭 Delete									
4	OBJECTID	Shape	osm_id	name	type	Area	Capacity	Shape_Length	Shape_Area	
	1	Polygon	4011809		park	6759	300	0.002546	0	
	2	Polygon	4011816		park	26627	300	0.005187	0.000002	
	3	Polygon	4011853		park	8462	300	0.003943	0	
	4	Polygon	4011912		park	8550	300	0.003247	0	
	5	Polygon	4011956		park	8236	300	0.002825	0	
	6	Polygon	4012007	Piazza Napoli	park	22109	300	0.004867	0.000001	
	7	Polygon	4012094		park	0	300	0.010713	-0.000004	
	8	Polygon	4012095		park	16954	300	0.003958	0.000001	
	0 of 19	1 selecte	4							

2. Convert the parks FCL into polygon using the polygon to feature class geoprocessing tool as below figure:

Geoprocessing		- □ ×
		_
e (E)	Feature To Point	=
Parameters Environments		(?)
Input Features		
natural_Study		- 🧎
🛕 Output Feature Class		
natural_Study_Point		🗎
Inside		
-		
1		
)		
0		
31		
9		
		Run 🕩
Catalog Geoprocessing		
Contracting Octoprocessing		

3. Buffer for the parks (Points) Feature class

•

The first catchment is created using the buffer of 10 miles instead of the 30 minute drive time as per the figure below:

€	But	fer
Parameters Environments		(
Input Features		
natural_Study_Point		- 🧎 🥖
Output Feature Class		
natural_Study_Point_Buffer		
Distance [value or field]		Linear Unit
	10	Miler
Method	10	ivines
Planar		
Dissolve Type		
No Dissolve		

4. calculate the provider-population ratio

A spatial join between the Parks Buffers with the Census Centroid. This also includes removing unneeded fields as per below Figure:

BUFF_DIST ORIG_FID (L STATEFP (T COUNTYFP (Delete Rename Merge Rule
GEOID (Texl,	Properties

Also, the sum of the population in the corresponding buffers will be calculated:



Figure 17 Sum of population

The Spatial Join will be as shown in Figure 18. Once done the tool to be executed:



Figure 18 details of Spatial Join

The result of the tool will be shapefile without changes, and the only difference is that population data has to be added for those new shapefiles.

Once done, the attribute table related to the LA_first_catchment will be opened for verifying as well as performing the provider/population ratio calculation as per Figure 19

Capacity	Total	Male	Female
100	2687945	1342298	1345647
100	275973	137436	138537
100	4051	2005	2046
100	1557817	759268	798549
100	3255792	1613750	1642042
100	1406713	689866	716847
100	2741734	1359687	1382047
100	2606658	1291304	1315354
100	3553191	1756351	1796840

Figure 19 Result

Accordingly, the Total population, Male, as well as Female to be added. And after performing the provider/population ratio.

This is achieved by adding a New Field namely ProToPop. And the datatype will be double.

By using the Field Calculator in ArcMap with the following formula: [Capacity]/ [Total]

Field Calculator	
Parser VB Script O Python Fields:	Т
FACILITY_L LONGITUDE LATITUDE TYPE_LIC Capacity Total Male Female ProToPop	0
Show Codeblock ProToPop = [Capacity]/ [Total]	

Figure 20 Calcualte the capacity per population

Capacity	Total	Male	Female	РгоТоРор
100	2687945	1342298	1345647	0.000037
100	275973	137436	138537	0.000362
100	4051	2005	2046	0.024685
100	1557817	759268	798549	0.000064
100	3255792	1613750	1642042	0.000031
100	1406713	689866	716847	0.000071
100	2741734	1359687	1382047	0.000036
100	2606658	1291304	1315354	0.000038
100	3553191	1756351	1796840	0.000028
100	543375	264141	279234	0.000184
100	3084139	1512034	1572105	0.000032
100	1425237	702127	723110	0.00007
100	3119937	1547673	1572264	0.000032
100	1230391	599916	630475	0.00081
100	2716771	1320414	1396357	0.000037
100	3668308	1810454	1857854	0 000027

Then the provider-to-population field will be added on the table.

Figure 21 Result of calculation

As per Figure 21, the number is too small and this is a normal result, as well as right. This indicates that the public don't have the enough park for each of us. Here we need to imagine the use of physician data that is 1 in terms of capacity. The resulted ratios will approach 0 as fast as possible.

For completing the first step, this needs to be joined back to the Parks layer and this is achieved by opening the join layer tool and filling it as shown in Figure 22.

Join Data 🛛 🗙
Join lets you append additional data to this layer's attribute table so you can, for example, symbolize the layer's features using this data.
What do you want to join to this layer?
Join attributes from a table
1. Choose the field in this layer that the join will be based on:
2. Choose the table to join to this layer, or load the table from disk:
♦ LA_first_catchment
Show the attribute tables of layers in this list
3. Choose the field in the table to base the join on:
FAC_NAME
Join Options • Keep all records All records in the target table are shown in the resulting table. Unmatched records will contain null values for all fields being appended into the target table from the join table.

Figure 22 Attribute Join

The result will be shown in the attribute Table and confirmed. From here and as seen the fields are duplicated. Then by exporting the resulted join table back for the desktop calling this as LA_Parks_ProToPop. And display the resulted shapefile on the map.

Next will open related attribute table for the LA_Parks_ProToPop and as we did in the previous stage remove the unwanted fields for cleaning purposes as shown on Figure 23.

TYPE_LIC	Capacity	Join_Count	ProToPop
General Acute Care	100	657	0.000037
General Acute Care	100	55	0.000362
General Acute Care	100	2	0.024685
General Acute Care	100	350	0.000064
General Acute Care	100	820	0.000031
General Acute Care	100	323	0.000071
General Acute Care	100	632	0.000036
General Acute Care	100	668	0.000038
General Acute Care	100	884	0.000028
General Acute Care	100	119	0.000184
General Acute Care	100	751	0.000032
General Acute Care	100	314	0.00007
General Acute Care	100	805	0.000032
General Acute Care	100	274	0.000081
General Acute Care	100	623	0.000037

Figure 23 Result of Join

By doing so we will complete the first step and go the second one.

4.2.3 Perform the second step

This is similar to the earlier step. And it starts by creating the Buffer associated with each Census Tract Centroid as per below steps:

1. Execute the buffer tool as per Figure 24 naming the result as A_Centroid_Buffer

,
Input Features
Los_Angeles_Centroid_Inside
Output Feature Class
C:\Users\a\Desktop\LA_Centroid_Buffer.shp
Distance [value or field]
© Field
Side Type (optional)
End Type (optional)
Method (optional)
Dissolve Type (optional)
Dissolve Field(s) (optional)

Figure 24 Buffer on ArcGIS Desktop

By doing the above operation, the result will look like Figure 25:



Figure 25 Result of buffer

With these buffers, and after performing a spatial join, and the name of the result is LA_Parks_ProToPop

Execute the spatial Join as per Figure 26. And deleting all un-needed fields on the LA_Parks_ProToPop and keeping the ProToPop field with Sum rule applied on this field. Naming the result as LA_second_catchment.



Figure 26 Spatial Join

Now, and by joining the LA_second_catchment with the Los_Angeles_Census_Tract as per Figure 27

Join Data X
Join lets you append additional data to this layer's attribute table so you can, for example, symbolize the layer's features using this data.
What do you want to join to this layer?
Join attributes from a table
1. Choose the field in this layer that the join will be based on:
Id2
2. Choose the table to join to this layer, or load the table from disk:
♦ LA_second_catchment
Show the attribute tables of layers in this list
3. Choose the field in the table to base the join on:
Id2
Join Options Keep all records All records in the target table are shown in the resulting table. Unmatched records will contain null values for all fields being appended into the target table from the join table.

Figure 27 Attribute Join to get the needed attributes

Now will select the Census_Tract with the join data from LA_second_catchment and run the export to the Desktop. Changing the name to the LA_2SFCA

Remove all the layers and leave only LA_2SFCA layer. Generally, the LA_2SFCA Census Tract layer. And this layer contains the spatial accessibility index data.

Change the LA_2SFCA layer symbology to Quantities- Graduate Colours. As well as to change the respective Value to ProToPop. In addition to changing the Colour Ramp.

Layer Properties						X
General Source Selection	Display Sym	bology Fields Definition G	luery Lat	oels Joins & Relates	Time HTML Po	pup
Show:	Draw quantiti	es using color to show v	alues.		Import	
Features Categories Quantities Graduated colors Graduated symbols Proportional symbols	Fields Value: Normalization:	ProToPop none		Classification Natural Brea Cla <u>s</u> ses: 5	ks (Jenks)	
Charts Multiple Attributes	Color <u>R</u> amp:					1
	0.00000 0.00053 0.00088 0.00116 0.00166	200 - 0.000531 32 - 0.000880 31 - 0.001159 50 - 0.001660 51 - 0.024685	0.00 0.00 0.00 0.00 0.00 0.00	0000 - 0.000531 0532 - 0.000880 0881 - 0.001159 1160 - 0.001660 1661 - 0.024685	Advance <u>d</u> •	
				ОК	Cancel	<u>A</u> pply

Figure 28 Symobolizing the result

Now here is the result.



Figure 29 Final Result

What you see here is the park-spatial-accessibility-esque map. You can see, however, that the more access is in the middle of the city LA, while the remaining outskirt will not have the same access level.



Figure 30 Result for full area

Figure 30 shows that the accessibility for the parks on the centre of the city is more and decrease while going to the outside areas.

5. Discussion

The final per capita area related to the green space using the 2SFCA method is shown in Figure 30. In the diagram, per capital area of green space goes down ranging from the dark blue to the dark red shown on the legend and represented by colours. With reference to the master plan related to Milan, the smallest value related to the per capital area of green space is equal to 5 m2 for each person. Meaning, in real supply demand relation for the green space, around half pilot area is failing for satisfying the lower limit mentioned above. Looking to the objective for the case study related to this research, for the local areas of greatest number related to the users as well as the smallest area related to the green spaces may be identified showing the areas related to the most urgent demands related to the micro green spaces. From Figure 30, it can be decided that the three types related to the areas with colours ranging from orange to dark red as per the legend are basically the key areas that micro green spaces to be added on. This result gives an important quantitative basis for the follow up surveys, the upcoming planning, as well as the design practices related to the project team.

On the Traditional approach related to the urban green space planning is almost based on the per capita index, and this in turn fails on the effective guide of the spatial distribution related to the green spaces. Besides, selecting the site related to the green spaces basically related to the service radius regardless of the population distribution. By combining the 2SFCA method along with the population distribution based on the mobile phone for the location data, the planning related to the green spaces for city, as well as the traffic analysis areas is based on the urban roads, this present study is evaluating the per capita green space in order to realize the evaluation for the service capacity related to the green spaces with reference to the own sizes. We believe that the methodology presented on this study can be generalized to be applied on the evaluation of the accessibility related to other public facilities as well as used on the site selection for the upcoming planning. When applied for different kinds related to the facilities, variables used may differ for calculating the service capacities. Examples of this is the service capacities related to the hospitals as well as school will not be represented on the land area, but the number of beds as well as floor areas related to the buildings, etc.

6. Conclusion

Generally speaking this study represents the effort related to offering a comprehensive as well as quantitative urban planning methods. Because the urban planning in general has been recognized as unscientific for using deeper qualitative related analysis, the existing researchers goes to the quantitative analysis. Going from the qualitative toward the quantitative studies, many problems may arise and one of the crucial problems is on the method of obtaining as well as using the data. Because of that, the big data as well as the smart city attracted more attention from the researchers with different disciplines ranging from the urban planning toward the urban geography. Accordingly, the era related to the mass amount related data had already come to practice. On the occasions with less difficult for acquiring the data, the methods for using those in the researches as well as the design introduces many issues and those will be urgently considered. With this reference this is a step on the direction. More specific, we believe that this research realizes the advanced progress related to both applying the 2SFCA method for getting the actual supply demand-based analysis with regard to the urban public green spaces; on the other hand, applying urban planning related to the residents' spatial distribution gained from the mobile phone locational based data analysis.

The research shows that by combining the valid data as well as the quantitative analysis related to the models will improve the rationality of earlier stages-based analysis before the process of urban planning as well as provide the directions related to the subsequent design practices. Mobile phone related data as well as the 2SFCA method offer new ways toward the supply/demand analysis, for the evaluation of differences in terms of accessibility related to the green spaces. During the acquiring of the data, the method can be done on similar big cities as well as for the evaluating the accessibility related to other types for the public facilities with service capacities computed by served populations. For this research, a limitation in the catchment area for the green space to be calculated based on the simple centroid range method. In the other hand analysis could be based on the urban road network can be advised, and on this method the residents' actual paths toward the green spaces will be used for measuring the travel distances. Further analysis can be conducted for the mobile phone data and those can be expected for evaluating the actual use related to the green spaces as well as the features related to users and this will give more specific references toward the decisionmaking related to the planning practices.

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