PLANNING CITY GREEN SPACE LOCATIONS FOR PUBLIC ACCESS: A CAPACITATED LOCATION-ALLOCATION MODELING APPROACH

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Xiaoling Li

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PLANNING CITY GREEN SPACE LOCATIONS FOR PUBLIC ACCESS:
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Xiaoling Li, Ph. D.
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Green spaces help build healthy communities and bring various social benefits for the public. In order to ensure the wellness of greening of cities, some space standards such as green space coverage and the average area of green space per person are widely adopted in green space location planning, and they were also widely accepted as indices for cross-city comparisons. However, using these standards alone ignores the fact that both green spaces and population are unevenly distributed in cities. And many cities do not have enough green spaces at adequate locations for public access. Using a real city as an example, this study presents a capacitated location-allocation modeling approach for planners and policy-makers to incorporate existing green space planning standards into location models to evaluate existing green spaces and select potential green space locations to meet public recreation needs. This approach is to find the locations of green spaces among all candidate sites which minimize the cost of green space construction, or in other words, to build the minimum amount of new green space area and make the best use of existing green spaces, such that the proportion of the population that can each share a certain amount of green space within standard catchment distance can meet green space service percent coverage standard. The author addresses the problem of applying some space standards directly into the models and points out that these standards have to be adjusted for feasible solutions. Taking the study case for example, the average green space area per person

is much higher than $15m^2$, but when uneven distributions of population were considered, the average accessible green space area per person is less than $5m^2$. Given the uncertainty of such planning standards as part of the model inputs, multiple model results with the various parameter inputs were generated. Finally an integration approach of these model results was proposed for the purpose of green space plan implementation: the green spaces in the solutions were classified into different groups according to their relative contributions to serve the demands, and different implementation strategies were suggested for each green space group.

BIOGRAPHICAL SKETCH

Xiaoling Li was born and grew up in China. She received B.S. and M.S. in City and Regional Planning at Peking University. After being an urban planning practitioner for 3 years in Shenzhen, China, Xiaoling came to Cornell University to pursue her Ph.D. degree in City and Regional Planning.

This dissertation is dedicated to my family.

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LIST OF ABBREVIATIONS

Adj-Network	Adjusted Network Distance
ADP	Approximating Demand Point
DP	Demand Point
GS	Green Space
LA	Location-Allocation Problem
MCLP	Maximal Coverage Location Problem

CHAPTER 1
INTRODUCTION

1.1 Motivation

City green space provides various environmental and social services towards the overall goal of urban sustainability. The contribution of city green space for improving the climate, air, hydrology and quality of life in cities is well realized and documented. First, green space is the main component of urban ecosystems. It plays a vital role in supporting biodiversity and providing important ecosystem services in cities (Wang 2007; Li et al. 2005; Kong et al. 2010; Gyllin & Grahn 2005). Environmental services offered by green spaces include sequestering CO_2 and producing O_2 (Johnson & Gerhold 2003; Balakina et al. 2005); improving microclimates and reducing the urban heat island effect (Hamada & Ohta 2010; Hilton 1984); protecting drinking water resources and purifying water, protecting soil, reducing air pollution (Warren, 1973; Yang, McBride, Zhou, & Sun, 2005; Jim & Chen, 2008; Escobedo & Nowak, 2009) and noise pollution (Gidlofgunnarsson & Ohrstrom, 2007). Green space also provides outdoor recreational services to the public (Chen & Jim, 2008; Cho et al., 2008; Konijnendijk et al., 2007; Wong, 2009) and is good for physical and psychological health (Nielsen, 2007; Gathright et al., 2006; Hansmann et al., 2007; Maas et al., 2006; Nilsson et al., 2010). What's more, research shows green space can affect housing prices (Jim & Chen, 2007; Kong et al., 2007; Mansfield et al., 2005; Yin et al., 2009). Green areas also have important aesthetic, cultural–historical values (Chen et al., 2009; Meyer, 2002) and have a positive impact on social safety (Maas et al., 2009).

However, an increasing population and a high rate of land consumption in the world is putting pressure on green spaces. Especially in recent decades, many places in fast developing areas are rapidly converting to urban and suburban landscapes, and many green spaces are decreasing rapidly in favor of exploitation and urban development. Because of heavy economic development pressure, green spaces in and around many cities in developing countries are being encroached upon or at least threatened by construction activities. Cities in fast developing areas are now experiencing fast growth by sprawling to surrounding areas which were once green lands, or wiping out green spaces within the urban areas for the higher economic benefit.

Fortunately, with growing awareness of nature and the improvement of quality of life by natural areas, more and more interest is placed on city green spaces and the importance of maintaining existing green space or creating new green space is well realized (Bengston et al., 2004; Breuste, 2004; Konijnendijk et al., 2007; McGuirl, 2004; Stewart et al., 2004; Zhu & Zhang, 2008). And under proper city policies, the pressures on green spaces can still be managed and green spaces can be conserved.

In order to conserve existing green spaces and maximize the utility of new green spaces, it is imperative to study the spatial distribution of green spaces. Among city policies of conserving green spaces, determining the spatial distribution of green spaces and identifying proper locations of green spaces that should be protected or newly built, as a main component in city green space planning, should be the first important step . Afterwards and under this condition, design, management and maintenance of individual green space can be more effective and efficient. Hereby, this study focuses on the locations of green spaces in cities. And in addition to ecological functions that any green space may have, what makes city green spaces unique from natural green spaces in rural areas is its social function served to a city’s dense population. These social functions come from city green spaces’ characteristic of location closeness to urban neighborhoods so that urban dwellers can frequently visit city green spaces for various benefits, recreationally, physically or mentally. Hence, this study concentrates on the locations of city green spaces from the perspective of public access.

A fundamental assumption of this study is that location-allocation models, which investigate where to locate certain facilities in terms of satisfying a set of demands and meeting certain objectives subjecting to certain constraints, with a combination of GIS spatial analysis, can be a useful tool to identify locations of city green spaces. This will be further discussed in Chapter 2.

1.2 Research Objectives

This study integrates location-allocation models and related planning standards of city green space location research to determine whether current green spaces are sufficient to meet public need and if not, where new green spaces or parks should be constructed. There are two major objectives in this study.

1) Incorporate green space planning standards into location-allocation models so that the location-allocation models can facilitate the location selection of green spaces in the planning process so that the numeric planning standards can be carried out in physical space.
2) Examine the current green space locations and coverage, and recommend the locations and corresponding strategies for future green space construction so that the geographic accessibility to green spaces can be improved.

In order to apply location-allocation models in green space location studies, the following are the major tasks in this study:

1) Address the green space specific problems that planners or decision makers may encounter with location-allocation models, and find reasonable solutions thereto.
2) Define proper planning standards and related values which are suitable for location-allocation models.
3) Structure location-allocation model(s) so that the selected planning standards can be properly incorporated in the model(s).
4) Integrate multiple models that can help achieve a better understanding of the green space location problems and handle uncertainty in planning standards related parameters.
5) Evaluate and access the current locations and their coverage of green spaces in the Luohu District of Shenzhen.
6) Compare location-allocation model results and determine how they would be impacted by changes in model parameters, which vary in planning (whether the various location-allocation models are sensitive to these parameters).
7) Determine where to locate new green spaces for the goal of improving public access and to provide implementation suggestions.

1.3 Study Area

Shenzhen is a coastal city in the Southeastern part of China, located in Guangdong Province, to the north of Hong Kong (Figure 1-1). The city has a total area of 2020 km^2 (780 square miles), with longitude between 113.46 and 114.37 degrees east and latitude between 22.27 and 22.52 degrees north.

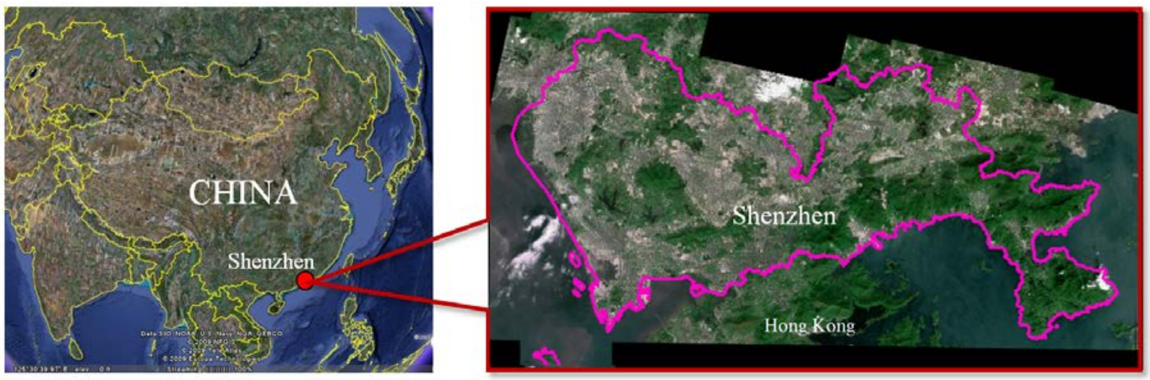


Figure 1-1 Location of Shenzhen

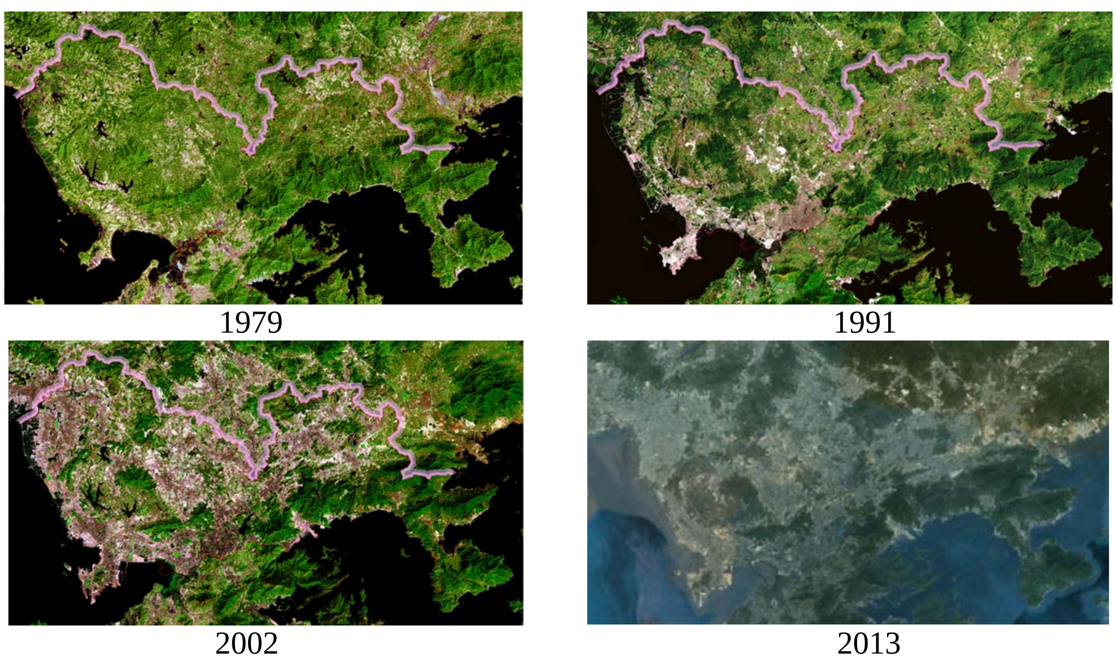


Figure 1-2 Fast development of Shenzhen in 35 years

The area has a history over 6700 years, though the city was only founded in 1979, by then it was a small border town with major residents farming or fishing for a living. Since its foundation 35 years ago, as the country's first Special Economic Zone, the city has experienced fast urbanization (Figure 1-2). It became the fourth most developed city in China mainland, and its population has increased from 30,000 to over 10 million. The city is considered as one of the fastest-growing cities in the world. While experiencing fast development, the city government understands the importance of green spaces and has devoted much effort to protect its green spaces. Green space covers 46.7% of the total area of the city, and the green space coverage in the urban area is as high as 39.2%, with the average public green space per person up to 16.7 square meters (Shenzhen Urban Management Bureau of the Municipality, 2014), and over 35 square meters of greenery area for each person on average[1].

Administratively, the city is divided into 6 districts: Luohu, Futian, Nanshan, Yantian, Baoan, Longgang. The former four districts constitute the city core. Each district is further divided into sub-districts. Then each sub-district contains several neighborhoods or residential communities.

Figure 1-3 Location of Luohu District in Shenzhen

[1] Source: http://203.91.45.57:8080/intro/details01.aspx?tid=201332528&cid=1384

The study area of this dissertation is Luohu district, located at the city center and is the oldest downtown (Figure 1-3). The area is 79 square km^2, with population 0.923 million. It is the second densest district in the city, with density of 11,726 people per km^2. There are 10 sub-districts and 115 neighborhoods in the district. By 2010, there were 87 parks in the district, including 7 city parks, 1 district park and 79 neighborhood parks. Total park area is 1067 ha, about 11.5 square meters per person. Though this district is a downtown district of the city, it contains a large amount of semi-natural and natural green spaces in its jurisdiction. Besides parks, a large number of open green spaces are not managed as parks. Taking all green spaces into account, the average green space per person is about 37 square meters.

1.4 Research Framework

This dissertation consists of five chapters. Chapter One introduces the research problem with motivation and the background of the study area. The next chapter overviews green space location related study and practices, and location-allocation models and applications. Chapter Three discusses the methodology. It forms the location-allocation models for the study area with green space planning standards concerns. Some general issues in regular location-allocation modeling problems are discussed, such as various distance measures, demand estimation, data aggregation for model efficiency, and types and related costs of supply facilities (in this study, green space). In this chapter, green space planning standards are explored and four of them are incorporated in the formulated location-allocation models: percent of population coverage by the green space service area, minimum size of a green space, average green space demand per person, and maximum distance threshold for walking to a green space. This chapter also discusses the specialties of applying location-allocation models to green space walking accessibility studies and corresponding adjustment

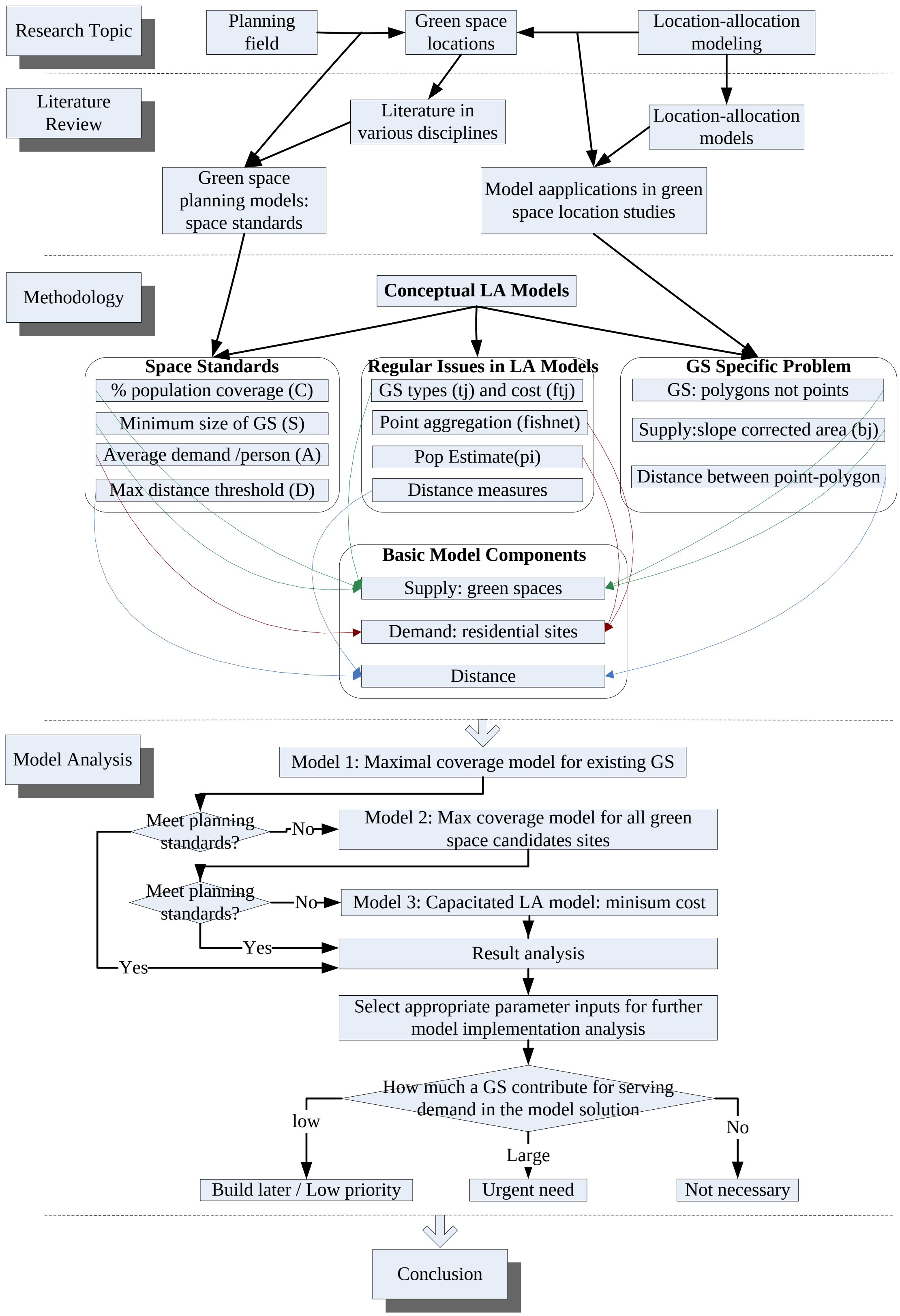


Figure 1-4 Flow diagram of the research procedure

solutions. Unlike facilities in many other location-allocation models, green spaces cannot be represented as points given their large spatial dimensions comparing with walkable distance. Therefore, the distances between residences to green spaces cannot be simply calculated as for point-point distances, point to polygon distance calculation has to be used instead. The third special issue is using correction factors to adjust appropriate areas of green spaces as supply inputs in the models. Each of the discussed issues is related to one of the three fundamental components of location-allocation models: supply, demand, and distance. Chapter Four presents the model results in a sequence of maximal covering location models for existing green spaces, the same model but for all green space candidates, including existing green spaces and potential ones, and the capacitated location-allocation model with the objective of minisum cost. Further analysis is also included to assess the impact of green space planning standards on the model results. The differences and commonalities of various distance measures as model inputs are explored in this chapter. Chapter Five summarizes the findings and contributions of this study.

CHAPTER 2
LITERATURE REVIEW

2.1 City Green Space Location Related Studies

2.1.1 City Green Space Location Analysis in Various Disciplines

Because green space has many different functions in cities, many disciplines study green space from different perspectives. Environmental scientists are concerned with biodiversity and environmental protection, and how green space provides people's ecological needs; sociologists might study people's behavior and attitudes on green spaces, such as how people use green spaces, for recreation, or people's social needs on green spaces; political scientists might focus on the rules or landownership of green space, they might also be concerned with subgroup differentiations such as gender and poverty issues; public health experts concentrate on the health benefit people gained from green spaces; economists look at the economic benefit from green spaces, either directly by production or indirectly by increase surrounding land price.

From an environmental perspective, for example, McGuckin and Brown (1995) developed a spatial distribution model to predict the pattern of stormwater catchment facilities in developing urban areas. Because of the need to act quickly with incomplete information, Hess, King and Rubino (Hess & King, 2002; Rubino & Hess, 2003) developed a process of selecting key species and of the rapid identification and verification of potential habitat for the focal species. Carles (1999) suggested that there is a need to identify places or settings where the conservation of the sound environment is essential, because of its salient informational content or because of the drastic impact of the loss of sound quality on observer appreciation, for example, in urban green spaces, natural spaces and cultural landscapes. From a study of noise and green spaces, Gidlöf-Gunnarsson and Öhrström (2007) drew the conclusion that in the process of planning health-promoting urban environments, it is essential to provide easy access to nearby green areas that can offer relief from environmental stress and opportunities for rest and relaxation, to strive for lower sound levels from road traffic, as well as to design "noise-free" sections indoors and outdoors. Chang et al. (2007) devised a method to detect and compare the local cool-island intensities of various urban parks and verified that it differs among parks, then determined that it was related to park characteristics such as park size or land cover types. An interesting finding by Sandström (2006) in Sweden directly relating biodiversity and planners was that planners were interested in the maintenance of biodiversity, but were limited by knowledge and by personnel lacking suitable qualifications. Only a minority of the respondents thought that local governments should have resources for biodiversity conservation planning. This finding was discovered by surveying planners in six large Swedish cities.

From a social perspective, a survey conducted by Balram and Dragićević (2005) in the West Island, Montreal, Canada showed that households are characterized by a two-factor attitude structure towards urban green spaces: behavior and usefulness. The attitude toward urban green spaces is a multidimensional construct which will influence people's behavior towards urban green spaces. A research by Pretty et al. (2007) measured the effects of ten green exercise cases (including walking, cycling, fishing, boating) in the UK on 263 participants. The author found that green exercise, no matter which type, led to a significant improvement in self-esteem and total mood disturbance. This study pointed out that green exercise has important implications for public and environmental health, and for a wide range of policy sectors. Takano et al. (2002) claimed living in areas with walkable green spaces positively influenced the longevity of urban senior citizens independent of their age, sex, marital status, baseline functional status, and socioeconomic status. Greenery filled public areas that are nearby and easy to walk in should be further emphasized in urban planning for the development and re-development of densely populated areas in a megacity. Tyrväinen (1997; 1998) studied amenity value and other social values of green spaces. Tyrväinen's research on over 1000 apartments in North Carelia, Finland indicated that urban forests are an appreciated environmental characteristic and that their benefits are reflected in property prices. Proximity of watercourses and wooded recreation areas as well as increasing proportion of total forested area in the housing district had a positive influence on apartment price (Tyrväinen, 1997). Further, in this case, most visitors were willing to pay for the use of wooded recreation areas and about half were willing to pay to prevent the conversion of forested parks to another land-use (Tyrväinen & Väänänen, 1998). Tyrväinen also developed a method to describe the experienced qualities of green areas for strategic green area planning purposes (Tyrväinen, Mäkinen, & Schipperijn, 2007). In her postal survey study in Helsinki, Finland, local residents were asked to identify areas that had particular positive qualities to them, by collecting individual residents' opinions, the most valued sites as well as problem areas within the study area were found.

From an economic perspective, Kumagai (2008) studied downtown Tokyo on the relationship between biodiversity and the residential housing value. By using a "green coverage ratio" to represent biodiversity and standardized data on land and rent prices to represent housing value, the study confirmed that the two factors: green coverage ratio and housing value were correlated. Mansfield (2005) claimed that though trees on a parcel of land may add value for house owners, the ecological value of these trees as habitat was far less than large, unbroken parcels of forest. In a North Carolina case study the author tested the hypothesis that trees on a parcel or in the neighborhood around that parcel were substitutes for living near large blocks of forest.

From a political perspective, Heynen et al. (2006) investigated the role of urban political economy, private-public property relations, and race and ethnicity in the social production of Milwaukee's urban forest, and found the distribution of urban trees is spatially inequitable in relation to race and ethnicity. This is an instance of urban environmental inequality that deserves greater consideration in light of contemporary and dynamic property relations within capitalist societies. On the other hand, Browne and Kubasek (1999) studied a communitarian green space between market and political issues. The authors claimed that changes in environmental law develop in a cultural context that embraces particular linguistic patterns. Those who wish to effectuate change in American environmental law, for example, must make their peace with the pervasive embrace of individualism in the culture with the consequent devotion to market solutions. Communitarian rhetoric here did not offer panacea to the U.S.

2.1.2 City Green Space Location and Distribution in Planning Field

Green spaces have been an integral part of modern physical planning system for over a hundred years, and various methods and concepts that related to green spaces have emerged over the years. Maruani and Amit-Cohen (2007) reviewed various types of open space planning models that were commonly used, with their merits and limitations as planning tools. Generally, planning approaches for urban green spaces can be categorized at least as following general types.

(1) Comprehensive green space system planning models

Modern citywide green space planning and location ideas appeared after the western industrial revolution, when urban environmental problems became serious.

The famed landscape architect Frederick Law Olmsted was a pioneer who founded the basis of modern urban green space system. In 1903 He noted that "No single park, no matter how large and how well designed, would provide the citizens with the beneficial influences of nature… A connected system of parks and parkways is manifestly far more complete and useful" (M. A. Benedict & McMahon, 2002). In 1887 he designed the world famous Boston's Emerald Necklace and it is one of the oldest systems of linked public parks in the U.S. (M. A. Benedict & McMahon, 2006; Zhou, 1999). In Europe, British Ebenezer Howard cited in his 1898 book *Garden Cities of To-morrow* that married town and countryside could retain the benefit of nature. Though never fully realized, garden city ideas had a profound influence and inspiration in later planning practices and are considered to be a cornerstone in planning (M. A. Benedict & McMahon, 2006; Howard, 1902; Zhou, 1999).

(2) Shape-related models

Since the green space system idea was put into practice, more and more shape-related green space concepts were created, such as greenbelt, green heart, green fingers or green wedges, and greenways (Maruani & Amit-Cohen, 2007), see illustration in Figure 2-1.

Greenbelt was a response to uncontrolled growth of cities at the end of the 19th century, conserving green spaces between urban and rural areas to prevent cities' expansion. It was first developed in London and then adopted in Europe, America and Asia. But practices have shown that greenbelts did not prevent urban growth effectively, yet can only be conserved as green space. Green heart, on the other hand, describes an open space – usually in large scale – encircled by built-up areas. However, again, it was found the urban development was sprawling into green heart areas. Green fingers / wedges are radial strips of green space that penetrate the built-up area, and

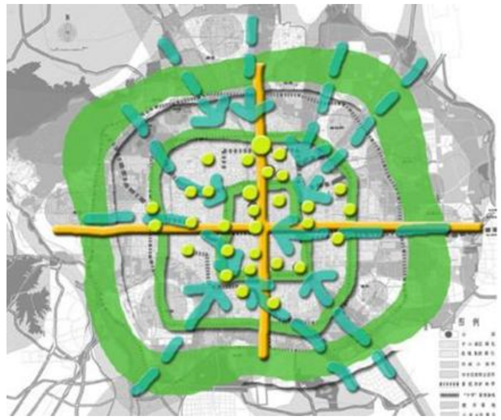


Figure 2-1 Greenbelts and green wedges in Beijing

Source: http://www.chla.com.cn/html/c47/2009-11/45566.html

are expected to improve accessibility to green spaces from inner cities. Greenways, referring to green spaces of a linear nature, are based mostly on existing linear surface elements such as streams or railways.

Generally, these shape-related models are all conceptual models which are usually based on existing landscape components and may serve certain city functions, but do not ensure a satisfactory response to either ecological or population needs. However, for the same reason that understanding of social or ecological processes is not necessarily required and the models are simple to apply, these models are extensively used by planners around the world (Maruani & Amit-Cohen, 2007).

(3) Landscape ecology related models

From the 1960s, ecological principles have been widely applied in the planning field and the landscape ecological planning approach became mature. Ian McHarg advocated an ecosystem-based planning approach in his landmark 1969 book, Design with Nature (McHarg, 1969). In the book, he claimed that "natural processes should be the basis for determining development (or non-development) priorities" (M. A.

Benedict & McMahon, 2006). Today, the landscape ecological planning approach is still a main subfield of planning for urban green spaces. Besides, more landscape ecology related planning concepts, such as green infrastructure and ecological infrastructure have been created in recent decades.

Green infrastructure is "the interconnected system of green spaces that conserves natural ecosystem values and functions, sustains clear air and water, and provides a wide array of benefits to people and wildlife" (M. A. Benedict & McMahon, 2002, 2006). Benedict and McMahon (2002) claimed that green infrastructure planning should be the first step in the land-use planning process. They stated that green infrastructure should be designed holistically, planned comprehensively, laid out strategically, planned and implemented publicly, grounded in the principles and practices of diverse professions, and founded up-front. Green infrastructure programs have been implemented on the city, regional, and state levels. At the city or comparative level, examples may include: Chicago Wilderness Biodiversity Conservation Plan, Twin Cities Minnesota Metro Greenways, Portland, Oregon Metro Greenspace Program, Legacy Open Space in Montgomery County, Maryland, Linked Open Space Network in Palm Beach County, Florida, Green Infrastructure Plan in Kinston/Lenoir County, North Carolina (APA, n.d.; M. A. Benedict & McMahon, 2002).

Ecological infrastructure is a similar concept with emphasis on ecology and network. Yu (1996, 2001) raised the concept of a security pattern, which was composed of strategic positions of the landscape that are critically significant in controlling certain ecological processes. He claimed that a security pattern is a way of identifying ecological infrastructure. Four components of buffer zones, intersource linkages, radiating routes and strategic points compose the ecological security patterns, which can be identified according to their various properties on a GIS surface. He has applied this approach in a few Chinese cities (Yu, Li, & Han, 2005; D. Li, Liu, & Kong, 2008; S. Wang, Chen, & Yang, 2008).

The University of Georgia developed a toolkit to evaluate land parcels for green space planning (Kramer & Dorfman, n.d.). The toolkit was designed for communities and tended to establish a detailed inventory for each subject parcel of on green space characteristics, and by weighting the various goals of a green space plan and ranking parcels based on the weighting.

As mentioned before, landscape ecological principles are widely used in city green space planning. For example, C.Y. Jim (Jim & Chen, 2003) directly applied the principles and developed a comprehensive green space plan for Nanjing, China. The plan consisted of green wedges, greenways and green extensions at three scales: metropolis, city and neighborhood scales.

(4) Space standards models

Space standards first appeared in London at the end of the 19th century. A number of studies on public facilities have been conducted on their spacing standards. McAllister (1976) pointed out that existence of a large number of small public facilities spread out for public access is of great importance in public service system design. Lucy (1981) stated that in practice a threshold of adequacy should be established for equality. He used neighborhood parks as an example, he pointed out that “a maximum distance standard and an acreage and density standard are suited to determining which parts of the jurisdiction are below the threshold of adequacy of access”.

Among space standards, one is the percentage of green space coverage in certain area. Another standard is quantitative matching between open space and respective user population, claiming that certain minimal area size of green space should be allocated to a given population, in terms of area per person. These standards are widely used in green space planning and all other public facility planning because of their simplicity. However, they can hardly instruct any spatial locations practically and sufficiently on their own because they only provide non-spatial related numbers on the amount of green spaces.

Given that using simple quantitative measures cannot guide green space locations based on existing demands, more elaborate studies on social needs have been carried out, incorporating criteria related to additional aspects of users' needs. The criteria may include green space service range, minimal size, residential densities (Maruani & Amit-Cohen, 2007). Among related research, most studies focus on the accessibility of green spaces by service range, claiming that residents would prefer having green space within certain distances (B. Li, Song, & Yu, 2008; Neuvonen, Sievänen, Tönnes, & Koskela, 2007; Van Herzele & Wiedemann, 2003).

The following are some examples of numerical standards that have been established or proposed.

The National Recreation and Park Association in the U.S. established park and recreation standards as follows (NRPA, 1983):

Table 2-1 The space standards for parks in the U.S.

Type	Service Area	Desirable Size (acres)	Acres/1000 Residents
Mini-Park	< ¼ mile radius	≤ 1	0.25 to 0.5
Neighborhood Parks	¼ to ½ mile	15+	1 to 2
Community Parks	1-2 mile	25+	5 to 8
Regional Parks	Several communities 1 hour driving time	200+	5 to 10

The Korea Urban Park Law suggested such thresholds of size and service distance as these (Oh & Jeong, 2007):

Table 2-2 The space standards for parks in Korea

Type	Service area (radius in meters)	Size (m^2)
Children's parks	< 250	> 1500
Neighborhood parks	< 500	> 10,000
Walkable area parks	< 1000	> 30,000

The Planning Department of Hong Kong set the regulation of the minimum standards of $1m^2$ per person (10 ha per 100,000 persons) for district and local open spaces respectively (Hong Kong Planning Department, 2014).

Besides being used as space standards, these figures can also be used for cross city comparison. Following are two space indices on green space coverage ratio and average area per person of large cities (Oh & Jeong, 2007).

Table 2-3 Comparison of green space related standards in large cities

Cities	Park area ratio (%)	Park area per capita (m^2)
New York	13.56	14.12
London	10.89	24.1
Paris	36.05	17.88
Seoul	26.02	15.45
Tokyo	2.79	5.14

2.1.3 Summary

The comprehensive green space system planning models first reveal the need of citywide green space planning and management and emphasize the interrelations among green spaces. These models, together with space standard models, focus on the social utility of green spaces, i.e., social demand. Shape-related models focus on the spatial structure of green spaces within a city; the utility or nature is always the second concern after deciding to form a certain structure. Landscape ecology-related models, on the other hand, focus on conservation from an environmental perspective, and discuss the green space base and supply for cities.

Considering the complexity of the planning process, space standards are easier to apply since they are just calculations of numbers; landscape ecology related models are always more complicated, take a long time and require higher skills for planners because these later models require a good understanding of ecological and natural principles.

Typically in the planning field, urban planners study the relationship between natural systems and land use systems, and landscape architects focus more on the interaction between socio-economic systems and land use systems (Zonneveld et al., 1989). For urban planners who pay more attention to social issues, the demand approach of the comprehensive green space system planning models, space standards models, and shape related models provides a response to human demands for recreation and quality of life. In these models, planners' concerns are more about population, residential distribution and density. Landscape architects or conservationists, by contrast, focus more on green space conservation for protecting natural values, and landscape ecology. In these models, ecological and spatial attributes of the existing natural environment play a key role.

This study focuses on city green space locations from the perspective of public access, using a quantitative optimization modeling approach, which is not generally adopted in the planning field because of limited data availability and the limitation of planning practitioners' knowledge of programming and mathematical modeling. However, with this location-allocation modeling approach, the widely applied space standards, which specify the area requirement and are extensively used as indices for measuring and comparing greenness across cities, can now be of practical help in identifying spatial locations of green spaces, as well as of other public facilities. Specifically, the modeling results can further be incorporated as an input in a multidisciplinary comprehensive city green space system plan, along with studies of green space functionalities. In such a way, location-allocation models can contribute to overall green space planning, not only help planning standards being met spatially, but also distributing green spaces reasonably to meet the majority's needs.

2.2 Public Facility Related Location-Allocation Models

2.2.1 Minisum Location-Allocation Models

Location-allocation models have been under development for almost more than a century since Weber's problem in 1909 where a single facility is to be placed to minimize the weighted sum of distances (Weber, 1909). Curry and Skeith (Curry & Skeith, 1969) formulated a location allocation problem to locate multiple(k) facilities in m candidate locations ($k \leq m$) and assign n demands so that the objective cost function is minimized. Cooper (1963), Goodchild (1978), Hodgson (1978), Juel (1981) and Tapiero (1971) were also among those who investigated the location-allocation problem in early decades.

Location-allocation models are a type of model in which the location problem (where to locate a certain number of facilities) and the allocation problem (the process of determining who at demand points is served by which facility) are treated simultaneously. In the most general form, location-allocation models are utilized to find locations for *k* facilities from *m* candidate sites as well as achieve an allocation of each demand point (DP), or fraction of a demand point, to some facility so as to optimize an objective function (Scott, 1970). In other words, it can be interpreted as procedure to locate a number of facilities and allocate the demand to be served by these facilities, so that the entire service system is efficient (Church & Murray, 2008).

A fundamental location-allocation problem can be formed in a discrete problem domain where facilities are to be located within a subset of predefined candidate sites (Church & Murray, 2008):

Mathematical notation for parameters:

$i \in (1,2,\ldots,n)$: index of demand areas

$j \in (1,2,\ldots,m)$: index of candidate facility sites

d_{ij}: the distance between demand areas i to candidate facility site *j*

a_i: demand in demand area *i*

p: number of facilities to be located

Y_j: 1 if facility at site *j* is located; 0 otherwise

X_{ij}: 1 if demand i is served by facility *j*; 0 otherwise.

Objective:

$$Minimize \ \sum_{i=1}^{n}\sum_{j=1}^{m} a_i d_{ij} X_{ij}$$

Subject to:

$$\sum_{j=1}^{m} X_{ij} = 1 \qquad \text{for } i = 1, 2, \ldots, n$$

$$X_{ij} \leq Y_j \qquad \text{for } i = 1, 2, \ldots, n \text{ and } j = 1, 2, \ldots, m$$

$$\sum_{j=1}^{m} Y_j = p$$

$$Y_j = \{0, 1\} \qquad \text{for } j = 1, 2, \ldots, m$$

$$X_{ij} = \{0, 1\} \qquad \text{for } i = 1, 2, \ldots, n \text{ and } j = 1, 2, \ldots, m$$

In this basic location-allocation problem, the objective is to minimize the total demand weighted distance. Constraints include: 1) each demand area *i* should be served by one facility; 2) corresponding demand at demand area *i* has to be allocated to the facility candidate site *j* that is chosen as a facility location; 3) *p* facilities are to be allocated; 4) binary requirements of either site *j* is chosen as a facility or not, and either *i* is served by facility *j* or not. This particular model is widely known as the p-median problem, and was first studied in 1960s by Hakimi (1964, 1965), Revelle and Swain (1970).

This p-median model does not address the issues of capacity and the cost of building a facility. It assumes that each facility can have enough capacity to handle all the demand that is assigned to it; it also assumes that the costs to build each facility are the same – so the total cost for p facilities is a fixed number, no matter where these facilities are located. However, these assumptions are not always true in real location problems. It is possible that a facility has limited capacity that may not be able to meet all the demand that is assigned. It is also possible that the construction costs of building a facility at various candidate sites are significantly different. To address these issues, a different location-allocation model is developed (Church & Murray, 2008):

Additional mathematical notation:

c_{ij}: cost of shipping one unit of demand between *i* and facility *j*

f_j: fixed cost to build a facility at site *j*

b_j: capacity of facility *j*

Z_{ij}: the amount of demand at *i* served by facility *j*

Model objective:

$$Minimize \ \sum_{i=1}^{n}\sum_{j=1}^{m} c_{ij}Z_{ij} + \sum_{j=1}^{m} f_jY_j$$

Subject to:

$\sum_{j=1}^{m} Z_{ij} = a_i$ for $i = 1, 2, \ldots, n$

$\sum_{i=1}^{n} Z_{ij} \leq b_jY_j$ for $i = 1, 2, \ldots, n$ and $j = 1, 2, \ldots, m$

$Y_j = \{0, 1\}$ for $j = 1, 2, \ldots, m$

$Z_{ij} \geq 0$ for $i = 1, 2, \ldots, n$ and $j = 1, 2, \ldots, m$

This fixed-charge capacitated location-allocation model (Church & Murray, 2008) minimizes the total cost, including both shipping and fixed costs of facility construction. Constraints have been set to ensure 1) all the demands are satisfied; 2) total demand served by facility *j* does not exceed its capacity; 3) basic variable restrictions that site *j* is either chosen as a facility or not, and allocated demand should not be a negative number.

Basic location-allocation models can be enriched in various ways by incorporating additional constraints or variables in certain given contexts, and it is always possible to change the specification of a problem to accommodate the particular case (Scott, 1970). Besides above capacity and the fixed cost extension from the basic location-allocation model, there are several other extensions that have been studied to accommodate a variety of complications in real world problems. For example, models with specified upper-bounds on inflows and corresponding outflows of each facility (Scott, 1970), models dealing with multiple commodities in each facility, and models with given pre-existence of some facilities (R. Chen & Handler, 1993; Reuven Chen, 1988; Drezner, 1995). These extensions have been widely used for not only public sectors, but also private sectors since their major objective is to minimize costs and maximize the system efficiency. For example, commercial and industry site selections, such as locations of factories in a fixed-resources – factories – fixed-customers system, or warehouses delivering multiple products.

2.2.2 Covering Problems

For public sector services, such as fire stations, police stations, ambulances, there are other spatial standards that have to be met while locating the facilities. A typical example of these spatial standards is maximal response time for a call on emergency services such as a fire or crime. These spatial standards indicate the notion of range – a facility provides its service within a distance-based range beyond which it is too far to serve or less desirable to serve demand (Church & Murray, 2008). In these situations, demands located outside of the range will be considered as uncovered. To solve these spatial standards based problems, two location models have been developed: the location set-covering problem and the maximal covering location problem.

The location set-covering problem, can be generally stated as: locate a minimum number of facilities so that all demand areas are covered within a maximal distance or travel time standard. For example, a possible problem is to locate fire stations in a city so that all the neighborhoods can be reached by firemen from a fire station within 5 minutes after an emergency call. The key point for this problem is that complete coverage is required. The location set-covering problem was first formulated by Toregas et al. (1971). Early researchers on algorithms and methods of the set covering problem also include Minieka (1970), Garfinkel et al. (1977), Moore and Revelle (1982), Beasley (1990), Lorena and Lopes (1994), Al-Sultan et al. (1996), and Caprara et al. (2000) (reviewed by Hale and Moberg (2003)).

Using the notation from the last section, the basic mathematical formulation for the location set-covering problem is (taken from Church and Murray (2008), notation revised to be consistent with previous formulation):

Objective:

$$Minimize \sum_{j=1}^{m} Y_j$$

Subject to:

$$\sum_{j=1}^{m} X_{ij} Y_j \geq 1 \qquad \text{for } i = 1, 2, \ldots, n$$

$$Y_j = \{0, 1\} \qquad \text{for } j = 1, 2, \ldots, m$$

The objective is to minimize the number of located facilities. The first set of constraints specifies that each demand area *i* must be covered by at least one facility. The second set of constraints regulates the binary restrictions on the decision variables Y_j, 1 for where a facility is located, 0 for the candidate sites that are not in the solution.

One the other hand, the maximal covering location problem deals with the problem of locating a pre-specified number of facilities so that demand coverage within a maximal service distance (or time) from the facilities is maximized. An example can be, given a limited budget, a city government wants to locate 20 fire stations such that the neighborhoods that are within 5-minute distance from a fire station are as many as possible. The maximal covering location problem was first formulated by Church and Revelle (1974). A few earlier studies further refined the maximal covering location problem for certain possible situations, for example, models with a secondary objective. These studies include, but are not limited to, Benedict (1983), Hogan and Revelle (1986), and Daskin (1983).

For the maximal coverage problem, an additional decision variable notation is included:

X_i: 1 if demand area *i* is served/covered by at least one facility; 0 otherwise

With this variable and employing notation from the previous sections, the basic maximal covering location problem can be formulated as follows (taken from Church and Murray (2008), notation revised to be consistent with previous formulation):

Objective:

$$Maximize \sum_{i=1}^{n} a_i X_i$$

Subject to:

$\sum_{j=1}^{m} X_{ij} Y_i \geq X_i$ for *i = 1, 2, …, n*

$\sum_{j=1}^{m} Y_j = p$

$Y_j = \{0, 1\}$ for *j = 1, 2, …, m*

$X_i = \{0, 1\}$ for *i = 1, 2, …, n*

The objective of the above maximal covering location problem is to maximize the total demand that is covered. Constraints are defined as: 1) whether demand area *i* is covered is based on the location decisions – if it is covered ($X_i = 1$), then it is at least covered by one facility ($\sum_{j=1}^{m} X_{ij} Y_i \geq 1$); if $\sum_{j=1}^{m} X_{ij} Y_i = 0$, then the demand area i is not covered by any located facility, then the decision variable X_i is constrained to be zero; 2) p facilities are to be located; 3) integer restrictions on the decision variables.

Similar to p-median model, these basic models may not be able to deal with complex real world problems, but they can be enriched by including additional constraints or variables, such as capacity constraints, or partial allocation variable, to accommodate the specific case.

2.2.3 Applications of Location-Allocation Models

Location-allocation models are used in a wide variety of applications to locate public services (resources) to serve the public. These services include, but are not limited to, fire stations, libraries, post offices, hospitals, schools, recycle facilities.

Location-allocation models have come to play an important role in health care facility location analysis, including evaluating the efficiency of existing facility locations and locating new health facilities (Abernathy & Hershey, 1972; Buzai G, 2013; Mohan J, 1983; Møller-Jensen, 2001; Musdal et al., 2014; Oppong, 1997; Rahman & Smith, 2000; Ross, ROSENBERG, & PROSS, 1994; Shariff, Moin, & Omar, 2012; Syam & Cote, 2010; Tim Ensor, 2012; Watts, Shiner, & Musdal, 2013).

Tewari and Jena (1987), Norrel (1990),Møller-Jensen (1998), and Ndiaye (2012), use location-allocation models to improve physical accessibility to schools. The models have also been brought to other regular public service location studies such as banking (Min & Melachrinoudis, 2001), traffic and transportation facilities (Garcia-Palomares, Gutierrez, & Latorre, 2012; Ohsawa, 1989), refueling stations (MirHassani & Ebrazi, 2013).

Researchers employed location-allocation models in emergency service locations, such as fire stations (Daniel Serra, 2005), ambulances (Branas, MacKenzie, & ReVelle, 2000), emergency services for disasters such as flood (Mirzapour, 2013), and forest fires (M. J Hodgson & Newstead, 1978; M. John, Newstead, Robert G Hodgson, 1983). General rescue centers (D., Zhang, Guo-xiang Wang, 2006) have also been studied with location-allocation models.

Location-allocation models were utilized for locating recycling and waste facilities, Valeo et al. (1998) applied the models to locate depots for material recycling programs in a town in Canada, Louwers and Peters (1999) used the models for facilities of reusing carpet materials, and Eiselt and Marianov (2014) analyzed the location of landfills for solid waste.

There are some other interesting applications of location-allocation models to real world problems that had rarely been considered to use modeling approach. For example, Church and Bell (1988) analyzed the ancient Egyptian settlement pattern using location-allocation models. Gerrard et al.(1997) adapt the location-allocation model to optimize conservation sites for maximum biodiversity protection within a limited budget for land acquisition.

All these model applications, with many others, have illustrated the potential benefits of applying location-allocation models in public facility location planning and decision making, and the models can provide planners and decision makers with quantitative support for choosing the proper locations for public services.

2.2.4 Location-Allocation Models' Application in Green Space Planning

Despite the large number of studies on facility location, there are not many studies that have applied location-allocation models to urban park or open space planning. Yeh and Chow (1996) are among the first who introduced location-allocation model into open space planning. With their case study of Hong Kong, the authors integrated GIS and a location-allocation model to identify optimal sites for open space and evaluate existing open space. Using block level demand data, they calculated the number of open spaces needed for each region with the standards of 9 ha for 100,000 people and 6 ha for the average size of open space. They used a continuous space p-median model to identify the optimal locations of open spaces, and then drew buffers at a radius of 0.4km around these sites to specify areas that are considered to be acceptable solution spaces for locations.

Similarly, Neema and Ohgai (2010; 2013) proposed a multi-objective model in a continuous surface for the best location of urban parks. However, within the context of a continuous space domain, the optimal locations may not be a practical solution since they may contain unsuitable areas. While it seems a discrete problem domain could handle the problem better, large effort has to be made for selection of candidate sites before running the model. Sefair et. Al (2012) constructed a multi-objective model for new neighborhood park selections. The criteria included coverage, sidewalk and road accessibility, connectivity with other facilities, the externalities of nearby facilities and cost. An ε-constraints approach is used to solve the problem with "a lexicographic order of evaluation criteria and maximum deterioration of the objectives with higher priority". Parameters included 417 meters as the maximum walking distance, and $2.24m^2$ as of park per inhabitant. Similar models have been constructed by Yuan (2011) with objectives of minimizing various kind of weighted distance such as air quality weighted, heat island weighted distance. Then the weighted sum of each objective was used to composite the multi-objective function.

In these multi-objective studies, various factor-weighted distances were involved as single objectives and they were summed to form the multi-objective model. These objectives include but are not limited to population, noise, land use, air quality. These models are more about multi-objective problem formulation; public access and unique characteristics of green spaces are not their main focus.

Learning from these modeling studies, rather than working on continuous space problem, this study adopted the discrete version of the location-allocation problem, which fits green space locations better than the continuous space problem. This is because green spaces cannot be anywhere; there are a lot of structures (physical constraints) in city environment that prevent green spaces from being located anywhere freely. Predefining some potential green space locations for the model is more realistic and practical.

CHAPTER 3
METHODOLOGY

This study employs location-allocation models and GIS spatial analysis, in conjunction with the widely used space planning standards approach, to identify locations of city green spaces that will satisfy public access needs.

First, GIS was used to analyze the existing green space distribution in the study area, the analysis results were compared with the planning standards to evaluate how well the study area meets these standards in terms of its green space amount and distribution.

Then a set of location-allocation models for green space locations was formed and solved. With the input variables prepared in ArcGIS (ESRI, Inc. of Redlands, California), the location-allocation models were solved in the Gurobi optimizer (Gurobi Optimization, Inc. of Houston, TX), which is a professional optimization solver for mathematical programming. Gurobi supports a variety of programming and modeling languages such as C++, Java, .NET, python, MATLAB, R. etc. The models in this study were built in Python. ArcGIS offers six location-allocation models in its Network Analyst tools for convenient use with user-friendly interfaces for non-programming users. However, these built-in models are for general location-allocation problems and users do not have much flexibility in setting specific objectives or constraints for complex models. For instance, demand points and facilities must be point features. By contrast, lines or polygons are not supported in the model. The demand points in the solution are considered either covered or not covered, but not partially covered. Demands at one point cannot be split into multiple facilities for allocation, and the built-in models force the demand points to the nearest facility. These settings may not be appropriate in some real projects, and using these built-in models improperly for these projects would lead to non-optimal facility location solutions. In this study, for example, there may be more than one green space near a residential site. So while people at the residential site are free to visit any of these nearby green spaces, it does not make sense to force people to visit the nearest one only. Besides, not everyone at the residential site would visit the same green space. According to their own choice, some of them may visit green space *A*, some may go to green space *B*, and the rest may prefer green space *C*. These problems cannot be solved in built-in location-allocation models in ArcGIS. So Gurobi, as a professional modeling package with more flexibility of building complex models, is used instead.

After the location-allocation models with existing population distribution and candidate green spaces are solved using various parameter inputs, the model results were brought back to ArcGIS to generate different scenarios and compared. With the model results, this study compares the green space solutions from the models with different inputs, to see which green spaces are robustly in high demand, which are not.

Furthermore, this study classifies green space locations into different categories according to their current status, their contribution to serve demand and their robustness in solution. In such a way, recommendation for existing green space conservation and new green space locations can be made, both for short-term and long-term planning.

Figure 3-1 shows how the sections in this chapter are organized. The models were formulated in Section 3.1, then three model components, supply, demand and distances were discussed in detail with various issues on related data preparation.

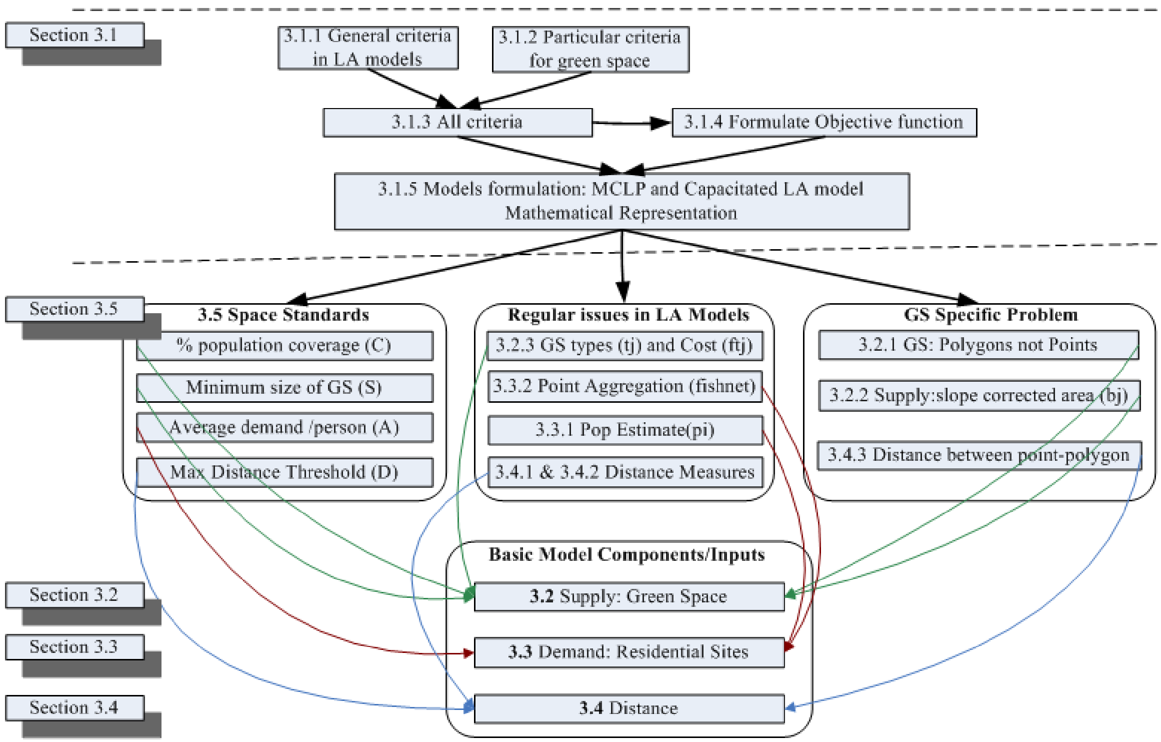


Figure 3-1 Methodology diagram

3.1 Model Formulation

3.1.1 Typical Criteria in Public Service Location Models

For public services, decision makers and planners are responsible for locating facilities to provide the best services possible to the public within budget restrictions. In other words, people attempt to locate facilities to be as accessible as possible while controlling the service construction costs. As measures of "accessible", one or more of the following criteria have to be specified in location-allocation models (Rushton, 1979), and the choice of the criteria will vary according to the preferences of the decision makers and the real application contexts:

- Minimum average distance or aggregated total distance for all people

- Minimax distance: minimize the farthest distance between people and their closest facility
- Equal assignment: the number of people in each facility service area is approximately equal
- Threshold constraint: the number of people in each facility service area is always greater than a specified number
- Capacity constraint: the number of people in each facility service area is never greater than a specified number

Besides these criteria, as in many similar studies in the literature, some other typical objectives in location-allocation models include:

- Minimum overall cost: to control the cost of the entire service system, such as facility construction cost and shipping or travel cost between facilities and people
- Maximum coverage
- Minimum number of facilities

3.1.2 Particular Issues that need to be Addressed for Green Space Location Models

For this particular problem of locating green space for pedestrian access, the location-allocation models have to be adjusted from a prototypical model to meet the following expectations:

(1) The models should be designed to meet the specific characteristics of the green space.

<u>Area and capacity</u>

In a traditional location-allocation model, facilities provide certain products or services and serve as “supply” in the system. In this study, green space, as a public service, provides space for public usage. So the amount of space, or the area of the green spaces, now becomes their "supply". The size of green spaces varies, but is obviously not infinite, which can be observed clearly from a map, and usually surrounded by construction. So the size of green spaces, or the supply in the model, is limited. This leads to capacity constraints.

Further, given that the area and spatial shape of green spaces matters in this study, green spaces should be viewed as polygons rather than points – which is a common fact of any regular location-allocation models for facilities such as fire stations or hospitals.

(2) The models have to adapt to the characteristics of pedestrians.

<u>Demand</u>

For this study, demand refers to people's need of green spaces. An over-crowded green space would reduce recreation experience quality and benefits to the visitors. So the model has to ensure people can share a certain amount of green spaces. The amount of shared green space becomes the "demand" at the demand points.

<u>Distance threshold</u>

Further, this study focuses on pedestrians' access to green spaces. Access to green spaces in the environment is associated with mental health and a lower level of physiological stress. Living in areas with better access to green spaces is associated with lower stress (Roe et al., 2013). It assumed that people visit green spaces within certain distances; if a green space is too far away from a demand point, the "visit frequency" from the demand point to this green space reduces considerably. So determining how far people would walk to a green space for frequent visits has to be included in the model. A typical approach is to set the maximum distance that people would travel as a threshold. People would only visit green spaces within this distance, or, green space can only serve people within this distance as its service area. Otherwise, it is assumed that it is too far for people outside of this service area to visit.

Allocation is needed

This leads to another issue regarding a demand point: there might be more than one green space within this distance threshold. So people from this demand point can visit any of these green spaces. In such a case, the demands from a demand point should not be forced to be assigned to its nearest green space – any green space within the distance threshold is possible to serve the demand point.

Partial allocation

From another point of view, people are independent individuals who can make their own decision on which green space to visit and when. So people at a demand point may visit different green spaces as long as these green spaces are close enough. Consequently, partial allocation is possible, which means demands at a demand point may be partially served by different green spaces in the model solutions.

One point has to be made here: that the concept of allocation in this model is not as mandatory as in regular location-allocation model solutions. In a typical location-allocation model, allocation is the process of determining who is served by which facility (R. L. Church & Murray, 2008). For example, in a factory location model solution, if certain demand at a demand point is allocated to a factory, the factory has to produce that amount of products and deliver them to the demand point. The allocation values are certain numbers that have to be applied if the model solutions are implemented. However, in this study, the allocation values assigned in the model solutions are not essential in themselves, since it is not necessary or realistic to force people to follow the model solution and visit the specific green space that is assigned to them in the model. It is not difficult to understand it because people can make their own choice in real life. People can adjust their visit activity according to green space occupancy condition. For instance, in the model 500 people's demand has been allocated to a green space given the capacity limitation. While the model results are implemented, it is possible that one day there are 800 people who come to this green space since modelers cannot control these people's activities, then the capacity is exceeded and the "allocation" does not exactly follow the model solutions. But this would be adjusted automatically through visitors' activities: when the green space gets too crowded, some visitors will leave right away for other green spaces that are not so crowed or change their destination for their next visit. So the entire system is adjusted automatically until everyone can have a certain comfortable place in green space. In short, the allocation variable here is used only to ensure that the demands are met and capacity of green spaces is not exceeded, and the allocation results are not key in the solution analysis.

(3) The models can incorporate typical planning standards.

These planning standards may include green space coverage requirement, average green space per person, or maximum catchment distance criteria.

3.1.3 The Overall Factors to be Considered in the Models

Given the typical criteria for regular public service location-allocation models and the specialty of the particular contexts of allocating green space for public access discussed above, in this study, the following factors may be worthy of consideration in the location-allocation model formulation:

- Number of facilities: in this study, it refers to the amount of green spaces rather than the number of green spaces. It is area that matters for green space service rather than number of green spaces, since area of green spaces varies dramatically. City policy makers may want the efficient use of green spaces, so that when the city has a limited amount of green space, it can still serve as many people as possible.

- Cost: there is no shipping cost in this study. Cost in green space planning mainly refers to green space construction. The cost would be much less for existing green spaces than new ones.
- Capacity: area of a green space is limited, so the amount of people that can be served is limited.
- Average distance: average distance that people have to travel to a green space.
- Minimax distance: here can be understood as the farthest distance that people would walk to a green space, which is called distance threshold in this study. Green spaces further than this threshold from a demand point would be treated as unreachable, demand points further than this threshold from a green space would be treated as not being able to be served by the green space. This distance threshold, or maximum catchment distance, is an index in planning standards system.
- Coverage: the amount of demand that facilities can serve. Here, green space coverage. In planning standards system, green space coverage refers to the area proportion of green space over the total city area. Given some green spaces or part of green spaces are too far from public access, the green space coverage has been derived to another standard in planning, the percent coverage within public green spaces service radius, that is, the proportion of land within a distance threshold over total land area. This coverage concept is widely used in GIS with buffer tool, which draws buffers for a certain distance around facilities.

However, in this study, this coverage concept is further adjusted. Population distributes unevenly over space, some land that is within green space buffer zones may be vacant; a large population may be in a small area that is not in green space buffer zones, for example, 30% of people are in the 10% of land that is not with green space service radius, hence, the land coverage is 90% but population coverage of only 70%. And the percent coverage of population within the green space distance threshold, which may not be exactly same as the percent coverage of residential sites with green space service, would be more meaningful for any policy-making. In such a case, the demands at demand points, or residential sites, vary according to the population distribution at these residential sites. So the population distribution is involved in this study.

- Population at demand points. As explained.
- Average amount of green space per person. In combination with population information, the demand at demand points can be estimated. It is also an index in planning standards system.

3.1.4 Objective Formulation

To formulate the models, the above factors were then investigated for use as possible objectives and constraints.

There are four potential objectives that may be involved in the models:

- Minimum cost
- Minimum amount of green spaces
- Maximum coverage
- Minimum average distance

When more than one of the above objectives are included in a model, the model is called a multi-objective model. There are various methods for multi-objective problems to model a decision-maker’s preferences, even in the face of multiple objectives. Generally, decision-makers can either indicate the relative importance of the objective functions before running the algorithm, or can select a single solution that is the most appealing from a set of solutions with a consistent variation in parameter inputs. There are some well-known methods to set the relative importance of the multiple goals. Weighted sum method is among the most popular ones. It combines multiple objective functions to form a single function via a weighted sum of these objective functions. The pre-defined weights of various objective functions indicate the decision-makers' preference on the objectives. The second method is called the constraint method, which keep one objective as the objective function, and then sets the rest of the objectives as constraints in the model. Goal programming is a third typical method, which seeks to minimize the total deviation of each objective from its corresponding goal (Hillier & Lieberman, 1967; Marler & Arora, 2004).

The above objectives for green space location-allocation models are examined below in order to choose a proper method to formulate the models.

<u>Cost and amount of green spaces</u> are closely related. Existing parks cost nothing; constructing new green space can be expensive. The objective of green space service efficiency which seeks to minimize the amount of green spaces is embedded in the minimum cost objective. When minimizing cost to meet green space demand, the existing green spaces are expected to be used to the utmost, after that additional new green spaces will be added in the green space system to fill the demand gap.

<u>The potential coverage</u> objective. A maximal covering location model can be structured, so that with the pre-defined amount of green spaces, how much green space coverage can be achieved. In a traditional maximal covering location model, the number of facilities is predefined. But in this study, it is not appropriate to predefine the total area or the number of green spaces. Instead, the maximal coverage by certain types of green spaces can be modeled, for example, how much coverage is provided

by current green spaces. It is unsure that complete coverage solution can be found with given demand requirements. However, since coverage is a popular planning standard that requires coverage be no less than a certain percentage, this standard criterion can be used as a coverage constraint in the model.

The average distance. Since people are assumed to be able to visit green space within a certain distance, the average distance has been partially handled by this distance threshold. As long as it is within the distance threshold, the minimization of average distance is less important than other objectives. For example, a small improvement of average distance from 200 meters to 190 meters might not make too much difference since people probably will not mind or even realize they have to walk 10 more meters to visit a green space. So this objective is less important and was eliminated from the model.

Therefore, this study attempts to find out solutions to meet certain planning standards with less expenditure. Theoretically, the fewer new green spaces with less cost that provides enough coverage and meets typical green space planning standards, the better the model is. The major problem is defined as: to find the locations of green spaces which minimize expenditure on green space construction, or in other words, to construct the minimum amount of new green spaces and make best use of existing green spaces, such that the proportion of the population that can each share a certain amount of green space within standard catchment distance can meet green space service percent coverage standard.

3.1.5 Mathematical Representation of the Models

Notation:

$i \in I$: index of demand points (residential sites); I: the set of demand points

$j \in J$: index of candidate green space sites; J: the set of green space sites

p_i: population at demand point *i*

b_j: capacity of green space site *j* (maximum area supply of *j*)

t_j: type of candidate green space site *j*.

f_{t_j}: fixed unit cost (￥/m^2) for green space of type t

A: average green space per person

D: distance threshold

d_{ij}: the distance between demand point *i* to candidate green space site *j*

$M_j = \{i \in I | d_{ij} \leq D\}$: the set of demand point within *D* distance to *j*

$N_i = \{j \in J | d_{ij} \leq D\}$: the set of green spaces candidates within D distance to *i*

C: percent coverage criterion

S: Minimum size of a green space

Decision variables:

X_{ij}: the amount of demand at demand *i* being allocated to green space *j* (allocation variable)

Y_j: 1 if green space at site *j* is located; 0 otherwise

With this notation, we can define the notation of demand at demand point i as:

$$Ap_i$$

(1) Maximal covering location model

First, a maximal covering location model was constructed to examine the coverage with certain types of green spaces (current green spaces, or all green space candidates), with given parameters. With the allocation variable involved, the model derives from classical maximal covering location model which ignores the capacity constraints.

The maximal covering location model is structured as follows:

$$Maximize \ \frac{\sum_{i \in I} \sum_{j \in N_i} X_{ij}}{\sum_{i \in I} Ap_i} \tag{1}$$

Subject to:

$$\sum_{i \in I} X_{ij} \leq b_j * Y_j \qquad \text{for all } j \in J \tag{2}$$

$$\sum_{j \in N_i} X_{ij} \leq Ap_i \qquad \text{for all } i \in I \tag{3}$$

$$\sum_{i \in I} X_{ij} \geq S \qquad \text{for all } j \in J \tag{4}$$

$$Y_j = \begin{cases} 1, & \text{if } t_j \in \text{current green spaces} \\ 0, & \text{otherwise} \end{cases} \qquad \text{for all } j \in J \tag{5}$$

$$X_{ij} \geq 0 \qquad \text{for all } i \in I \text{ and } j \in N_i \tag{6}$$

The objective function (1) is to maximize the percentage of demand that can be met by certain green space types such as existing green spaces, which is equivalent to the percentage of the population that can be served by these green spaces. The numerator is the total allocated demand. Constraints (2) are green space capacity constraints which specify that the demands that allocated to green space *j* should not exceed its capacity. Constraints (3) are demand constraints, stipulating that at demand point *i*, the demand that is allocated to certain green spaces within distance *D* should not exceed its total demand. They indicate the possibility that the demand at a demand point may be partially met in the model solution, that is, some people can reach a nearby green space within a given distance threshold and enjoy a certain amount of green space but other people from the same demand point are not allocated at all, since the nearby green spaces are already too occupied. Constraints (4) restrict the minimum size of green spaces, which is required in green space planning to ensure necessary variety of recreation functions. Constraints (5) bound the supply point to be current green spaces only, and all the current green spaces will be involved in maximum coverage calculation. Potential green spaces are excluded from the model. Given this setting, Y_j is a predefined parameter input in the model rather than a decision variable. Finally, constraints (6) impose non-negative restrictions on the decision variable X for the demand point and green space pairs within distance threshold D.

If the maximal coverage for existing green spaces in solution is <u>equal to or higher</u> than the coverage objective stated in the related planning standard, it indicates that existing green spaces are sufficient to meet or may be even more than the public need. Therefore, there is no urgent need to build new green spaces for the study area. Further investigation can be explored if the maximal coverage in solution is higher than the coverage standard: how many existing green spaces and their locations are sufficient enough to meet the coverage standard? So another location-allocation model can be developed for existing green spaces, to minimize the amount of green spaces with capacity and demand coverage standard constraints.

Otherwise, if the solution in the maximal covering location model for current green spaces is <u>less</u> than the expected coverage standards, new green spaces have to be built in the study area to fill the demand gap. Then, a minisum capacitated location-allocation model has to be structured to involve all candidate green spaces. Since new green spaces are introduced to the model, their construction cost becomes a big concern.

(2) Capacitated location-allocation model

The cost of green space is related to its unit cost and supply that it has to offer. However, this supply does not mean green space capacity, or in other words, the maximum amount of supply that a green space can provide. For example, the capacity of potential green space sites is the maximum area of available land, however, if the site is selected to establish a park, the cost is related to the size of the park which can meet the allocated demand, this size may be much smaller than the land area of the entire candidate site. So the cost of green space j is not $(f_{t_j} * b_j * Y_j)$, instead,

$$\text{The cost of green space site j } = f_{t_j} \sum_{i \in M_j} X_{ij}$$

Summing this value across all candidate green space sites, this is the total cost:

$$\sum_{j \in J} \left(f_{t_j} \sum_{i \in M_j} X_{ij} \right)$$

So, the minisum capacitated location-allocation model can be structured as follows:

$$Minimize \sum_{j \in J} \left(f_{t_j} \sum_{i \in M_j} X_{ij} \right) \tag{7}$$

Subject to:

$\sum_{i \in I} X_{ij} \leq b_j * Y_j$	for all $j \in J$	(8)
$\sum_{j \in N_i} X_{ij} \leq Ap_i$	for all $i \in I$	(9)
$\sum_{i \in I} \sum_{j \in N_i} X_{ij} \geq C \sum_{i \in I} Ap_i$	for all $i \in I$ and $j \in N_i$	(10)
$\sum_{i \in I} X_{ij} \geq S$	for all $j \in J$	(11)
$X_{ij} \geq 0$	for all $i \in I$ and corresponding $j \in N_i$	(12)
$Y_j = \{0, 1\}$	for all $j \in J$	(13)

The objective function (7) is to minimize the total cost of green space construction. The $i \in M_j$ bounds to consider only green space and demand point pairs that are within the maximum service distance threshold. As explained before, this objective indicates the embedded goal of efficient usage of green space: meet demand requirements with minimum amount of green space, and use existing green spaces as much as possible since they cost least, then establish necessary new ones for demand gap.

Constraints (8) are green space capacity constraints which specify that the demands that allocated to green space j should not exceed its capacity.

Constraints (9) are demand constraints, stipulating that the demands that are allocated to certain green spaces at demand point *i* should not exceed its total demand. They indicate the possibility that the demand at a demand point may be partially met in the model solution, that is, some people can reach a nearby green space within the distance threshold and enjoy a certain amount of green spaces but other people from the same demand point are not allocated, since the nearby green spaces are too occupied. Constraints (10) are demand coverage constraints, stipulating that the total demand that can be served by green spaces should be no less than the percent coverage standard. Constraints (11) restrict the minimum size of green spaces, which is required in green space planning to ensure necessary variety of recreation functions. Finally, constraints (12) and (13) impose non-negative and binary restrictions on the decision variables X and Y, respectively.

In this study, there are three main components in the models, residential sites as demand points, green spaces with corresponding supply, and distance between demand points and green spaces which build the link network between demand and supply. The following sections will explore characteristics and challenges of these components, with their associated model inputs and data preparation. Then space standards related parameters are discussed.

3.2 Supply Sites: Green Spaces

3.2.1 Supply Polygons Rather Than Supply Points

A challenge in this study is that green spaces, as the supply facilities in the model, are area and spatial shape sensitive and cannot be treated as supply points as in traditional location models. Different from typical location problems with supply facilities such as hospitals, fire stations or factories which are treated as supply points, green spaces should not be viewed as supply points in the circumstances of modeling pedestrian accessibility. This is because the dimensions of many green spaces are usually as large as or even much larger than a couple of hundred meters – a walkable distance. If these large green spaces are treated as points and their centroids were chosen to represent the locations of these green spaces, the estimation error of the distances from demand points to a green space can be severely exaggerated. Taking Central Park in New York City for example (Figure 3-2), assume there is a demand point at the south edge of the park, on 59th Street and 7th Avenue. People at this demand point only need to cross the street to enter the park. However, if the centroid of the park is used to represent the location of the park, the measured distance from the same demand point to the park now is over 2100 meters (1.33 miles), which may be too far for most pedestrians' frequent visits. Apparently, this overestimation is too large to be ignored and will underestimate the visit frequency of people living nearby – because the park is considered "too far" to walk. And no one would trust any model results with such distance measurement error.

Figure 3-2 Overestimation from south edge to the Central Park

The same problem exists throughout the study area. The size of green spaces ranges from a few hundred square meters to over 30 square kilometers (12 square miles). Given a few hundred meters' scale of walking distance that this study mainly focuses on, to achieve convincible model results, centroids or any other points inside the green spaces should not be used to represent the entire green space(s).

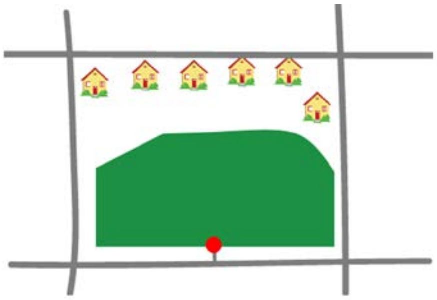
Then how to measure the walking distance to the green space? The points at green space boundaries where people can reach and then enter the green spaces are more appropriate than the inside ones.

For green spaces that have limited entrances (Figure 3-4(a)), these entrances can be used as representative points of the green spaces for the purpose of travel distance calculations. If a green space has *n* entrances, distances from a certain demand point (residence) to each of the green space's entrance points are calculated and compared. The shortest one will be selected to be the distance from the demand point to the green space, assuming pedestrians will travel to the nearest entrance point.

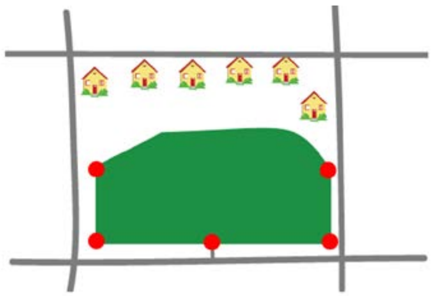
Figure 3-3 An open green space facing both a street and a neighborhood in the study area

For open green spaces, the situation is more complicated because people may enter the green space anywhere along the boundaries (Figure 3-3). However, it is impossible to include innumerous points on the boundaries for later distance calculations. To choose proper points to stand for a green space for later distance calculation is a big concern.

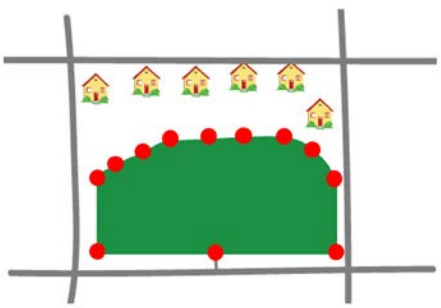
For the frontages of open green spaces facing streets (Figure 3-4(b)), we can expect people would reach the green space at those points where they can cross the street. If the street network is dense and blocks are small, these points are always at the street intersections; if the blocks' frontages are long, there may be pedestrian crosswalks, flyovers, or tunnels between intersections. So with such information, the entrance points on green space boundaries can be defined. If there is no such information available, equally spaced points with reasonable distance along green space boundaries can be viewed as possible locations of pedestrian crosses. In the study case, besides boundary vertices at street intersections, points of every 100 meter distance at open green space frontages can be chosen as possible green space entrances for distance calculation.



(a) A green space with only one entrance, the entrance was used as a representative point for travel distance calculation.



(b) An open green space. The frontages facing streets: points on the boundary where people can cross street were selected as representative points for distance calculation.



(c) An open green space. For the boundary directly facing residence, denser points along the boundary were identified for distance calculation.

Figure 3-4 Illustrations of representative point selection for different green space situation

For the boundaries not facing streets (Figure 3-4(c)), the selection of possible access points of the open green spaces can be more flexible, so denser points along boundaries can be identified, for example, every 10 meters or 20 meters.

In general, for green spaces with limited entrances, the entrances were used for distance calculations; for open green spaces or green spaces without entrance information, green space boundary vertices and points on the boundaries with certain distance were used as approximating green space entrance points for distance estimation.

After these points on the boundary of a green space were located, the distances from a demand point to each of these points were calculated, and the shortest distance was used as the final distance estimation from the demand point to the green space.

3.2.2 Supply Measurement: Feasible Area for Recreation with Slope Correction

Area of the green space was the key measurement of green space supply in the model. However, is it appropriate to use total area of a certain green space as its supply? The answer is no. The study focuses on public access and usage of green space, so this “supply” variable of green spaces should be the areas that can be used and enjoyed by the public, which means, for the modeling purpose the area measured as supply variable should be feasible for public recreation, so that this area measurement can be used as green space capacity constraints.

By examining the topography of the study area (Figure 3-5), we can see some of green space lands are steep and may not be adequate for the public to visit frequently.

These steep areas are usually less feasible for public daily visits. These places

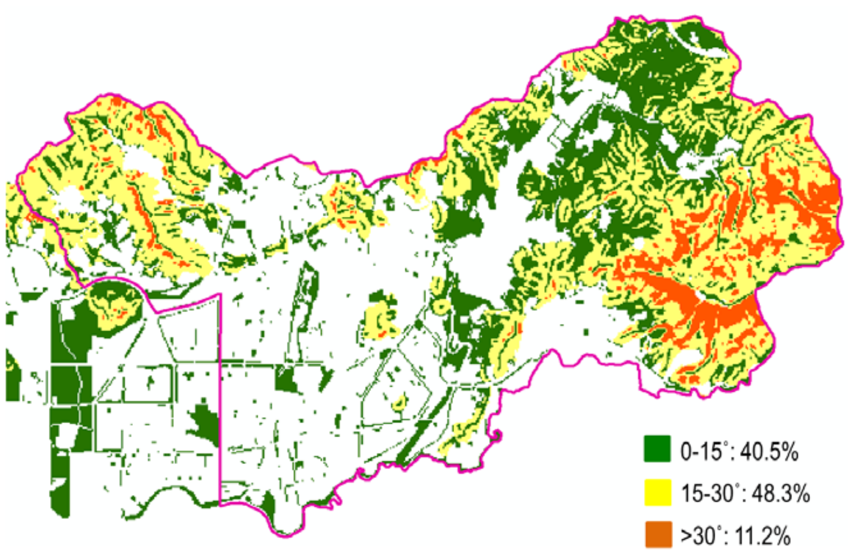


Figure 3-5 Slope varies in the study area

with steep slopes may be good places for weekly or monthly hiking, but are not good for the general public's regular visit. Steep areas usually have fewer infrastructures and it costs much more for new infrastructure construction such as paths and trails in steep areas. This steepness makes these areas harder to access. Besides, in a steep slope area, the places that can be reached and enjoyed by the general public are fewer than those in a flat area. People have to walk along paths and trails, and large areas far from the trails are not safe enough, especially for children and elders.

Compared to climbing up and down a steep hill, after a day or two of hard working and studying, generally people are more willing to visit a flat green space with lawns, small landscapes and better infrastructures for relaxation. In flat areas, people can engage in more activities that cannot be done in steep areas, such as sports and playground exercises, having a picnic, or visiting gardens and landscapes. Besides, when the areas that can be enjoyed and accessed are much larger, people don't have to walk along the trails. They may step on the lawns or under trees without safety concerns.

So, steep and flat areas play different roles in people's recreation. People visit flat green spaces more often, and the feasible places of flat areas for public visit are much more than those of steep areas. Apparently, the capacity of $500m^2$ of a flat green space and the same area on a steep hill is different. The area of a green space needs to be adjusted by its feasible area to visit before being used as a green space supply.

An example is in Hong Kong, the planning department recognizes that the steep parts of a site may not be useful for recreation. So a set of slope correction factors is employed to modify the feasible area to the space standard (Hong Kong Planning Department, 2014):

Table 3-1 Slope correction factors in Hong Kong Planning Standards and Guidelines

Slope Gradient	Flat	Slope < 1:5 (11 degrees)	Slope between 1:5 – 1:3 (11 to 18 degrees)	Slope > 1:3
% to count as standard	100%	60%	30%	0%

In this study, the green space areas are categorized into three groups according to slope gradient: flat areas (0-15 degrees), median slope areas (15-30 degrees), and steep areas (slope greater than 30 degrees). The flat areas with slope less than 15 degrees are completely counted into adjusted areas of the green spaces. Half of the median slope areas with slope from 15 to 30 degrees are also counted. The other half of the median slope area and steep areas of slope greater than 30 degrees are excluded from the adjusted areas of the green spaces as supply in the models.

When a piece of green space is flat, its supply is exactly the same as the total area of this green space. Most small green spaces in the city center are such cases. When the topography of a green space varies, from flat lawns and forests to steep hills, its supply used in the models may be much less than its total area. This is especially significant for rural green spaces in the study area.

3.2.3 Other Issues Related to Green Space

(1) Green space types

There are many types of green spaces: Parks, gardens, green corridors along rivers and canals, natural green spaces, outdoor playgrounds, roadside green spaces, cemeteries, productive plantation areas, green space for environmental protection, and roof gardens. Given that this study focuses on the public access of green space to obtain recreational benefits, the urban green spaces are generalized into the following categories, according to their current status:

Existing green spaces:

1) Existing city parks, district parks and neighborhood parks that are in the park management list by the Urban Management Bureau of the municipality[2]. The government is responsible for regular park maintenance.
2) Neighborhood parks that are not in the city park management list. These parks are maintained by neighborhood property managers.
3) Existing non-park green spaces that are not in the city park management list, such as riverside or street side green spaces. According to the Green Space System Plan of Shenzhen, these green spaces can be served as public parks for public recreation use if they are wider than 8 meters. These green spaces are maintained by the government. They may not have the full recreation functions as parks, and may take a certain amount of government budget for necessary recreation facility construction.

Besides these existing green spaces, there are some non-green places that may be turned into green space. These potential green spaces are also included in the models, to determine the locations of possible future new green spaces if existing green spaces cannot meet the public need.

Several plans have been developed by the Urban Planning and Land Resources Commission of Shenzhen Municipality, Green Space System Planning of Shenzhen (2004-2020) and the contents on green space plan in Shenzhen Master Plan (2010-2020) and Shenzhen District Planning (2005-2020)[3]. The green space lands were extracted from these plans' layouts, after removing the existing green spaces

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[2] Park list for Luohu District, Shenzhen can be found on http://www.szum.gov.cn/html/FWXX/2011728/582011728152045648.htm
Park list for Futian District, Shenzhen can be found on http://www.szum.gov.cn/html/ZWGK/TJSJ/YWTJSJ/2011728/582011728151714239.htm

[3] The plans were issued by Urban Planning and Land Resources Commission of Shenzhen Municipality, The Master Plan was approved by the State Council, other two plans were approved by the municipality government.

mentioned above, the rest was planned green spaces. Among these planned green spaces, there are two types according to their current status:

4) Planned green spaces which are now vacant lands. According to the city's plans, these vacant lands will be converted to green space in the future.
5) Planned green spaces which are now occupied by other land usage. Follow the plans, these occupied lands will be renewed, structures on the lands will be removed, and be replaced by green spaces.

There is a sixth type of potential green spaces.

6) Vacant lands that can be potentially converted to green spaces. Though they are not planned as green space, it is possible and affordable to convert them to green spaces if there is really a need. It is much more economical and implementable to convert vacant land to green spaces than to convert construction land.

All of the above types of green spaces were involved as green space candidates in the location models. In such a way, not only the effectiveness of existing green spaces can be evaluated – how they can be reached by public – but also the locations of potential green spaces that make up the existing green space deficiency can be identified.

(2) Green space related cost

Location models always have to take cost into account, such as the cost of service facilities or cost of transportation. In this study, the main cost is the green space construction cost, including greening/planting, recreational facilities, small landscapes, trails and paths, other necessary infrastructures, and roads for connection to the green space. In this study, the unit cost (CNY per square meter) for each of the six green space categories is generally estimated for modeling purposes by referencing the budget estimations in a few Chinese green space projects. Roughly the unit cost of green space construction is between 150-500 CNY per square meter, although some may cost more[4].

1) There is no cost for the first two categories. These two types of green spaces are existing parks, no matter on the city management list or not, so the construction cost is zero.
2) 50 CNY per m^2 for existing non-park green spaces. Though they are green spaces, additional facilities may have to be built to meet public recreation demand.
3) 300 CNY per m^2 for vacant lands which are either planned or not planned for green space. Greening and facilities are necessary expenditures.
4) 1000 CNY per m^2 for renewal sites. The cost of renewal is hard to estimate, it varies from case to case. Given these lands are planned to be renewed and converted to green spaces, it is possible to assume the government can allocate a certain amount of budget; on the other hand, renewal indeed cost a lot. So 1000 is assigned arbitrarily, maybe much less than real cost, but much higher than construction for vacant lands.

[4] Cost refers to green space construction projects on the following webpages:
http://www.xiangyang.gov.cn/public/msfw/ggsy_2403/yllhfw_2412/cslh/201212/t20121213_363570.shtml
http://wenku.baidu.com/view/44895969011ca300a6c390b9.html
http://doc.mbalib.com/view/c5407a57a324eb3a3dfcbd163f9a677f.html

3.3 Demand Points: Residential Sites

The data collected to be the demand points in this project are building footprints[5] in the entire study area in GIS. To represent the location, the centroids of all the residential buildings are selected as demand points.

3.3.1 Population Estimate

In order to collect demand information at each demand point, population data in each residential building are needed. However, such detailed population data are not available for collection, so they had to be estimated instead.

To estimate population in each residential building, the most detailed population information at the smallest available geographical units was collected. The total population in Luohu District was 0.92 million, and population data within each of 10 sub-districts were also collected[6], which ranged from 63,000 to 115,000 people.

In the collected building footprints data set, characteristics of the buildings, such as building type and usage, floor, as well as gross floor area were also included. With gross floor area and building type, the population information was roughly estimated, with additional information on a citywide average of GFA per person for different building type: 100m^2 single and multiple family buildings, 40m^2 for apartments, 15m^2 for group quarters, 12m^2 for self-use buildings in urban villages, adjusted from similar indices from various Shenzhen demographic studies. These values were slightly adapted for each sub-district, according to their total population. Finally, the estimated population in a residential building was calculated by dividing GFA of the building by the estimated average GFA per person for the type that the building

[5] Data from Urban Planning, Land and Resources Commission of Shenzhen Minicipality
[6] Data from 2010 Population Census of China.
Population of Luohu District and its sub-districts:
http://www.szlh.gov.cn/tjj/a/2011/h02/a176392_572158.html

belongs to. Figure 3-6 shows the population density in the study area using the population estimation results. A strong uneven distribution of population can be observed from the map, large population is clustered in the center of the study area, where there are only a few small green spaces. On the contrary, much less people live in suburb areas where large green spaces are available.

It is worthwhile to note that the data from decomposing these highly aggregated sub-district level population data to each building will not be very accurate, and there will be large estimation errors for certain buildings. The model results, in turn, will likely be impacted by the inaccurate residential population estimates for buildings in the sub-districts. But this is the best estimation that can be done with available data. Moreover, given that the purpose of this study is to form a location-allocation approach with proper models and analysis for a certain type of location problems, the implementation of the model results for this exact case is not the main focus. Hence

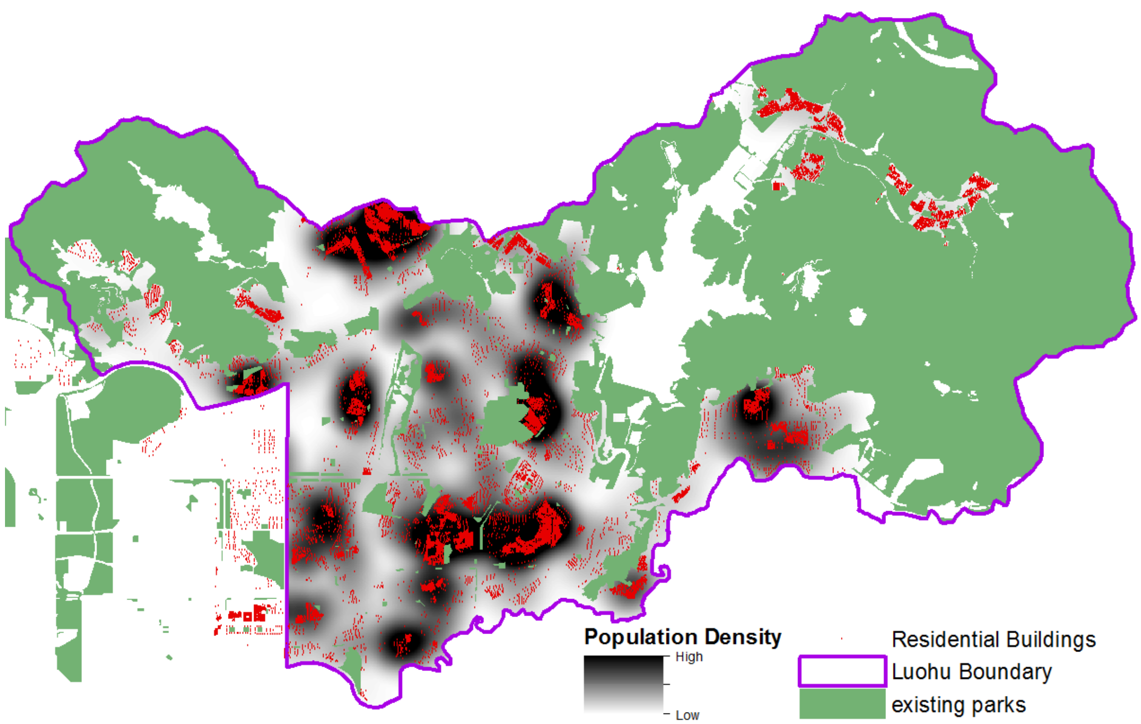

Figure 3-6 Population density in the study area

the potential population estimate errors are acceptable in this study. If in the future more detailed population data are available, the estimation results can be closer to real population distribution, and model outputs may be more realistic.

3.3.2 Demand Points Aggregation

A big challenge with applying a location-allocation model to this real-world problem is proper aggregation of data to achieve a balance between model efficiency and data accuracy after aggregation. This is a common difficulty in modeling location problems, when the number of demand points may be very large. It may be too time-consuming, impossible, or unnecessary to include every single demand point in later calculations and models (Francis et al., 2009). Then how many demand points are efficient enough and to what extent can the raw data be aggregated? There is no general agreement, and it is a tradeoff between data accuracy concerns and budget and time cost in data collection and modeling.

In this study, the raw demand points are all residential buildings in the study area, of which more than 15,000 exist. The large amount of the demand points caused problems even in early steps of preparing data for the models. For example, the time spent on calculating network distances from each demand point (residential buildings) to nearby green spaces took over 500 hours, which is not practical for planning practitioners. Reasonably, the number of demand points need to be reduced and data aggregation is expected.

However, on the other hand, the accurate estimation of distance is crucial in location models. A study by Hillsman and Rhoda (1978) revealed that using a single point to represent the population of a spatial unit can lead to distance measurement errors, especially in real spatial problems. And the aggregation error arises from the number of demand points that are aggregated. In the study case, for example, when aggregating the demand points (here, buildings) in a certain area to one point, *A*, this point represents the locations and characteristics of all demand points in the area, no matter from which part of the area these buildings are located. When a lot of demand points are aggregated to Point *A*, some of them may be far away from Point *A* but will be represented by Point *A*. Using only Point *A* to measure the distance from these demand points to a certain feature, the distance measurement errors can be tremendously large.

Though “the ideal way to aggregate DP (demand point) data is not to aggregate it”(Francis et al., 2009), to solve a lot of real problems, demand point data have to be aggregated. Then a proper aggregation approach has to be applied to improve model efficiency and ensure measure accuracy at an acceptable level.

(1) Aggregation approaches

The purpose of aggregation from n demand points to m approximating demand points (ADP) is to reduce the value of m so that $m < n$, and at the same time ensure that the aggregation will not lead to much estimation error in future distance calculations and modeling. To achieve this purpose, each demand point (building site) would be replaced by a closest approximating demand point, and in turn, each approximating demand point would replace one or more demand points. Obviously, when the number of approximating demand points $m = n$, which is the number of the demand points, there is no aggregation at all, so there is no aggregation error either. When there is more aggregation, which means m decreases and each approximating demand point may represent more demand points, the error caused by aggregation may increase. A very small m can lead to large error (Francis et al., 2009). The extreme case is $m = 1$, when all demand points are aggregated to one approximating demand point, the error is too large to make the aggregation meaningful.

The aggregation of spatially distributed points to fewer points is an instance of the general spatial aggregation procedures for combining spatial data to a coarser level from the level of finer collected raw data. Besides aggregation of various points to fewer points in this study, by necessity, other common aggregation possibilities may include aggregation of small polygons to large polygons, points to polygons, polygons to points, lines to lines, point to lines, lines to polygons (point). Aggregation from or to lines is less common, and transportation and road networks can demonstrate these situations well.

The following are examples for different aggregation situations.

- Aggregation from polygon to polygon: data are collected at small geographical unit level such as blocks, but need data at larger geographical units, such as neighborhoods, for later study.
- Aggregation from polygons to points: interest may be in the amount of population that can be served by fire stations, and block level population data near each fire station have to be added up.
- Aggregation from points to polygons: with known convenient stores' data of a city, and want to know the overall store services in each neighborhood in the city.
- Lines to lines: join street segments to the entire street to estimate street length.
- Points to lines: count number of houses along a street.
- Lines to polygons: to calculate road density (total length of roads per unit, e.g. sq. km, of land area), the length of all road segments in an area of interest is added then divided by the land area.

Aggregation Approach One: aggregating to existing geographical units

In this study, in order to aggregate residential buildings (points) to fewer points, one approach is to aggregate the building points to existing geographical units, such as blocks, which are bounded by surrounding streets. Then the population information on all the buildings in the same block would be summarized as the population information of the block. Finally, if point rather than polygon is needed for later study – in this case, yes, the block centroid can represent the entire block and contain the block population information.

However, among most existing geographical units which are commonly available, city blocks, as the smallest unit, may not be a proper unit for green space accessibility studies.

As we know, city blocks differ in size, from city to city. Some can be smaller than 10,000m^2 (100 meter in width), others can be much larger than 20,000m^2. Siksna (1997) collected typical block size and dimensions of some western cities for comparison. For example, Portland, US: 85*79m; Seattle, US: 93~130*98m; Chicago, US: 122*140m; Indianapolis, US: 158*158m; Toronto, Canada: 201*140m; Sydney, Australia: 51~127*151~360m. Given its grid structure, it is not too hard to estimate the dimensions of a typical Manhattan block, which is about 80*150~275m, the average block length in the east - west direction (distance between avenues) is 225 meters, or 750 feet. Generally, a size of 80-100 meter, which is about 15 to 20 blocks per mile, as a dimension for city blocks is used by city planners and engineers for calculation estimates.

Then how much would the distance error be if we aggregate all the buildings in a block to the centroid of the block? Taking a small block with size 80*100m as an example, if we assume a building's centroid is 10 meters from the block frontage, the largest of error that could be made through aggregation is 50m, which is relatively large comparing with only a few hundred meters of tolerable travel distance by pedestrian to a green space. Assuming the travel distance from the building to a green space 500 meters, the aggregated distance error of 50m would lead to up to 10% error in distance measure. And when the block size is larger, the distance between buildings (demand point) and centroids of the block (approximating demand point) would be larger, and aggregation will cause considerable more errors.

In the research area of this study, since the city street network is not condensed,

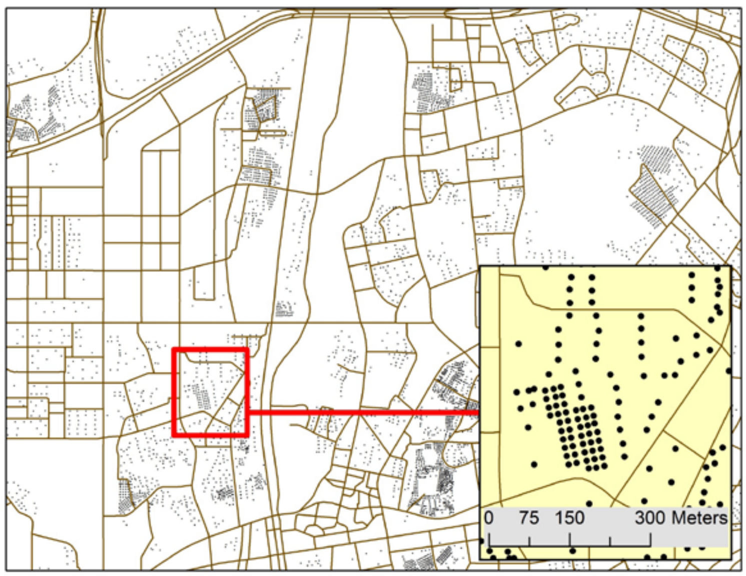

Figure 3-7 Street structure in urban center of Luohu District, Shenzhen
(Building centroids are marked as dark dots)

Figure 3-8 Non-recorded streets in the block, observed in the satellite image

most frontages of blocks are much larger than 100m, (Figure 3-7). For example, the four frontages of the block on the call out map of the Figure 3-7 are 220, 350, 440, 420m, and there are 90 buildings (dark dots on the map) in the block. However, from a satellite image of the same block (Figure 3-8), clearly there are a few neighborhood streets that are not on the record of the city street network data set shown in Figure 3-7. However, this data set was the best among the available data. Besides, even with the missing neighborhood streets, most dimensions of the sub-blocks are still larger than 100m. So, the city street network data set was used in this study for calculation.

Following the approach stated above, these 90 buildings will be aggregated to the centroid of the block as the approximating demand point. Even though the amount of demand points significantly dropped, the distance errors are huge, for some points, the errors will be larger than 200m.

In fact, besides blocks, the city has another small geographical unit, grids, in its city grid management system. This system splits the entire city into irregular grid cells for city management purposes. Large blocks are separated into several small cells, and several small blocks may be combined into one cell. So, grid cells are not consistently the smallest units and quite often they are still as large as over 200m in one dimension (Figure 3-9).

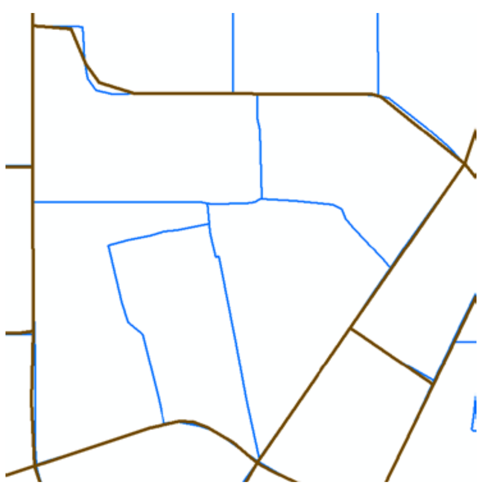

Figure 3-9 Grid cells (blue) in the sample block

Apparently, using this aggregation approach will result in inaccuracy in later steps of calculating distances to nearby green spaces, which are usually within a few hundreds of meters.

Since the physical block is too large a unit for aggregating building points for research purposes, an alternative aggregation approach has to be used. Given that existing geographical units are not suitable for aggregation, a set of intuitive units can be generated, and points that are located in one unit will be collapsed. Among the approaches of generating units, the fishnet polygon approach is commonly used.

Aggregation Approach Two: aggregating to fishnet cells

In the GIS world, fishnet (Figure 3-10) refers to a net of rectangular cells created by a user. It is widely used in data sampling and resampling, index creation, or anywhere that needs regular grids. With fishnet grids, the aggregation of points can follow these steps:

- First, construct a fishnet polygon mesh using predefined cell size or cell numbers, and overlay the mesh with the points to make sure every demand point is covered by the mesh.

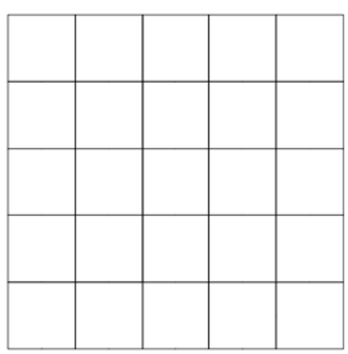

Figure 3-10 Illustration of fishnet

- Then, count the demand points or combine the expected characteristics of all the points in each polygon cell.
- Finally, select one point, typically the cell's centroid, to represent a polygon cell's location, and this point will be the approximating demand point for all the demand points in the cell.

Thus, a large number of demand points will be reduced to fewer approximating points, and usually the number of approximating points is equal to or less than the number of cells -- these two numbers are the same when all cells contain at least one demand point; the former is less than the latter one when some cells do not contain any demand point.

However, some additional details need to be discussed before applying this approach.

- Choose proper fishnet cell size: 50*50m

In step 1 of constructing a fishnet polygon mesh, the first issue is how large the fishnet cell size should be. Again, it is a tradeoff between accuracy and cost in aggregation. For the same demand point data set that needs to be aggregated, a larger cell size usually means fewer polygon cells to be used to cover all demand points, which also means fewer approximating demand points and more aggregation of the data. On the other hand, if the cell size is too small, more approximating points are needed. Though the aggregation error is small, it may not meet the need of aggregation, such as significant reduction of computing time and cost. In this case, 50*50m was defined as the cell size, so that all the demand points in 50*50m cell will be aggregated, and be represented by a point.

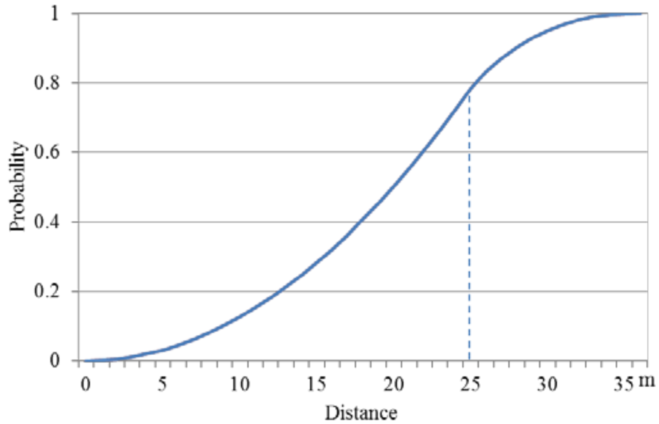

Figure 3-11 Accumulated probability of aggregation distance
(From demand points to approximating demand points)

Mathematically, if this approximating demand point is at the center of the cell, there is a 78.5% chance that the distance from an actual demand point to the approximating demand point is less than 25m, and the largest aggregation error is 35.4m (Figure 3-11).

Assuming the travel distance by a pedestrian from a building to a green space is 500 meters, it is very unlikely (4.1% of chance) that the distance between approximating demand point and a green space is less than 475m or over 525m (measurement error > 5%).

Moreover, real data from the study case are examined for aggregation effects on distance measure. Here, the average distance to nearest green space per person was used as a measure to compare the difference before and after the aggregation.

In order to calculate the average distance to the nearest green space per person before aggregation, the distance from each building ($i \in I$) to its nearest green space, d_i, has to be calculated. Then the following equation was used to calculate the average distance:

$$Average\ Distance\ to\ Nearest\ Green\ Space = \frac{\sum_i (d_i * P_i)}{\sum_i P_i}$$

i = index of building where $i \in I$

d_i = distance from building site i to its nearest green space

P_i = Population at building i

The same process was repeated to calculate the same distance measure after aggregation, using population at each approximating demand point and distance from each approximating demand point to its nearest green space to replace the corresponding variables in the above calculation.

Here are the calculated results: before aggregation, the average distance to nearest green space is 97.2 meters for people, it changes to 96.4 meters after aggregation with fishnet approach. The aggregation error for this measure is only 0.8%.

- Use proper points as approximating demand points: population weighted centroids

After aggregating demand point information to their respective fishnet cells, in Step 3, a point has to be created as the approximating demand point to represent each cell's location. A regular approach is to use the geographic centroid of the square cell. This centroid works well if a researcher only cares about the location representation itself, or if the interested features and their attributes such as points or individuals are evenly distributed in the cell.

However, since this study is heavily population related, and as it is likely the numbers of people at demand points (buildings) are not evenly distributed across the cell, the geographic centroid is not the best solution. So instead, the population weighted centroid was used in this study. The population weighted centroid is a reference point in the center of the population in a cell. It is less likely to be right at the center of the cell. The location of this point is based on the distribution of population in the same cell.

To calculate the population weighted centroid of a cell, assume:

There are m demand points in the cell, the coordinates of the demand point *i* in the cell are (x_i,y_i), and the population at the demand point *i* is P_i. $i \in I$ is the set of demand points in the cell. Then the coordinates of the weighted population centroid is:

$$\left(\frac{\sum_{i \in I} x_i * P_i}{\sum_{i \in I} P_i}, \frac{\sum_{i \in I} y_i * P_i}{\sum_{i \in I} P_i}\right)$$

Figure 3-12 shows four fishnet cells from the study area. For the cell 2, there is only one demand point, so population weighted centroid sits right at the location of the demand point which is far from the cell's geographic center. In this case, using the population weighted centroid does not lead to any distance measure error.

For the cells of 1, 3, 4, there are 4, 3, 2 points to be aggregated, respectively. Observe the locations of the population weighted centroids, they are much closer to demand points with large populations, see cell 3, 4. In cell 1, since the numbers of people at four demand points are close, the population weighted centroid is roughly in the middle of the four demand points.

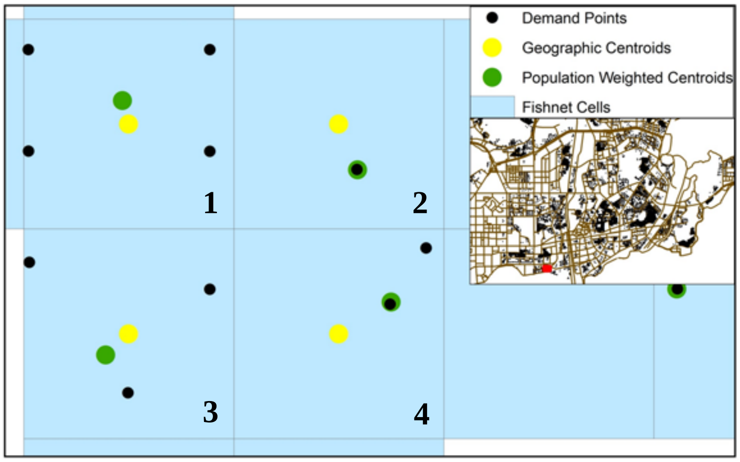

Figure 3-12 Sample cells for aggregation illustration

From Figure 3-12, it can also be observed that for each of these four cells, none of the population weighted centroid is at the exact location of the geographic center of the cell. Apparently, using these two sets of points as approximating demand points will lead to different distance measure results. In order to compare which set of points can return smaller distance measure errors, three distance measures were calculated for each demand point: 1) distance from the demand point to its nearest green space, d_i; 2) distance from the geographic center of the cell to which the demand point belongs to its nearest green space, d_i^{ct}; 3) distance from the population weighted centroid of the cell to which the demand point belongs to its nearest green space, d_i^{pw}.

With these three sets of distance measures, two scatter plots are created and overlapped: d_i vs. d_i^{ct}, and d_i vs. d_i^{pw}, see Figure 3-13. By visually comparing the scatter plots and fitted lines in the figure, one can see d_i^{ct} and d_i^{pw} distributions are quite close. Generally, the majority of d_i^{pw} are closer to d_i than d_i^{ct} (Generally, red

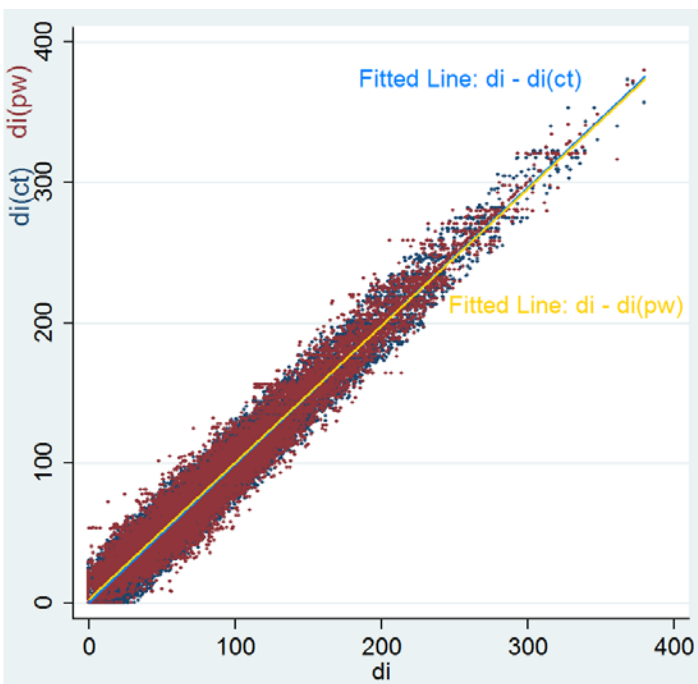

Figure 3-13 Scatter plots comparison: d_i vs. d_i^{ct} and d_i vs. d_i^{pw}

points that are tighter along the diagonal), except that a few d_i^{pw} are further, which can be seen from the red points that are far from majority along the diagonal. The theoretical explanation of these exception points could be: the maximum distance error using cell geographic center is half of the diagonal length of the cell (35.35m), when the demand point is located at a corner of the cell. The maximum distance error using population weighted centroid is the diagonal length of the cell (70.7m), when the demand point with few people is located a corner of the cell, and another heavily weighted demand point with large population is at the opposite corner of the cell, then the population weighted centroid will be extremely close to the demand point at the opposite corner, and the distance from population weighted centroid to the first point can be up to 70.7m, which is much larger than the distance from the point to the cell center. So the chances of having $d_i^{pw} > d_i^{ct}$ do exist. And in these rare cases, distances from population weighted centroids can lead to larger errors than distances from cell centroids.

For further comparison of d_i^{ct} and d_i^{pw}, two simple linear regressions on distance pairs were run: one regression on the variables of 1) d_i^{ct} (ct_dist in regression results) and 2) d_i (true_dist), the other regression on the variables of 1) d_i^{pw} (pw_dist) and 2) d_i (true_dist). The regression results in the Table 3-2 and Table 3-3 reveal that d_i^{pw} performs better than d_i^{ct}, given that the R^2 coefficient in the second regression is larger, the t statistic for d_i^{pw} is larger, and the coefficient of d_i^{pw} is closer to 1 than that of d_i^{ct}.

Table 3-2 Regression between true distances from DPs (di) and distances from cell centroids (di(ct))

Source	SS	df	MS
Model	53707295.2	1	53707295.2
Residual	2625043.67	14529	180.676142
Total	56332338.8	14530	3876.96757

Number of obs =	14531
F(1, 14529) =	.
Prob > F =	0.0000
R-squared =	0.9534
Adj R-squared =	0.9534
Root MSE =	13.442

true_dist	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ct_dist	.967212	.001774	545.21	0.000	.9637347	.9706893
_cons	3.538879	.1938307	18.26	0.000	3.158946	3.918812

Table 3-3 Regression between true distance from DPs (di) and distance from population weighted centroids (di(pw))

Source	SS	df	MS
Model	54112301.1	1	54112301.1
Residual	2220037.76	14529	152.800451
Total	56332338.8	14530	3876.96757

Number of obs =	14531
F(1, 14529) =	.
Prob > F =	0.0000
R-squared =	0.9606
Adj R-squared =	0.9606
Root MSE =	12.361

true_dist	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
pw_dist	.9847849	.0016548	595.09	0.000	.9815412	.9880286
_cons	.9255743	.1814104	5.10	0.000	.5699869	1.281162

Given all above analysis, population weighted centroids are finally chosen as approximating demand points for later models. However, there is one more question about point aggregation that needs to be addressed in practice: are the arbitrary fishnet cells adequate for aggregating demand points?

- Adjustment of fishnet

A 50*50m fishnet mesh has been generated and overlaid on top of demand points. However, there may be some other constraints in a real project that indicate the inadequateness of aggregating all demand points in one cell. While overlaying a rectangular grid to an area of interest in the real world, it is very likely that there is a boundary mismatch between the grid and the existing geographical units. In such a situation, if the aggregation of demand points has to take the geographical units into account, using a rectangular grid for aggregation cannot meet this need. A fishnet cell may cross more than one geographical unit, and demand points from different geographical units with different characteristics are now placed in one cell. If they are aggregated improperly into one approximating demand point, the geographical unit to which the approximating demand point belongs may not be properly defined, and the associated characteristics of the approximating demand point are unclear or can be mistakenly assigned. Furthermore, the overall characteristics of all approximating demand points that form a geographical unit may not be able to match the characteristics of the geographical unit, and some statistics may differ before and after aggregation. For example, for a Block A with population 1000, a few cells are completely in the block, but there is another cell that crosses the block boundary and it contains two demand points, M and N, one in Block A and the other in Block B, a block next to Block A. If this cell is treated as in in Block A, the demand point N in Block B is aggregated to the cell, so the population in Block A will be larger than 1000, vice versa.

Therefore, adjustment of the fishnet cells is a necessary step to avoid a spatial mismatch of the cells and existing geographical units that a researcher is interested in. In this case study, the following geographical units have to be taken into account in adjusting fishnet cells:

- Blocks. As explained in the above example, the aggregation is expected to be in the same block, and cells should not cross streets.
- City Grids. As the standard unit in city grid management systems, it would be preferred to not aggregate across multiple grids, so that potential implementation of the research results may be more positively effective.
- Different land use types. The residential land is classified into four types: R1, single- to multi-family land; R2: apartment land, R3: group quarter land; R4:

residential land for self-use in urban villages. Some blocks may contain multiple residential land types. These land use types regulate the residential buildings built on the land. It is reasonable to not aggregate buildings of different types, so more interesting findings may be found in later analysis.

(2) Summary: aggregation of raw demand point data

The aggregation process becomes more complicated when the issues noted above are taken into account. Fishnet mesh approach was adopted and adjusted for the project need. The following steps were finally carried out to reduce the amount of demand points in the raw building data.

Firstly, a fishnet polygon mesh with cell size 50*50m was created, and was laid over the raw demand points to ensure it covers all the points. Then the cells that did not contain any demand point were removed. There were 4583 effective cells with demand points.

Secondly, these fishnet cells were adjusted. The fishnet cells that intersected any of streets, city grids, or residential land use classes were split according to the miss-match boundaries. Then the sliced cells (polygons) that contained no demand points were removed. After this step, there were 4870 cells in total. Comparing to the result from last step, the number of cells only increased by 287. With this slight increase of approximating demand points, however, the aggregation was more informative and meaningful with these additional factors being involved.

Finally, population weighted centroid coordinates were calculated for the 4870 adjusted cells, and then 4870 points were created using the coordinates. These points became the approximating demand points for later modeling.

The block example used in the previous section can illustrate this adjustment process. Thirty three fishnet cells were generated (Figure 3-14), and then using the adjusted factors including streets, city grids and land use types (Figure 3-15), these cells were adjusted to 37 cells (Figure 3-16). 90 buildings were finally aggregated to 37 approximating demand points (Figure 3-17). Figure 3-18 compared the aggregation result of the 37 points to the 90 building sites before aggregation. It can be observed that more buildings are aggregated in compacted areas, and less or no aggregation happens for the dispersed areas where buildings have few neighbors.

Figure 3-14 33 Fishnet cells that contain demand points in the sample block

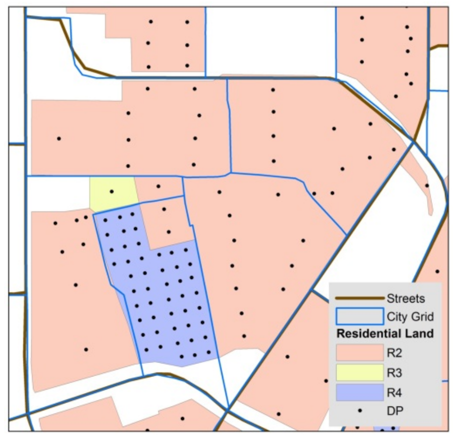

Figure 3-15 Three factors used for cell adjustment

Figure 3-16 37 Cells after adjustment

Figure 3-17 37 Population weighted centroids of the cells

Figure 3-18 Aggregation results: locations of 37 approximating demand points and 90 demand points in the sampling block

With this aggregation approach, over 15,000 demand points have been reduced to less than 5000 approximating demand points. This aggregation, with some other time-saving techniques, has significantly reduced later calculation time for network distances from demand points to green space sites, from over 500 hours to a tolerable number of less than 100 hours. Besides, from previous analysis, with a relatively small cell size and population weighted centroid technique, later estimation on travel distance to green spaces is very unlikely to have large error of over 5%, especially for green spaces that are a few hundred meters away – a distance threshold that residents are willing to walk into a green space frequently. For a nearby green space, though the relative estimation error caused by aggregation will increase, it will not make much difference in people's willingness of visiting a green space.

3.4 Distance Measures

This section focuses on distance measures of the distances between demand points (residential sites) and their nearby facility sites (green spaces in the study case). Distance measure between facilities and demand points is a cornerstone and crucial input for location models.

3.4.1 Euclidean Distance, Manhattan Distance and Network Distance

Generally, there are three distance measures: Euclidean distance (straight-line shortest distance), Manhattan distance (distance measured along axes at right angles named after the grid layout of Manhattan streets), and network distance (the shortest distance along a public transport network) (see Figure 3-19 for illustration). Besides these direct distance measures, travel time or travel cost along the existing street network is infrequently used.

Assuming the coordinates of two points P and Q are (x_1,y_1) and (x_2,y_2), then:

The Euclidean distance between P and Q is the length of the line segment that connects these two points:

$$d^{eu} = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

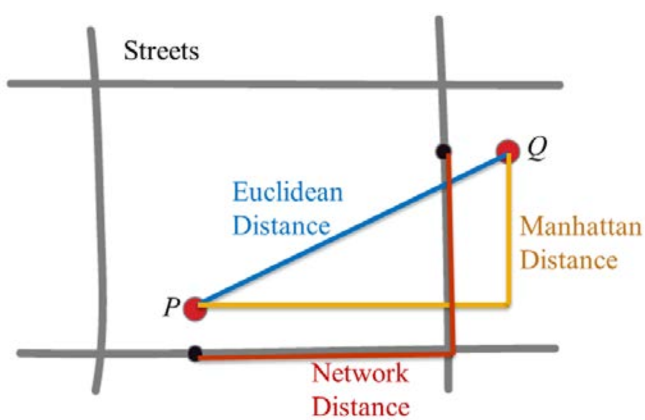

Figure 3-19 Euclidean, Manhattan and Network distance measures

The Manhattan distance between P and Q is the sum of absolute difference between the x- and y-coordinates of these two points:

$$d^m = |x_1 - x_2| + |y_1 - y_2|$$

The network distance between P and Q is based on the network, a street network for example, that P and Q are in. Hence a general formula cannot be expressed but how this distance is calculated will be discussed.

Euclidean distance is the most widely used distance measure by planners and location modelers, given its simplicity of calculation. Manhattan distance would work well to measure distances along grid like streets in urban areas. When there is a network, network distance may be presumably a good measure. In a survey by Francis et al. (2009), among 38 published articles between 1978 and 2005, half of which are on real data, Euclidean distance was the predominant measure. Only 7 articles use Manhattan distance besides Euclidean, and 4 use network distances. However, do all these measures return similar results? Is Euclidean always an appropriate measure?

Bach (1981) conducted an investigation on distance measures and found the correlation was close to one for network and Euclidean distances for his two case studies in Germany, which indicate that it does not matter which distance, network or Euclidean, is used in location models (Carling, Han, Håkansson, & Rebreyend, 2012). The same finding can be found in Love et al. (1988) for large scale studies.

In another study, Carling et al. (2012) compared the Euclidean distance and a road network distance in a rural environment in Sweden. The outcome of their p-median model for up to 8 facilities with different distance measures was compared, and the authors found out that, however, their study case was quite sensitive to distance measures, and Euclidean distance did not work well in non-homogeneous rural areas and led to sub-optimal location solutions. To further test their conclusion, Carling et al.

(2012) did an experiment with more facilities and a refined network. The same conclusion was obtained that Euclidean measure was potentially problematic since it may lead to model solutions with excessive travel distances for the population.

Different from literature discussed above, this study focuses on urban rather than rural areas, and at the pedestrian walking distance scales rather than the geographic scale involved in long driving distances between cities. So the conclusions from the above reviewed literature may not be appropriate for this study. In order to explore how different distance measures perform in a small scale urban environment, all Euclidean, Manhattan and network distances are calculated for the distances of each demand point to its nearby green spaces.

3.4.2 Mathematical Differences Among Distances Measures for Points

Mathematically, the Manhattan distance between two points P and Q should always be greater than or equal to the Euclidean distance of these two points, and should be no more than 1.414 times of the Euclidean distance. The relative difference of the two measures depends on the locations of the two points. If they are horizontally or vertically located, the Euclidean and Manhattan distances would be exactly the same; if one point is located at a diagonal direction to the other point, the Manhattan distance would be $\sqrt{2}$ ($\approx$1.414) times the Euclidean distance.

However, the relationship of the network distance and the Euclidean distance is not as simple as that of the Manhattan distance – which is always 1 to 1.414 times of the Euclidean distance. The network distance, somehow, can be smaller than the Euclidean distance. It may sound impossible as we all know the Euclidean distance is the shortest distance between two points. The problem of having smaller network distance is caused by how the network distance is being calculated.

The network distance is the shortest distance along a network, but situations vary. If two points, P and Q, are on a street network, the shortest path between these two points is recorded as their network distance correctly in GIS. However, if one or both of the points do not intersect with any street (network component), but rather are offset from the streets instead, the network distance calculation will be different. First, the points P and Q that are not on the network have to be snapped to their nearest streets at the corresponding nearest points P' and Q' on the streets, this ensures that the new inputs, P' and Q', are located on the street network which is required for any network calculations. Then the shortest path between P' and Q' are calculated, and finally recorded as the network distance between P and Q. So though P, Q and P', Q' are different points, the network distances for these two pairs are exactly the same, and the offset distances of P and Q to their nearest streets are ignored in the network distance calculation. For example, in the circumstance of Figure 3-20, the network distance between P and Q is much smaller than their Euclidean distance.

The offset distances of points to streets should not be ignored at such a scale of this study, because it wouldn't make sense that the actual walk distance between two points are less than the shortest-line distance (Figure 3-20). Even if the calculated

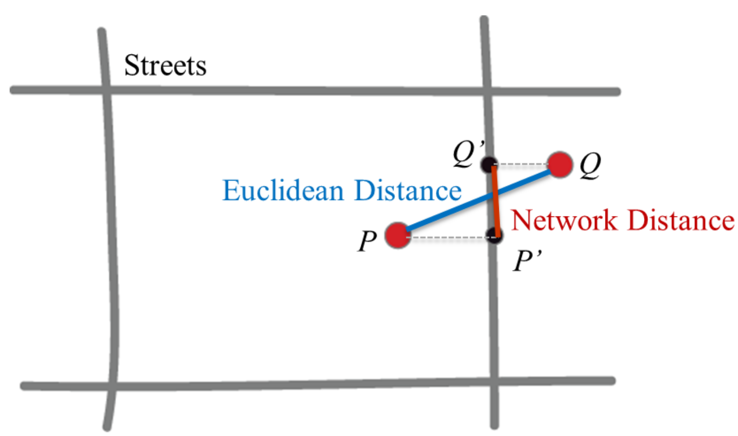

Figure 3-20 A scenario that the network distance is less than the Euclidean distance

network distance is still longer than Euclidean distance, ignoring the offset distances from points to their nearest streets may still lead to large distance measure errors because these offset distances may be comparatively large at such small scales.

No discussion has been found on this offset distance problem in rural and regional studies. The reason is that, compared with the long travel distance on the road network, the offset distances from the points of interest to their nearest roads are relatively small and will not lead to too much error in model results.

In brief, at a relatively small scale with a relatively sparse network, such as in this study, the offset distances have to be taken into account if the network distance measure is to be used. An adjusted network distance (Figure 3-21), as a fourth distance measure, can be calculated by adding the value of network distance and the offset distances of the two points P and Q to their nearest streets.

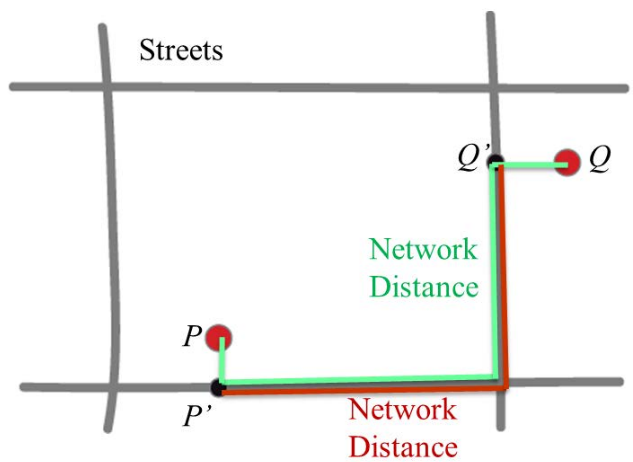

Figure 3-21 The adjusted network distance

The adjusted-network distance *PQ* =
network distance of *P'Q'* + offset distance *PP'* + offset distance *QQ'*

3.4.3 Distance Calculation for a Point and a Polygon

As discussed in previous sections, in this study, a green space cannot be simply viewed as a point; its area in the physical space has to be calculated. Rather than using a centroid point as the location of a green space for distance calculation, a set of points at its boundaries as “entrance points” to the green space, have to be used instead.

Assuming Q_1, Q_2, … Q_n are n entrance points on the boundary of a Green Space G:

For the Euclidean distance between Demand Point P to Green Space G, the Euclidean distances of Point P to each of the entry Point Q_1, Q_2, … Q_n need to be calculated and compared, then the shortest one will be the Euclidean distance between Demand Point P to the Green Space G. The entrance point with the shortest Euclidean distance is denoted as Point Q_h. This process was illustrated in Figure 3-22, and in this example, the distance between P and the Green Space G was defined as the distance between points P and Q_2.

$$d^{eu}{}_{PG} = \min(d^{eu}{}_{PQ_1}, d^{eu}{}_{PQ_2}, \dots, d^{eu}{}_{PQ_n})$$

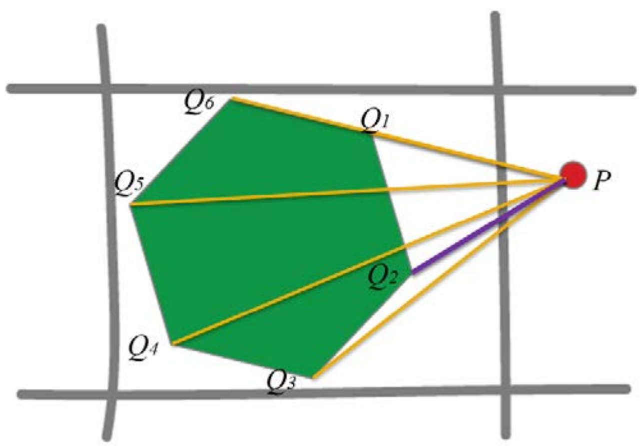

Figure 3-22 Euclidean distance of a point P to a green space polygon G

$$d^{eu}{}_{PG} = d^{eu}{}_{PQ_2}$$

Then the Manhattan distance between Point P and Green Space G, is not computed simply by taking the coordinates of Point Q_h with that of Point P for calculation. The Manhattan distances of Point P to each of Point Q_1, Q_2, … Q_n have to be calculated and compared, the shortest one is recorded as the Manhattan distance between Point P and the green space. Note entrance point Q_i for shortest Manhattan distance may be different from the one for Euclidean distance.

$$d^m{}_{PG} = \min(d^m{}_{PQ_1}, d^m{}_{PQ_2}, \dots, d^m{}_{PQ_n})$$

Similarly, the network distances of Point P to each of green space entrance points Q_1, Q_2, … Q_n have to be calculated in GIS and choose the shortest one as the network distance of P and the green space. And the entrance point chosen, Q_j, may not be Q_h or Q_i.

$$d^n{}_{PG} = \min(d^n{}_{PQ_1}, d^n{}_{PQ_2}, \dots, d^n{}_{PQ_n})$$

In the same way, the adjusted network distance between Point P and Green Space G is not simply taken to be the network distance between Point P and Entrance Point Q_j, $d^n{}_{PQ_j}$, then add the offset distance of P to its nearest street, plus the offset distance of Q_j to its nearest street (the offset distance from a point to a street is the Euclidean distance between them). Instead, the network distances from all the entrance points and the offset distance of these entrance points to their nearest streets should all be considered, and the entrance point Q_k may not be the same entrance point of Q_j from the previous network distance calculation.

$$d^{adj\_n}{}_{PG} = \min(d^n{}_{PQ_1} + d^o_{Q_1} + d^o_P, d^n{}_{PQ_2} + d^o_{Q_2} + d^o_P, \dots, d^n{}_{PQ_n} + d^o_{Q_n} + d^o_P)$$

-- d^o: the offset distance of a point to its nearest street/network segment.

3.4.4 Empirical Measure Differences Among the Four Distances Measures

The four distance measures, the Euclidean, Manhattan, network and adjusted network distances, were calculated from each demand point to its nearby green spaces within a certain distance. In this section, to determine if these measures lead to significantly different distances results and if it is necessary for further study of their impacts on later models, the values of these four distance measures are compared for 4870 approximating demand points to their nearest green spaces, and for 4870 approximating demand points to their nearby green spaces with 1500m.

(1) Nearest green spaces found by different distance measures

For each approximating demand point, its nearest green space can be found by comparing its distance to all nearby green spaces and choosing the shortest one. Since it depends on distance, with different distance measures, the nearest green space found for an approximating point by one distance measure may not be the same green space found by a different measure. Or more generally, the nearest neighbor of a point found with different distance measures may not be the same one. So distances were calculated, using four above mentioned measures, from each approximating demand point to green spaces within a reasonable distance (i.e. 1500m or less).

Figure 3-23showed that among the 4870 approximating demand points for which

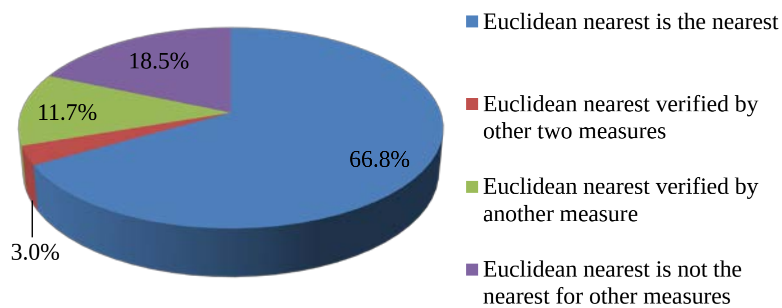

Figure 3-23 The nearest green space changes while using different measures

distances were calculated, 3251(66.8%) of them identified the same specific "nearest green space", no matter which distance measure was used. Secondly, 570 (11.7%) of the approximating demand points have a nearest green space which was identified by three of the four distance measures including the Euclidean distance measure. That is, only one distance measure pointed to a different green space as the nearest one. Third, for 901 approximating points (18.5%) the nearest green space identified by Euclidean distance was also the nearest one measured by one of other three distance measures, but not identified as the nearest green space using the other two measures. Lastly, for 148 approximating demand points (3%), the nearest green space identified by Euclidean distance measure is absolutely not the nearest one identified by any other distance measures.

(2) Distances from points to their nearest and all nearby green spaces

Whereas the previous section concerned only with the distance from demand points to their nearest green spaces, this section analyzes the consequences of measuring distances to nearby green spaces as well as nearest. As indicated above, four types of distances from a demand point to its nearest green space are investigated. For each of 4870 approximating demand points, among all nearby green spaces, the nearest one to the point with Euclidean distance measure was found. The furthest distance of the 4870 pairs of each point to its nearest green space is less than 400m. Then the corresponding Manhattan, network and adjusted network distances from the point to its nearest green space defined by the Euclidean distance measure were calculated. To examine the effects of using different measures, an analysis was conducted on the relationship of these distances for 4870 pairs of points and their nearest green space, having straight-line distances of up to 400m.

Furthermore, to increase the number of pairs for a more powerful analysis of the relationship between four distance measures, in addition to these 4870 pairs of points and their Euclidean-nearest green spaces, more pairs of points and their nearby green spaces were added to the analysis. It is quite likely that there are multiple green spaces within a certain distance from a demand point. All the pairs of points and their nearby green spaces with 1500m straight-line distance are involved in further analysis. This results in over 200,000 pairs with straight-line distances of up to 1500m.

<u>Manhattan distance vs. Euclidean distance</u>

From the scatter plots for both the distances from 4870 approximating demand points to their nearest green spaces and the distances from these points to their nearby green spaces within 1500m, Figure 3-24 and Figure 3-25 respectively, it can be observed that all the points were located between two lines: y=x as the bottom line and y=$\sqrt{2}$*x as the top line, which supports previous mathematical analysis.

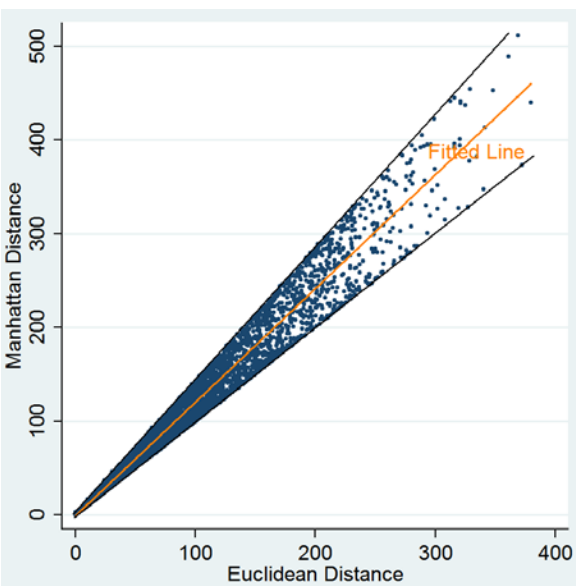

Figure 3-24 Manhattan distance vs. Euclidean distance between 4870 pairs of each point to its nearest green space

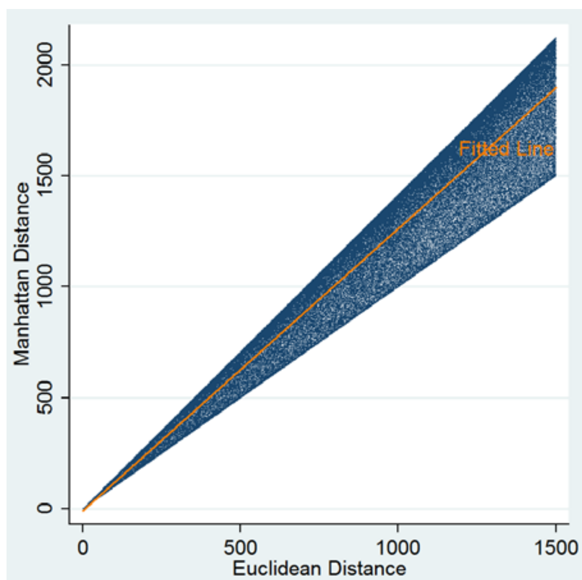

Figure 3-25 Manhattan distance vs. Euclidean distance between over 200,000 pairs of each point to its nearby green spaces

While these two distances are apparently associated positively, the megaphone shape of the scatter plot clearly reveals that when distance increases, the absolute difference between these two measures may also increase.

Network distance vs. adjusted network distance vs. Euclidean distance

First, the scatter plots of the network distance and the adjusted network distance (Figure 3-26 for 4870 pairs of points to their nearest green space, and Figure 3-27 for over 200,000 pairs of points to all nearby green spaces within 1500m) show a clear association between network distance and adjusted network distance. A simple linear regression between these two distances for over 200,000 pairs supports this by high R^2 and a significant slope around 1:

Adjusted Network Distance = 83.84 + 1.0038*Network Distance,

R^2 = 0.9951; P-value of the slope = 0.000

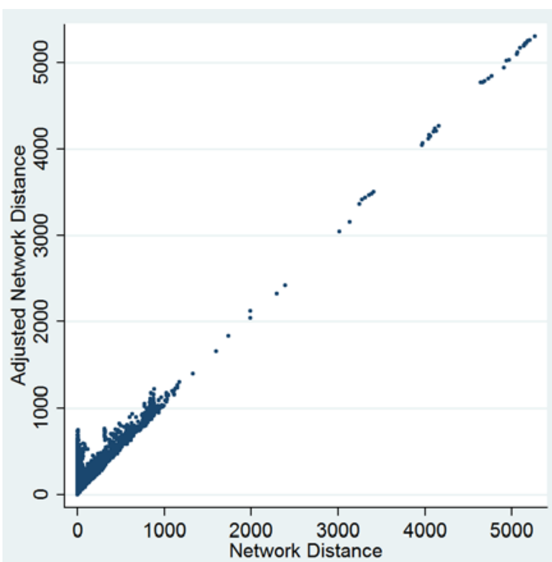

Figure 3-26 Network distance vs. adjusted network distance between 4870 pairs of each point to its nearest green space

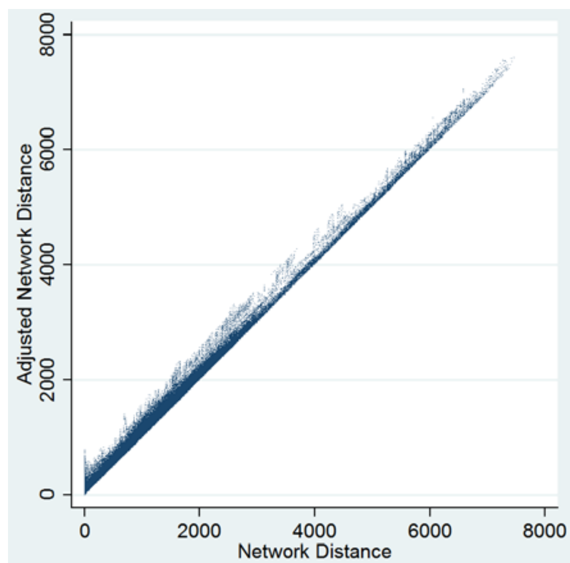

Figure 3-27 Network distance vs. adjusted network distance between over 200,000 pairs of each point to its nearby green spaces

However, we can also see that these two distances are quite close for large distance measurements; the relative differences between these two measures are large on short distance measurements. For those whose adjusted network distance is much larger than network distance, the reason is either the demand point, or the green space, or both are far from existing streets in the street network. If the measured network distance for two points is 2000m, and the total offset distances of the points to their nearest streets are 300m, then the adjusted network distance is 2300m, which is not a big increase. However, if the measured network distance of these two points is 400m, a 300m adjustment to 400m is relatively large: while 400m is a walkable distance, 700m, may seem too far to walk for some people.

<u>Network distance and adjusted network distance vs. Euclidean distance</u>

The relationship between (adjusted) network distance and Euclidean distance may be the most complicated but important one. Which is closer to real distances? Are they consistently in a linear relationship so Euclidean distance can replace the network distance for easier calculation?

As we discussed before, some researchers found high correlations between Euclidean distances and network distances and claim Euclidean distances might be used for analyses of accessibility (Bach, 1981), others found distance measures can lead to different results in rural environments (Carling, Han, Håkansson, et al., 2012; Carling, Han, & Håkansson, 2012). Then how these measures perform for a small scale study in an urban context?

Generally, network distance and adjusted network distance increase while the straight-line distances between points increase, however, the overall goodness of fit is not strong if simple linear regressions are run between the network distance or adjusted network distance and Euclidean distance, and R^2s are low (Table 3-4). The low correlation between Euclidean distances and (adjusted) network distances indicates that these distances are significantly different. Then using different types of distance measures may significantly impact the results of the location models, in which distance variable plays a key role.

Further, some interesting phenomena can be observed from the scatter plots of the network distance - Euclidean distance points overlaying with the adjusted network distance - Euclidean distance points, see Figure 3-28 and Figure 3-29 with different numbers of residence-green space pairs.

Table 3-4 Regression results between different types of distance measures (for nearest green space sample and extend sample of nearby green space with 1500m)

sample	n	Variable Y	Variable X	R^2	slope	p-value	intercept
Points to nearest GS	4870	Network Dist.	Euclidean Dist.	0.1544	2.47	0.000	-61.01
		Adj. Network Dist.	Euclidean Dist.	0.1390	2.37	0.000	45.94
Points to nearby GSs	209334	Network Dist.	Euclidean Dist.	0.3020	1.29	0.000	226.27
		Adj. Network Dist.	Euclidean Dist.	0.2975	1.29	0.000	316.96

1) Points at the top of the scatter plots (Figure 3-28 and Figure 3-29): short Euclidean distance and large network distance

Even though a demand point is quite close to a green space if measured by Euclidean distance, they may be very far from each other using network distance or adjusted network distance measures. For example, a green space which is just a few hundred meters away in Euclidean distance becomes 5000 meters away as measured

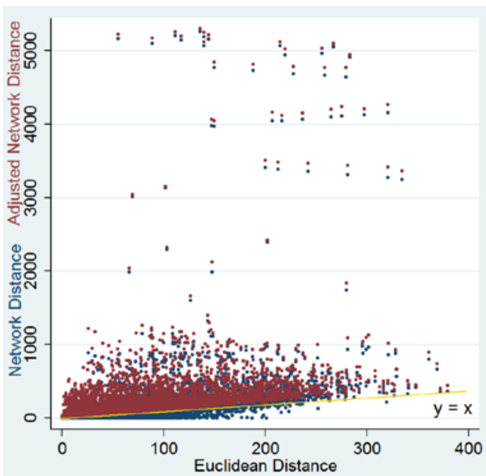

Figure 3-28 Network distance and adjusted network distance vs. Euclidean distance between 4870 pairs of each point to its nearest green space

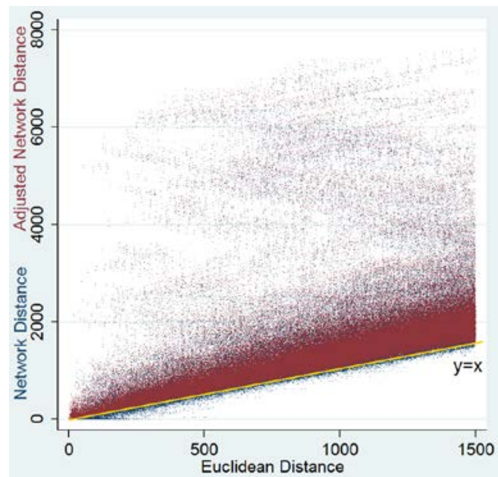

Figure 3-29 Network distance and adjusted network distance vs. Euclidean distance between over 200,000 Pairs of each point to its nearby green spaces

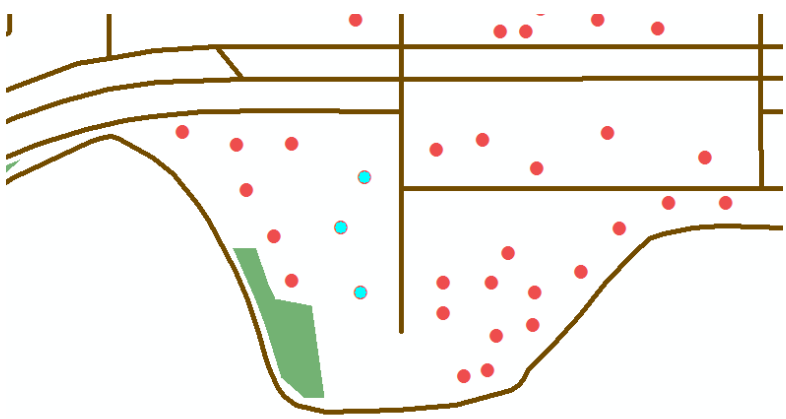

Figure 3-30 Short Euclidean distance (<200m) with large network distance(>5000m): points to green space

by network distance and is too far to be utilized by walking if the network distance measure is used. In Figure 3-30, three approximating demand points (cyan colored) are quite close to the green space in southwest (lower left of the map), the distances are 55, 90, 150 meters. However, in network analysis, the green space is snapped to its nearest road at the bottom, and the three demand points are snapped to the dead-end street on the right, which is not directly connected to the road at the bottom. And unfortunately, this road is poorly connected to the city streets, so the network distances measured for these three points to the green space are huge, 5167, 5098, 5066 meters, respectively, and the adjusted network distances are 5224, 5176, 5120 meters.

In fact, pedestrians are much smarter than network analysis. They are not restricted to walk along the streets. They can walk along sidewalks and pedestrian paths that are not on the street network. They can walk between the buildings, or even through buildings. They have more flexibility of choosing a much shorter path. In such cases, using Euclidean distance or Manhattan distance would make much more sense, and Manhattan distance may work best.

For a small scale study of pedestrians in an urban environment, this exaggeration of network distance measurements can only be reduced when the following steps are applied when preparing the street network:

- Refine the network by adding detailed streets in neighborhoods, and all possible walkable paths such as sidewalks, pedestrian and bike trails. The more detailed, the better. – However, these data may not be available to practitioners at all.
- For one-way streets, remove direction restriction when builds the street network, because pedestrians can walk either way.
- Remove non-walkable roads from the network, such as overhead roads.

2) Points at the bottom of the scatter plots (Figure 3-28 and Figure 3-29): network distance is smaller than Euclidean distance

Though Euclidean distance should be the shortest distance between two features, the network distances sometimes are smaller than Euclidean distance because only the distances on the street network are counted – and that's why the adjusted network distance measure is created. See the points below the y=x line on the scatter plots. Here's an example. Among 4870 pairs of demand points to their nearest green spaces, 3026 pairs (62.1%) have smaller network distances than Euclidean distances. There are 774 pairs with non-zero Euclidean distance but zero network distances. In Figure 3-31, from the cyan demand point to the open green space at the bottom, the Euclidean distance is 131 meters, Manhattan distance is 161 meters, network distance is 0, and the adjusted network distance is 131 meters, the same as the Euclidean distance.

These examples are in accordance with the argument in an earlier section that the technical network distance is not an appropriate measure in such a case, and it is necessary to adjust the network distance.

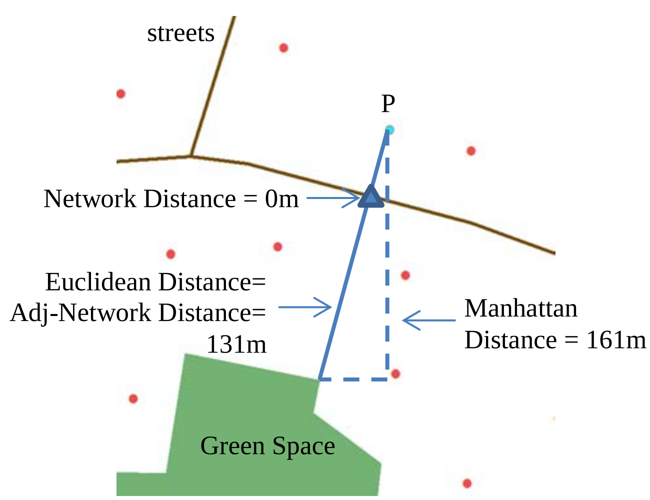

Figure 3-31 Large Euclidean distance and zero network distance

From all above analysis, none of the four distance measures is the best, or the most accurate one for such a small scale pedestrian study in an urban area. How would these different measures impact the location model results? Will the results be completely different? These four sets of distances will be used in the location models for further study of their impacts.

3.5 Space Standards Related Parameters

To evaluate wellness of greening of a Chinese city, multiple indices are used as standards in these national regulations in China: Evaluation Standards for Urban Landscaping and Greening (Ministry of Housing and Urban-Rural Construction of the People's Republic of China, 2010a), State Standard for Garden City of China(Ministry of Housing and Urban-Rural Construction of the People's Republic of China, 2010c), and Standards for China habitat Environment Award (Ministry of Housing and Urban-Rural Construction of the People's Republic of China, 2010b).

3.5.1 National Standards

National standards on green space include amount of green spaces and location requirements (Table 3-5):

- Greenery coverage in urbanized area. In 2008, the average coverage for 660 Chinese cities is 35.3%; and 39.7% for designated National Garden Cities.
- Green space ratio in urbanized area, the main difference from above index is roof gardens are excluded. In 2008, the average green space ratio for 660 Chinese cities is 31.3%, and 36.8% for National Garden Cities.
- Urban park green space per person. Only the green spaces in the built area are counted. Again, in 2008, the average value of this index for 660 Chinese cities is 8.98m^2, and 11.12m^2 for National Garden Cities.

- Park Service Radius Coverage (%), or the coverage within the public green space service radius. And this radius is specified as 500 meters. The Evaluation Standards also clarified that "given the possible population with 500 meter service radius", the minimum size of the parks refers to 5000m^2. For parks less than 1000m^2, the service radius can be as small as 300m.
- The green space area per person for downtown area should be at least 5m^2/person.

Table 3-5 National standards on green spaces in China

<table>
<tr><th colspan="2" rowspan="2">index</th><th colspan="3">Standard</th></tr>
<tr><th>National Garden City</th><th>National Eco-garden City</th><th>China Habitat Environment Award</th></tr>
<tr><td colspan="2">greenery coverage in urbanized area</td><td>≥36%</td><td>≥40%</td><td>≥40%</td></tr>
<tr><td colspan="2">Green space ratio in urbanized area</td><td>≥31%</td><td>≥35%</td><td>≥40%</td></tr>
<tr><td rowspan="3">park green space per person</td><td>Cities of built area/person < 80m^2</td><td>≥7.5m^2/person</td><td>≥9.5m^2/person</td><td rowspan="3">≥12</td></tr>
<tr><td>Cities of built area/person 80~100m^2</td><td>≥8m^2/person</td><td>≥10m^2/person</td></tr>
<tr><td>Cities of built area/person >100m^2</td><td>≥9m^2/person</td><td>≥11m^2/person</td></tr>
<tr><td colspan="2">Min green space area per person in city downtown area</td><td>≥ 5m^2/person</td><td>--</td><td></td></tr>
<tr><td colspan="2">Park Service Radius Coverage</td><td>≥70%</td><td>≥90%</td><td>≥80%</td></tr>
</table>

In Opinions of the State Council on Strengthening Urban Infrastructure Construction (the State Council of the People's Republic of China, 2013), the State Council further reinforced construction of green space in cities. It required that by 2015, for all cities, the green space service radius of coverage should be no less than 60%, and for downtown area the minimum green space area per person should be no less than $5m^2$/person.

3.5.2 Local Standards

From the city's Green Space System Planning (2004-2020), the planning standards of green spaces are:

- The general goal at 2020 is $18m^2$ public green space per person (in 2013, this figure is $16.7m^2$ published by Shenzhen Urban Management Bureau of the Municipality (2014));
- Green space ratio of over 50%;
- Service radius of neighborhood parks should be between 500 to 1000 meters;
- The minimum size of a green space should be no less than 500 square meters.

3.5.3 Space Standards Defined for the Models

Consider both national and local standards, the model parameters were set as follows:

- Green space minimum size: $S = 500m^2$
- Distance threshold: $D = 500m$
- Percent population coverage criterion $C = 80\%, 90\%$

  The national standards of park service radius of coverage are the percentage of residential land area that is within park service areas (radius =

500m), and 60%, 70%, 80%, and 90% have been used in related standards. The parameter C defined in the model, however, is the percentage of population within the park service areas which taken population uneven distribution into account with the national standards. Given the slight difference in the coverage definition and high expectation from local government, 80% and 90% were possible inputs for C, and possibility of 100% coverage was also explored.

- Average green space per person A = (1,2,3,… 5,… 18m^2)

The city's Green Space System Planning set the goal of 18m^2, but this figure includes all urban and rural spaces, as long as in the city's jurisdiction. And from the above analysis of the city green spaces, apparently some rural hills are not feasible for public access purpose. If these infeasible green space areas are removed from the calculation, the average green space area per person should be much less than 18m^2, especially for city centers.

The State Council requires a green space area per person for the city downtown areas to be no less than 5m^2 by 2015 which make much more sense for public access studies. Though, it is still a general average across the entire area of both dense and sparse neighborhoods. So, even if a city meets the average 5m^2 goal, the per capita green space area may be much larger than 5m^2 for some neighborhoods in downtown, and much lower than 5m^2 for other neighborhoods.

This parameter will be used in this study for demand allocation rather than as a simple average value. With 5m^2 the coverage of dense neighborhoods may be very poor, which will in turn reduce the overall percent population coverage. So this parameter is not a static number in the models, a set of numbers will be used to find the tradeoff of it with coverage.

3.6 Summary

Existing park and green space distribution in the study area was first analyzed in GIS and location-allocation models, then potential green spaces sites were included in the second set of location-allocation models to examine the proper green space distribution with related costs. In order to formulate appropriate location-allocation models, the complexity of green space location related specific problems has been explored in this chapter. Beside model formulation, the following related issues were discussed, and different parameters with various values would be used in the models.

Table 3-6 The model-formulation related issues that were discussed in this chapter

<table>
<tr><th>Model Major Components</th><th>Regular Topics in LA Problem</th><th>GS Specific Topics</th><th>Space Standards</th></tr>
<tr><td rowspan="3">Green Space (j)</td><td></td><td>As polygons, not points</td><td>% population coverage (C)</td></tr>
<tr><td></td><td>Supply: slope corrected area (bj)</td><td>Minimum size of GS (S)</td></tr>
<tr><td colspan="2">Types (tj) of gs and related cost (ftj)</td><td></td></tr>
<tr><td rowspan="2">Residential Sites(i)</td><td>Population estimate (pi)</td><td></td><td>Average demand per person (A)</td></tr>
<tr><td colspan="2">Point Aggregation (fishnet)</td><td></td></tr>
<tr><td>Distance(dij)</td><td>Distance measures</td><td>Distance between a point and polygon</td><td>Maximum distance threshold (D)</td></tr>
</table>

CHAPTER 4

RESULTS AND DISCUSSION

The main components of this chapter are shown in Figure 4-1. Firstly, the existing green spaces in the study area were analyzed. Two popular green space standards, which are also widely used for cross city comparisons, were also calculated. These two standards are average green space per person, and percent green space coverage. Secondly, the maximal covering location model was run for existing green spaces, followed by the same model applied to all green space candidates including potential ones. Then, with the analysis results from these models, the capacitated location-allocation model was run with the objective of minimum green space construction costs. Various parameter inputs were used, and the most appropriate ones were selected from the cost-effectiveness curves. Finally, the models outputs with these selected parameter inputs were further analyzed: for each green space candidate site, the amount of demand it can serve in the model solutions were compared, site by site. Therefore, the relative importance of each green space sites was able to be achieved, so that all green space candidate sites can be classified into various groups according to their performance in the selected model outputs, and implementation strategies can be proposed for each class of green space sites. In addition, the impact of applying different distance measures to the models is also discussed in this chapter.

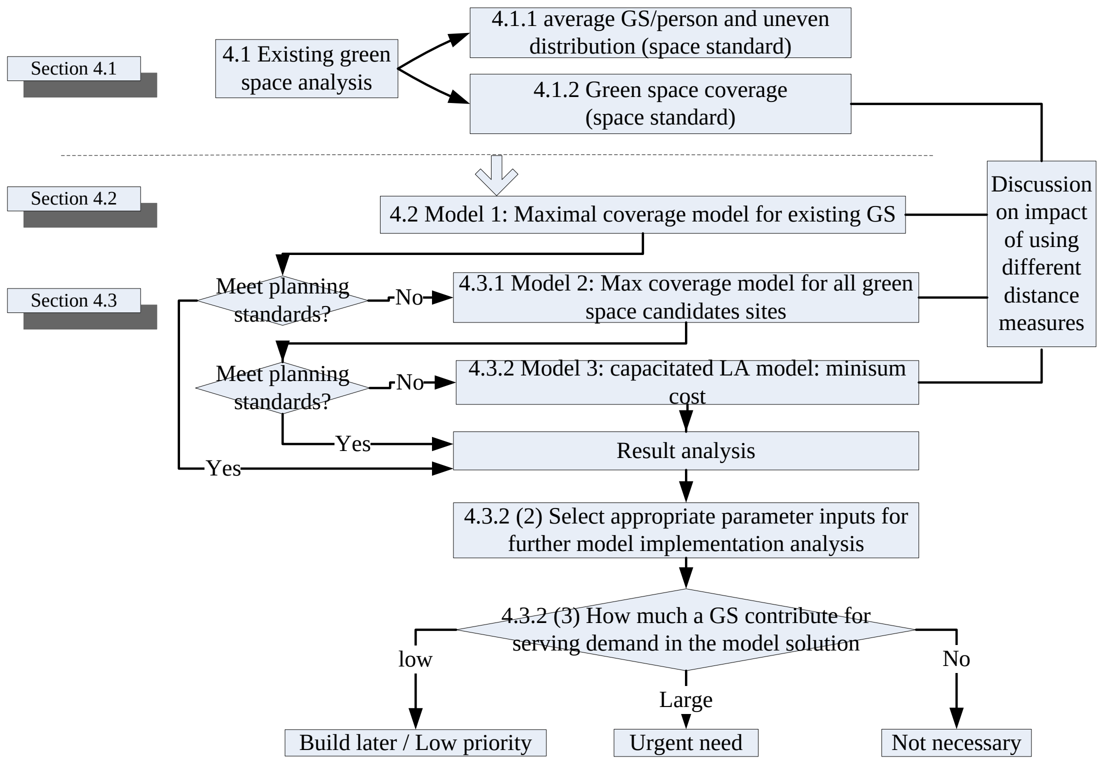

Figure 4-1 Diagram of result analysis

4.1 Existing Green Space Distribution in Study Area and Related Indices

4.1.1 Average Green Space per Person Value

Green spaces are unevenly distributed in the study area. The following figures have been calculated for Luohu District: the average green space per person is about 37m^2/person, which is a very enjoyable amount from a health viewpoint. However, from the green space distribution, the majority of green spaces in the district are too far to visit (Figure 4-3). Taking only the green spaces that are within 500m to

Figure 4-3 500m buffers around residential buildings: most green spaces can hardly be reached

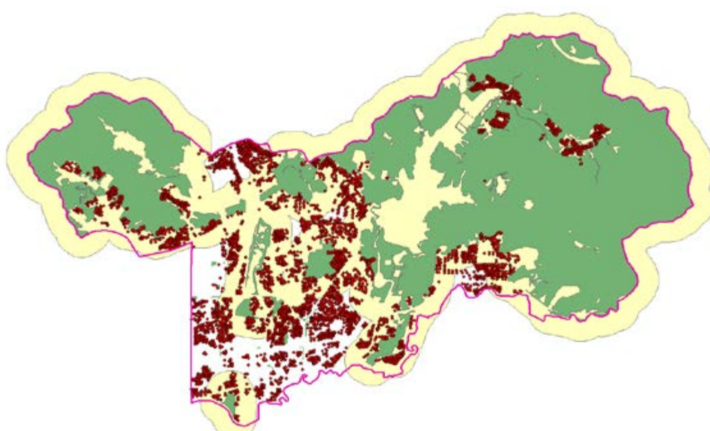

Figure 4-2 500m buffers around large green spaces residential sites into account, the average “accessible” green space for each person is $15m^2$.

Another set of buffers is created for large city parks, neighborhood parks and open green space with area greater than $10,000m^2$, see Figure 4-2. These three types of green space account for about 99% of the total area of green spaces in the district, but only serve 62% of population if 500m Euclidean Distance is used as service radius. The two largest green spaces, one to the west and the other to the east, only cover 26% of the population, but the area is 92% of the total green space area.

Feasible area modified by slope correction factors

Topography of the study area shows that many green spaces are too steep for public recreation access (see Figure 3-5, or DEM model in Figure 4-4). The slope ranges from 0-54 degrees. 40.5% are between 0-15 degrees, 48.3% of green spaces are between 15-30 degrees, and 11.2% of green spaces are too steep with slope over 30 degrees (Figure 3-5).

Using the slope correction factors discussed before, the total green space area was modified to reflect that area where land is flat or low slope. For the corrected green

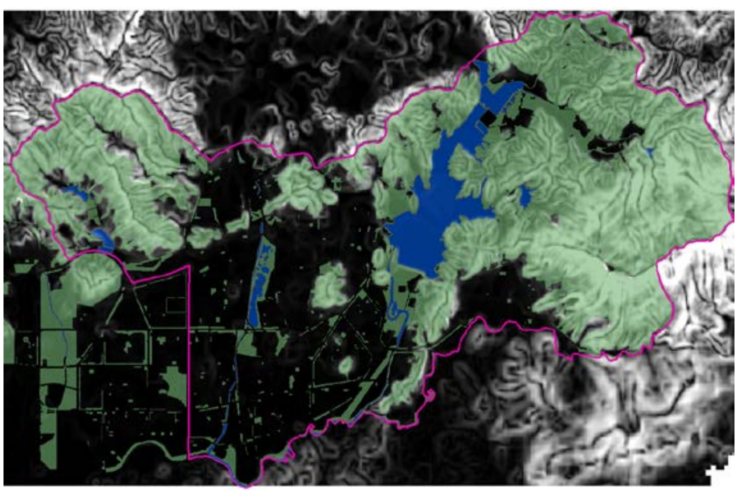

Figure 4-4 DEM in Luohu, slope range 0-54 degrees

space area, the average adjusted area of green space that can be reached from residential buildings in 500 meters reduced to 11m^2 per person.

<u>Green spaces in the city center</u>

By removing the two largest suburban green spaces and their nearby neighborhoods within 500 meter service distance, it was determined that the rest of population, 74%, who live in urbanized areas, the average green space per person is only 3.8m^2, and 2.97m^2 after slope correction.

In short, the following table and figure (Figure 4-5) reveal that the average green space per person decreases dramatically from 37m^2/person to only 3m^2/ person after corrections for additional factors, including locations in center city or suburban, slope correction, and within 500 meters of the residences.

	district	distance concern		district center (8% GS serve 74% pop)
		GS in 1000m (74.2% of GS)	GS in 500m (41.8% of GS)	
GS/person	36.8	27.3	15.4	3.8
Slope-corrected GS/person	23.7	19.3	11.1	3.0

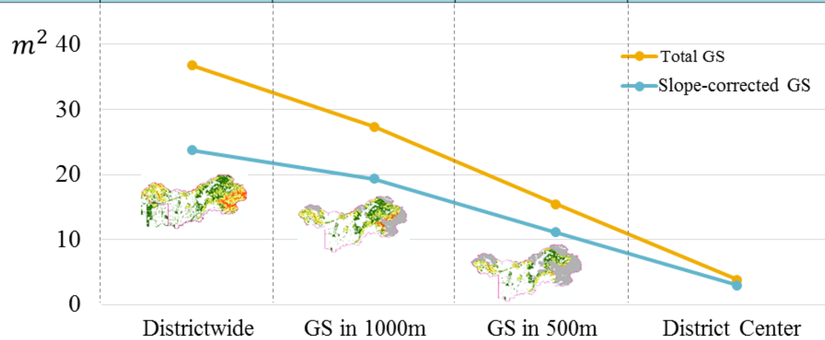

Figure 4-5 Average green space area per person (m^2)

4.1.2 Green Space Service Coverage

The basic percent coverage of green spaces in service radius refers to the percentage of residential land that is within green space service radius. Using count of residential sites can improve this figure by changing the meaning to percent of residential sites that are within green space service radius; and population can make even better sense, by which it means how many people in total population are in green space service areas.

The percentage of residential sites and the percentage of the population that are within a 500m service area of existing green spaces, including parks and non-park green spaces, were calculated. In calculating the percentage of residences and of population within a 500m area, not only Euclidean distance was used as a classical service radius measure, but the other three distance measures discussed in Chapter 3 (Manhattan distance, network distance and adjusted network distance) were also applied in calculating the 500m distance measurement. The calculation results in

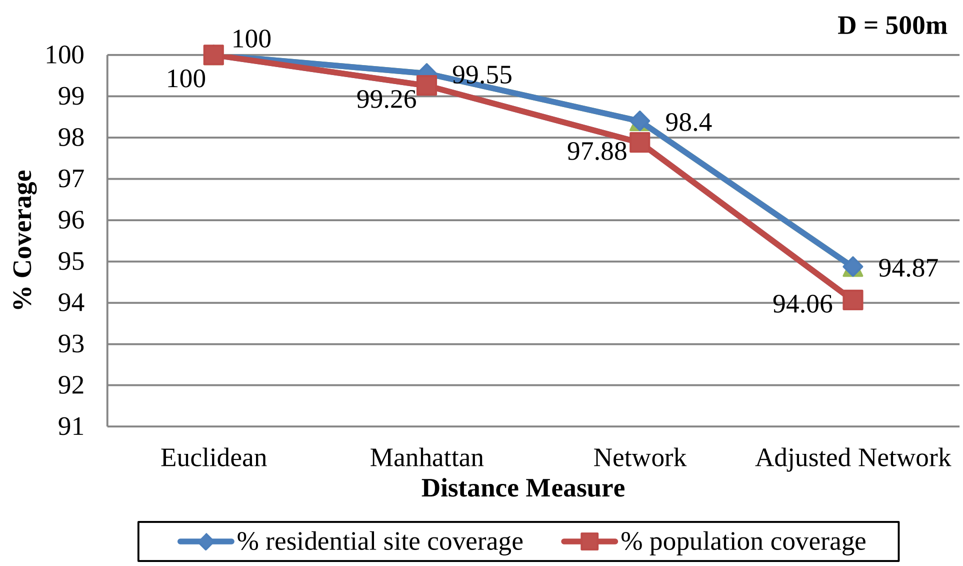

Figure 4-6 500m green space coverage in the study area

Figure 4-6 shows that the residential sites coverage is higher than population coverage with existing green spaces' 500m service distance. That indicates the population proportion in residential sites that cannot access a green space with 500m is larger than the proportion of those residential sites, which mean some residential sites with high population are not covered by existing green space 500m service area.

All residential sites, and all people living in those residential sites, can access at least one green space within 500m Euclidean distance. However, if the 500m service area is measured by other distance measures, the both percent coverage for residential sites and population drops. Percent coverage measured by Manhattan distance is less than one percent lower than that by Euclidean distance measure (100% coverage). Percentage coverage drops by about 2 percent is use network distance measure. Adjusted network distance lead to larger decrease of coverage, 94.87% of residential sites and 94.06% of the population can access green space within 500m adjusted network distance.

Then, how would these four distance measures perform if a different distance threshold was used? Alternatively, distance thresholds of 300, 400, 500, and 600m were calculated separately. The results in Figure 4-7 reveal that as the distance threshold increases, the differences among the coverage figures calculated by the four distance measures are not large, since the coverage figures are all approaching 100% when the distance threshold increases, no matter which distance measure is used. On the other hand, when the distances from residences to green spaces are relatively small, different distance measures can lead to significantly different results. For example, when using 300m as service area threshold, the residential site and population coverage are 96.5%, 96.0% with Euclidean distance measure, 93.1% and 91.9% with Manhattan distance measure, 98.9% and 88.1% with network distance measure, and only 77.5% and 73.3% with adjusted network distance measures. There is a large

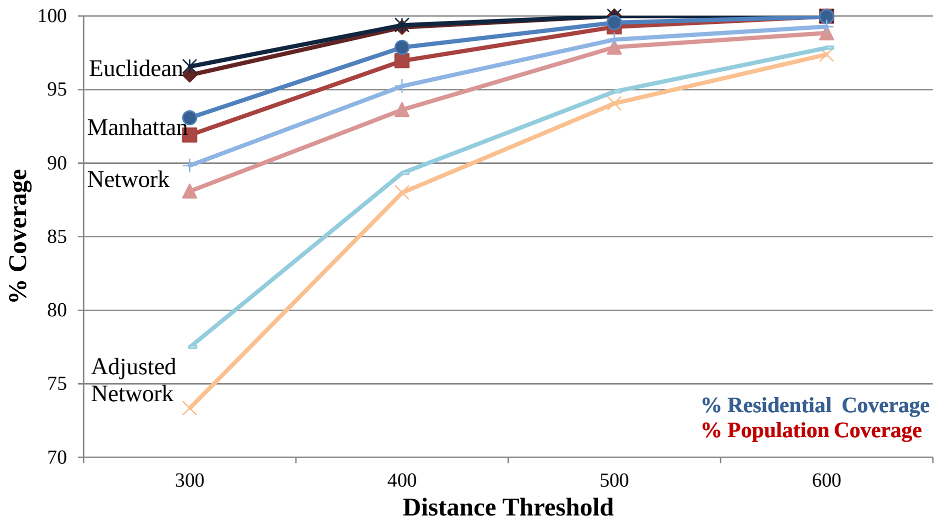

Figure 4-7 Coverage with different distance thresholds

difference between the results from network distance and adjusted network distance, especially when small distance thresholds are used, this is because that the offset distance to the streets, the values used to adjust the network distance, weigh heavily in short distance calculations.

In short, using different distance measures can return different coverage results. Since Euclidean distance measures the nearest distance between two features, the calculated coverage is always higher than, if not equal to, other distance measures. This is especially observable when using small distance thresholds.

4.2 Current Green Space Maximum Coverage

In this section, the solutions to the capacitated maximal covering location model for current green spaces are presented. The maximum coverage of existing parks and green spaces are compared, with different distance measures and expected average green space per person.

Figure 4-8 shows the cost-effectiveness acceptability curves for the capacitated maximal covering location model defined for current green spaces with the maximal distance threshold fixed at $D = 500m$. The four curves are the model results with different distance measure inputs, Euclidean, Manhattan, network and adjusted network distances, respectively. The curves represent optimal solutions of the capacitated maximal covering location model with dynamic input parameter of average green space per person standard. Generally, no matter what distance measure is used, the population coverage of green space service area decreases significantly when each person shares more green spaces.

With Euclidean distance measures, the decrease in the number of people covered by increasing one square meter of average green space per person standard increases as the standard increases between 0 and 8m^2/person, and for the standard over 9m^2/person, the number of the population covered decrease gradually. With Manhattan distance, the number of people decreases evenly less than and greater than 9m^2/person of the standard, though the decrease when less than 9m^2/person is larger

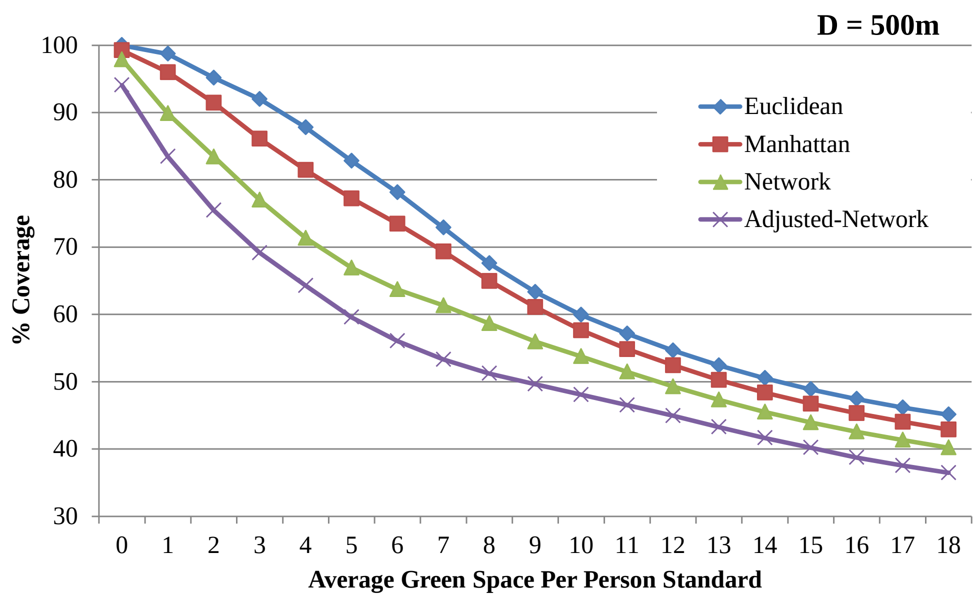

Figure 4-8 Comparison of coverage with different average GS/person input for current green spaces: D = 500m

than when the standard increases to be larger than $9m^2$/person. With network and adjusted network distances, the decrease in number people covered by increasing $1m^2$ of the standard decreases as the average green space per person input increases to $7m^2$/person, then a consistent decrease of the population covered by unit increase of the standard input when it is greater than $7m^2$/person. Generally, if the average green space per person standard input is between $1m^2$/person and $10m^2$/person, the maximal population coverage within green space service area decreases significantly while the standard increases. Using Euclidean and Manhattan distance measures can return higher maximal coverage results; the maximal coverage will be much lower when using network and adjusted network distance measures.

The city's goal is to have average public green space per person of $18m^2$ by 2020. If $18m^2$ is used in the model as input, which means the average green space within 500m distance for each person is $18m^2$, the maximal coverage is below 50% (45.1% with Euclidean distance measure, and only 36.5% with adjusted network distance measure). That is, only less than half of the population can be ensured to $18m^2$ of green spaces with 500m, and the majority of the population, though can reach green space within 500m, the amount of green spaces are not guaranteed, and some green spaces can be too occupied with large amount of people.

The slope corrected green space per person within 500m calculated in Chapter 3 is $11m^2$. However, this average doesn't ensure that each person has green space of $11m^2$. The maximal covering location model results shows that when $11m^2$ is used for demand allocation and capacity restriction, the maximal coverage is less than 60%: 57.1% with Euclidean distance measure, 46.5% only with adjusted network distance measure. This means that less than 60% are allocated with $11m^2$. Over 40% of people are not assured for the amount of green spaces, and again, some existing green spaces may be too occupied to meet public need.

Five square meters of green space area per person in the downtown area are an index of the national standards, which is also a minimum requirement to 60% of green space coverage by the State Council. When $5m^2$/person is used in the model for demand allocation, the maximal coverage is 82.8% with Euclidean distance measure, and 59.6% with adjusted network distance calculation. Using Euclidean distance, 82.8% of the population's demands of $5m^2$/person are satisfied. It may be surprising that the calculated average green space per person is $11m^2$ which is much higher than $5m^2$/person, still there are large amount of population (17.2% if use Euclidean distance, and more if other distance measures are used) cannot be ensured for than $5m^2$/person. The reason is the uneven distribution of population and green spaces. Apparently, there is a supply gap of green space in dense neighborhoods, on the contrary, people in sparse neighborhoods can enjoy more than $11m^2$ Green space on average. So apparently there is a need to increase the amount of green space areas in dense areas.

Alternatively, the relationship between values of average green space per person standard and coverage can be interpreted as below:

Table 4-1 Maximal values of green space/person for coverage percentage benchmarks (Unit: m^2/person) – existing green spaces only

	90% Coverage	80% Coverage	70% Coverage	60% Coverage
Euclidean	3.5	5.6	7.5	10
Manhattan	2.3	4.4	6.8	9.2
Network	1	2.5	4.3	7.5
Adjusted-Network	0.4	1.4	2.8	4.9

With Euclidean distance measure: as much as 90% of the population can access a green space within 500m with 3.5m^2 demand of green space for each person. If the standard increase to 5.6m^2 Green space for each person, only 80% of population's demands can be met. If we want the standard to be as high as 7.5m^2, only 70% of demand can be met, and when the average green space per person increase to 10, only 60% of demand can be achieved by existing green spaces. Similar interpretation for another three sets of values for Manhattan, network and adjusted network distance measures.

Apparently, Euclidean results seem much more inspiring, for example, 90% of residents can access green space within 500m with at least 3.5m^2 of green space for each person, compared with the statement that 90% of residents access green space within 500m along streets with less than 1m^2 green space each.

4.3 Location-Allocation Model Results for All Candidate Green Spaces

Besides existing parks and non-park green spaces, additional potential green space sites are involved in the following models, including additional planned green space (on vacant land or on renewal sites) and vacant land. With all candidate green spaces, the average green space within 500m increases from 11.1m^2 to 11.9m^2.

4.3.1 Maximum Coverage of All Candidate Green Spaces

Maximum covering location models were solved for all green space candidate sites, including both existing ones and potential ones. Figure 4-9 shows cost-effectiveness acceptability curves for the capacitated maximal covering location model defined for all green spaces (including current ones and potential ones) with the maximal distance threshold fixed at $D = 500m$, overlaid with the cost-effectiveness curves for existing green spaces from the previous section. The curves in dark colors represent optimal solutions of the models for all candidate green spaces with a dynamic parameter A up to 18m^2/person. The curves in light colors are the corresponding results in the last section for models on only current green spaces. Clearly, the patterns of the curves for green candidate green spaces are very similar to that for current green spaces. When more area of green space is assigned to each person, the population coverage of green space service area decreases. And there is no doubt that the population coverage level is overall improved when potential green spaces are involved in the models.

Table 4-2 is a summary table on percent coverage benchmarks and corresponding maximal the green space per person. It can be interpreted in the similar way to the table in the last section. As much as 90% of the population can access a green space within 500m with 4.5m^2 demand of green space for each person, or alternatively, in order to achieve 90% of the population coverage goal, the average green space for

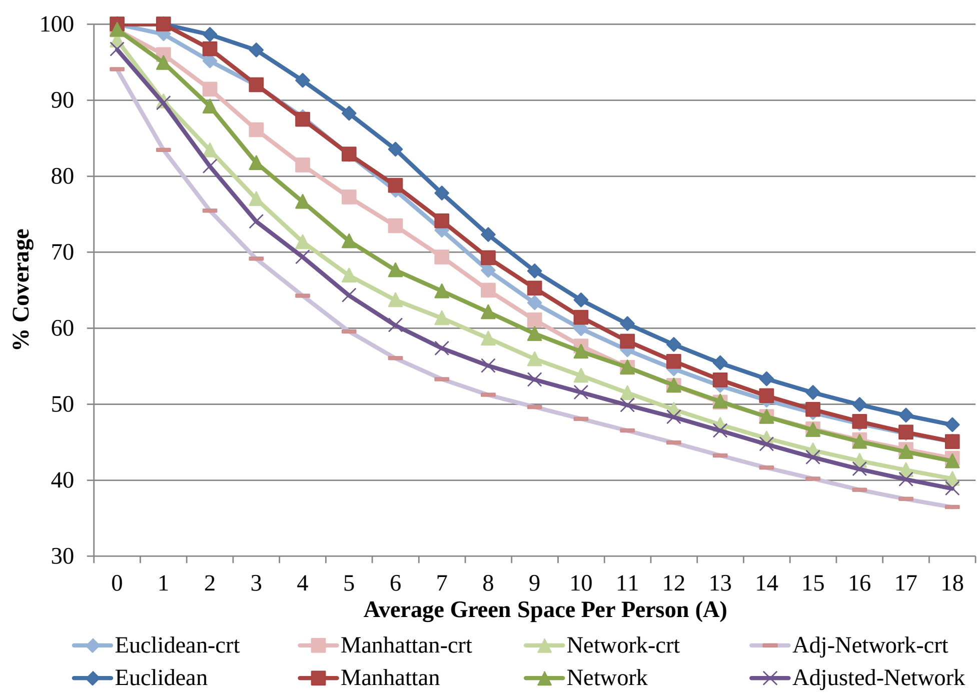

Figure 4-9 Comparison coverage with different average GS/person input for green spaces candidate sites: D = 500m

each person can be no higher than 4.5m^2; if more than 4.5m^2 green space for each person is expected, 90% of the population coverage cannot be reached with all candidate green spaces input. If 4.5m^2 and 90% coverage is mandatory, extra places have to be found as potential green space sites and added to the candidate green space pool.

Table 4-2 Maximal values of green space/person for coverage percentage benchmarks (unit: m^2/person) – all candidates

	90% Coverage	80% Coverage	70% Coverage	60% Coverage
Euclidean	4.5	6.6	8.4	11.2
Manhattan	3.4	5.7	7.9	10.4
Network	1.8	3.3	5.4	8.7
Adjusted-Network	0.9	2.2	3.9	6.1

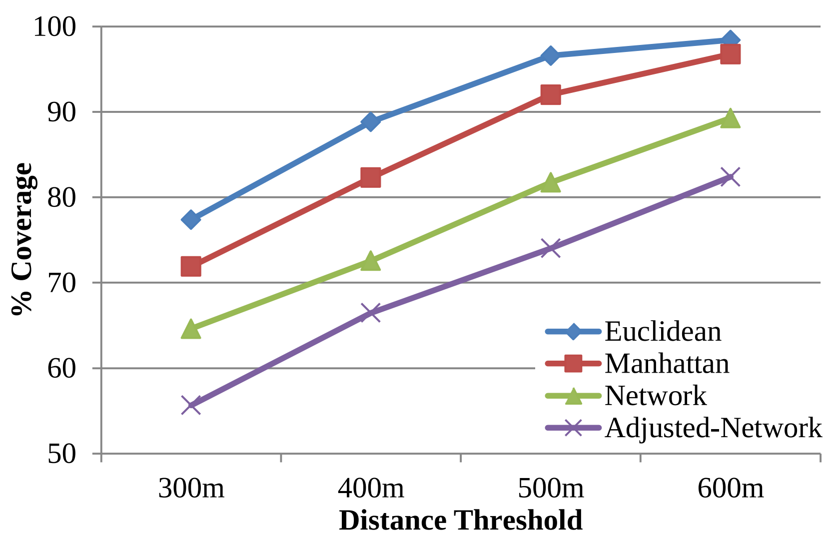

Figure 4-10 Green space max coverage with all green space candidates: A = 3m^2/person

Next, take a closer look with fixed A = 3m^2/person. With A = 3m^2/person as average green space per person as input, the maximal coverage is calculated for different distance measures and distance thresholds of 300, 400, 500 and 600m (see Figure 4-10). The results show significant differences between different distance measures, and while distance threshold change, the maximal coverage is also much higher, similar to the findings in the last section.

Then the model results are compared with those of a maximal covering location model for existing green spaces with a fixed average green space per person at A = 3m^2/person and distance threshold D = 500m (Table 4-3). With additional potential green spaces, the maximal coverage of the population that can visit a green space within 500m with 3m^2 green space per person allocated is 96.58%, the distance measured by the Euclidean distance measure. While with network distance measures, 90% population coverage at A = 3m^2/person and D = 500m can never be achieved, and with the adjusted-network distance, the maximal coverage cannot even reach 80%.

Table 4-3 Maximal Coverage Improvement with Additional Potential Green Spaces: A = 3m^2/person

	Euclidean	Manhattan	Network	Adjusted-Network
Max Coverage for Existing Green Spaces (%)	91.98	86.11	77.00	69.14
Max Coverage for all Green Space Candidates (%)	96.58	92.02	81.74	74.03

4.3.2 Minisum Capacitated Location-Allocation Model Results

(1) Impact of the four distance measures on model results

The maximal covering location model returns the maximal coverage with all green space candidates without any preference or priority given to any green spaces being chosen. While in practice, efficient use of existing green spaces and sufficient new green spaces for demand gap is always expected, so the second model was introduced to reduce green space construction cost so that new green spaces will not cost much while certain service area coverage can be achieved.

In order to further explore the potential impacts of distance measures on model results, feasible model solutions have to be obtained. From last section and also observed from Figure 4-11, it can be observed that with A = 3m^2/person and D = 500m, both network and adjusted-network measures would not lead to feasible solution if the population coverage constraint is set as greater than or equal to 90%; even if the

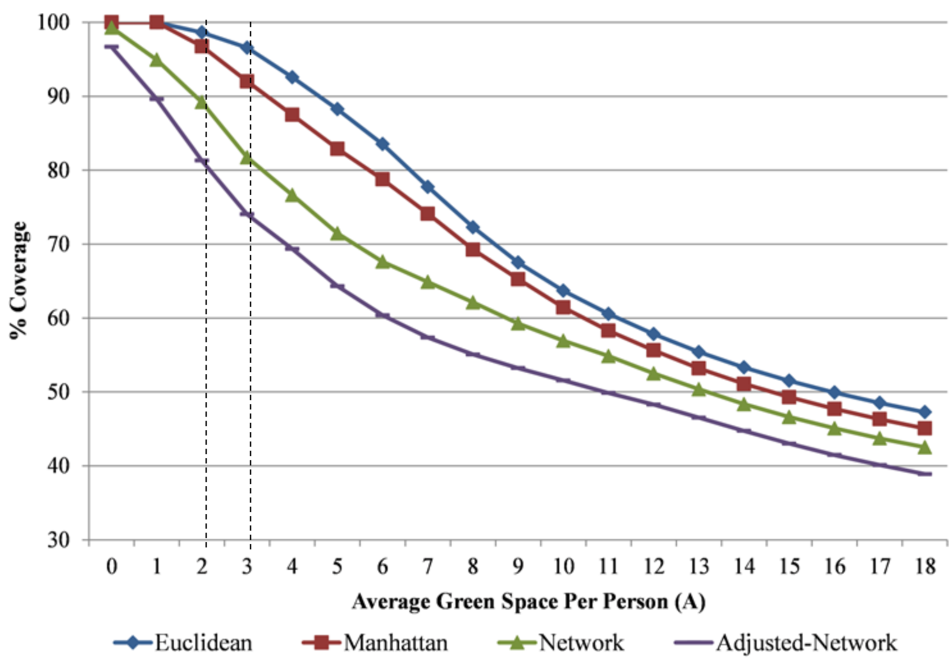

Figure 4-11 Cost-effectiveness curves:
A = 2m^2/person, C > 80% for the four distance measures

coverage constraint is set to be no less than 80%, it is still impossible to get a solution when adjusted-network distance is used. The highest parameters with which a feasible solution can be found for adjusted-network distance at D = 500m and C = 80% (population percent coverage of green space service areas) is A = 2m^2/person (average green space per person is 2m^2/person), or in other words, with adjusted-network distance, 80% of population can reach a green space within 500m distance measured by adjusted-network distance with demand of 2m^2 green space for each person. So the minisum capacitated location-allocation model is performed at A = 2m^2/person, C = 80%, D = 500m, for the four distance measures separately.

Results in Figure 4-12 shows that in order to achieve 80% of population with access to a green space within 500m for 2m^2 each, cost for the model with the adjusted network distance measure is tremendously large, more than 20 times of the cost with Euclidean distance measure, 8 times of that with Manhattan distance measure, and 5

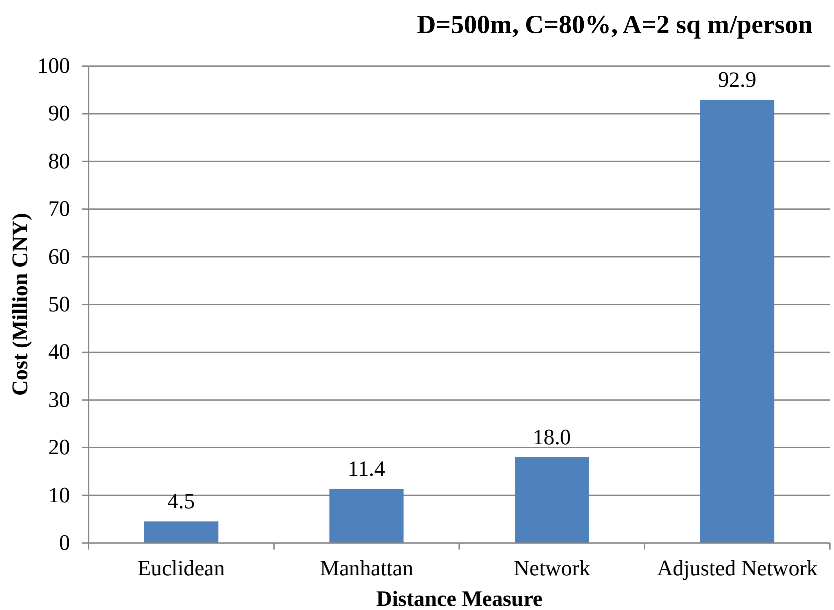

Figure 4-12 Cost estimate with the four distance measures:
D=500m, C=80%, and A=2 sq m/person

times of the cost with network distance measure – though it is just a slight adjustment of network distance by adding the offset distances of demand points and green space sites to street network. The large cost difference between the network distance measure model and the adjusted-network distance measure model is also because the network distance is underestimated given the fact that a large amount of demand point-green space pairs have a shorter network distance estimate than the straight-line distance. If this problem is fixed, the cost with same parameter inputs for the network distance model should be much higher than the presented result and close to the cost in the adjusted-network distance model, given that the adjusted-network distance in fact fixed the problem though generating some overestimates in short distance measurements, as discussed in Chapter 3.

Though the cost solutions with these distance measures differ so much, some common conclusion can be drawn if the model results on green space selection are examined in depth. For example, Table 4-4 shows a part of model solutions for existing non-park green spaces with their percent contribution to meet overall demand. For each of four models with different distance measures, non-park green spaces are ranked according to their corresponding demand contribution. Top 10 of each model are listed below.

There are some non-park green spaces with high ranks in all four models, such as green spaces with ID 179, 134, 268, 309 and 82, marked in red color. These green spaces served a large amount of demand, especially in network and adjusted-network measure models, though some of them may not serve much in Euclidean model, they still have high ranks, that means if there is a need to convert existing green spaces into parks with more recreation facilities and infrastructures, these green spaces should have priority.

Another group was marked in yellow, including green spaces with ID 216, 11, 90, 181 and 22. These green spaces in some of the models can serve more than 0.5% of demand, though their contribution in Euclidean and Manhattan models are poor, that's because most demand in these models can be met by existing parks.

The rest of green spaces with ID 81, 211, 23, 341, 117, 77 and 103 are marked in light blue. No matter what its rank is, none of them in any model serve more than 0.5% of demand. Since they will not contribute much, they are not in urgent need of more investment in facilities and changing to well-managed parks.

Table 4-4 Model results of non-park green space ranked by served demand: A=m^2/person, C=80%, D=500m

GS ID	Euclidean		Manhattan		Network		Adjusted Network	
	assigned demand	rank	assigned demand	rank	assigned demand	rank	assigned demand	rank
179	0.46	2	0.67	5	2.78	2	2.78	1
134	1.13	1	3.31	1	3.17	1	2.49	2
268	0.36	4	0.87	2	1.29	3	1.73	3
309	0.23	6	0.77	3	0.77	5	0.77	4
216	0.00	-	0.23	10	0.41	10	0.75	5
11	0.00	-	0.21	13	0.69	6	0.69	6
82	0.27	5	0.69	4	0.69	7	0.69	7
90	0.00	-	0.00	-	0.77	4	0.61	8
181	0.02	22	0.06	36	0.60	8	0.60	9
81	0.00	-	0.00	-	0.04	57	0.60	10
22	0.01	31	0.02	44	0.54	9	0.54	11
211	0.00	-	0.33	7	0.33	13	0.49	12
23	0.19	8	0.36	6	0.35	11	0.36	17
341	0.23	7	0.23	11	0.08	39	0.23	26
117	0.15	10	0.14	18	0.11	29	0.16	31
77	0.17	9	0.29	8	0.17	21	0.10	44
103	0.41	3	0.29	9	0.27	14	0.04	67

(2) Green space cost and service improvement

Last section compared cost with different distance measures, with same parameter inputs of A=2m^2/person, C=80%. This section investigated the relationship between cost and green space service improvement, including an increase in both percent population coverage and the average area of green space per person. Parameter A changes from 2m^2/person to 6m^2/person; C changes from 80% to 90%. Euclidean distance measures are applied in this section. The cost results were shown in Figure 4-13.

Costs increase smoothly for 80% coverage (blue bars in the figure), until when average green space per person increase to 6m^2/person, the cost jumped to about two

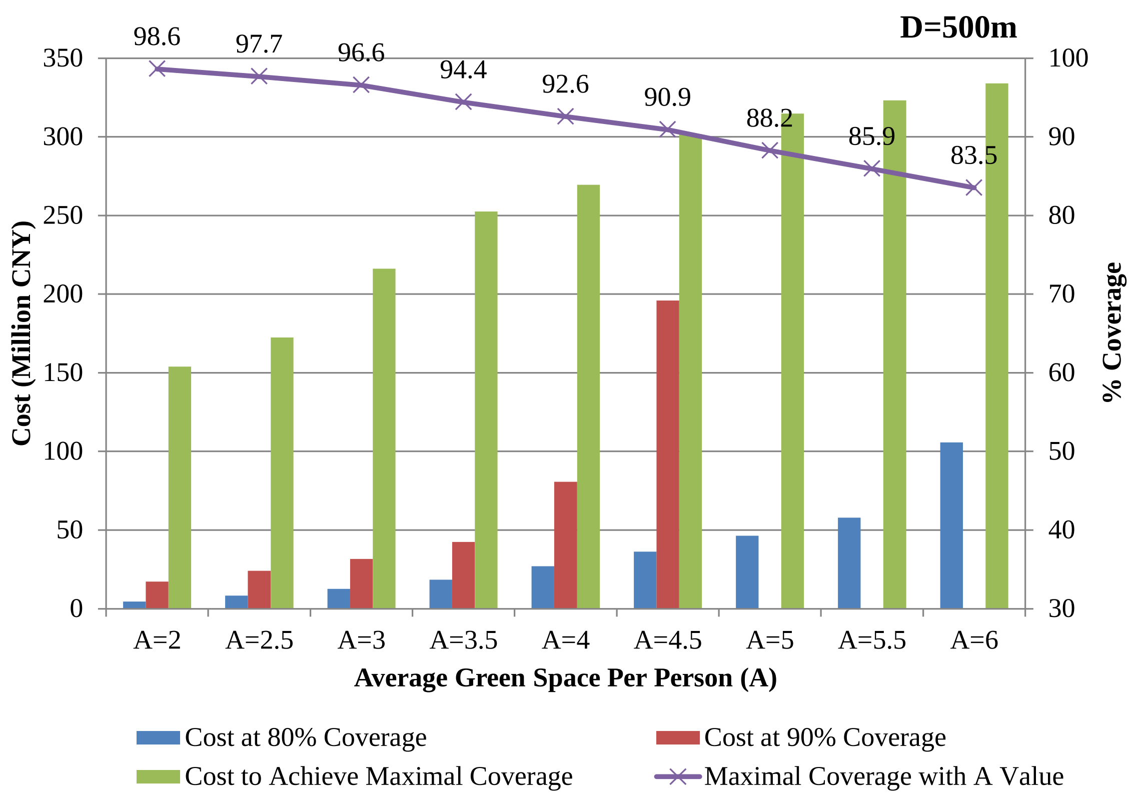

Figure 4-13 Green space costs derived for C=80% and 90%

(Cost at maximal coverage is also placed aside for comparison) times of the cost at A=5.5m^2/person. The cost at A=5.5m^2/person for 80% coverage is between the costs at 3.5m^2/person and 4m^2/person for 90% coverage. If 90% coverage is expected (red bars in the figure), costs increase smoothly, then have a slightly large increase when A increase to 4, and from A=4 to A=4.5m^2/person, the cost to meet 90% coverage goal increase excessively with more than twice of the cost at A=4m^2/person. For A equal to or greater than 5m^2/person and coverage = 90%, no feasible can be found which means with all green space candidates, the goal of 90% of the population being able to enjoy 5m^2 or more green spaces cannot be reached at all, no matter how much would be spent. So from the perspective of cost's marginal utility, A=3.5 can be the most recent goal, that is, 90% of the population can access 3.5m^2/person on average within 500m, then increase to 4. The long-term goal is to increase the average green space per person to 4.5. Of course, if there is enough budget, or new potential green spaces are found in the future, the goal of A = 4.5 become a medium-term goal and long-term goal can be reset to coverage higher than 90% or average green space per person higher than 4.5m^2/person or both. Though the costs for some solutions are quite close, for example, 80% coverage at A=5 and 90% at 3.5, the model with 90% coverage at 3.5m^2/person is preferred than a 80 % solution, from public equity perspective. It is expected that more people can visit certain amount of green spaces, rather than a smaller group of people visit large green spaces but demand for the rest cannot be met.

The auxiliary bars of cost for maximal coverage at corresponding A value show that these costs are much higher than the cost of meeting 80% or even 90% coverage. For example, at A=4, the cost related to 80% coverage is 27 million CNY, 81 million for 90%, and 270 million for the maximal coverage of 92.6%. From 80% to 90%, an expenditure of 54 million can improve green space coverage by 10 percentage points, however, from 90% to 92.6%, 189 million CNY has to be spent for 2.6 percentage point improvement. So it will not be monetarily efficient to attain the maximal coverage objective, at least it is not proper to be a short-term goal.

4.4 Green Space Site Selection Strategies

In the last section, A=3.5, 4 and 4.5m^2/person were selected as proper standards with 90% of the population visit a green space in 500m distance. The basic goal is to let 90% of population visit green spaces within 500m distance, and 3m^2 for each person is confirmed. The related minimum cost was 42.4 million CNY. An improvement is that 4m^2 can be enjoyed by each of 90% population, and related cost was 80.7million. Increasing green space per person to 4.5m2 is a further improvement, though it will cost much more than the using lower standards, which is 196 million CNY.

To analyze the green space locations with these parameters, the results of three models with D=500m, C=90%, Euclidean distance measure, and A=3.5, 4 and 4.5m^2/person were investigated here (see Figure 4-14, Figure 4-15 and Figure 4-16, respectively). Similar findings in the previous section, the model results of whether a green space is selected or not, and the demand being allocated to each green space is gathered, such that the demand contribution in the entire model solution for each green space can be calculated and ranked. And the following are model results on green space selection, maps colored by the percent of demand being allocated to a green space over overall allocated demand, or it can be called, the green space's contribution to demand.

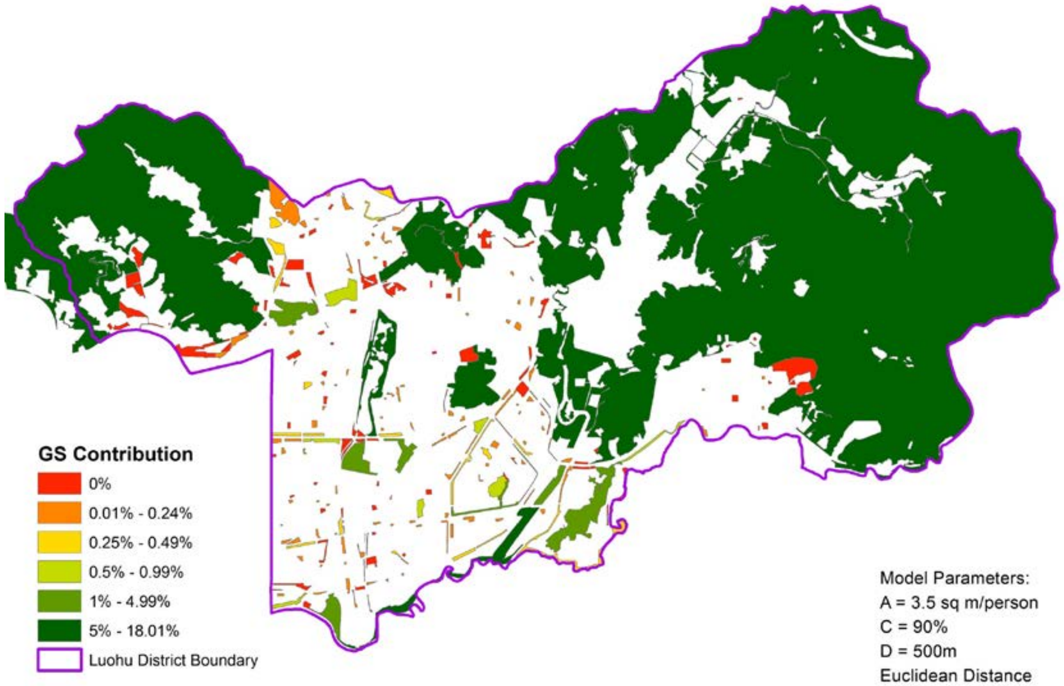

Figure 4-14 Minimal cost - capacitated location-allocation model results: *D* = 500m, *C* = 90% with Euclidean distance: *A* = 3.5

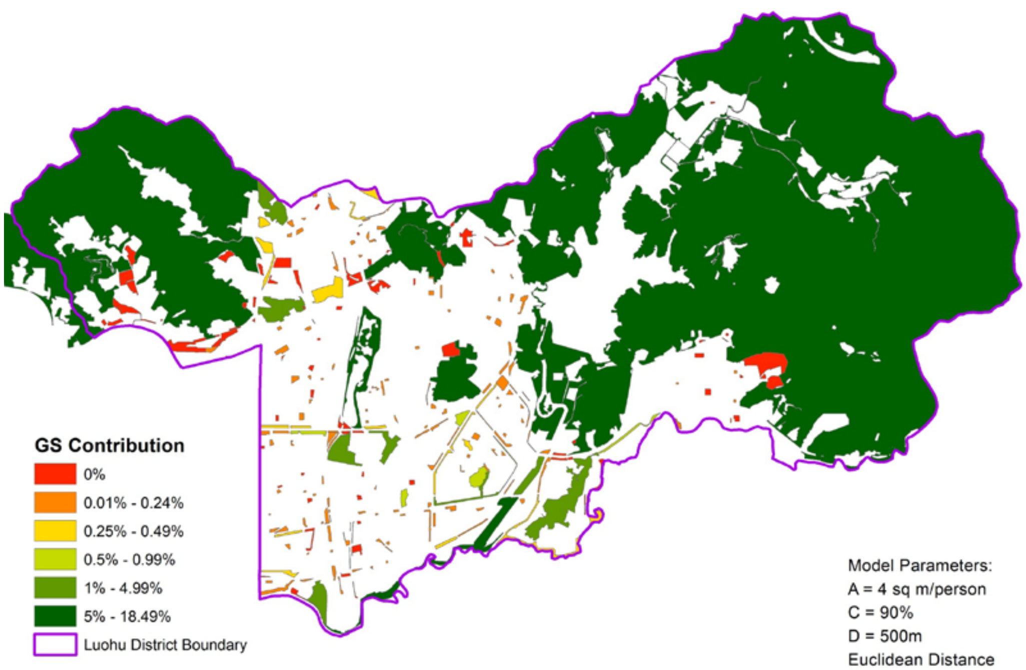

Figure 4-15 Minimal cost - capacitated location-allocation model results: *D* = 500m, *C* = 90% with Euclidean distance: *A* = 4

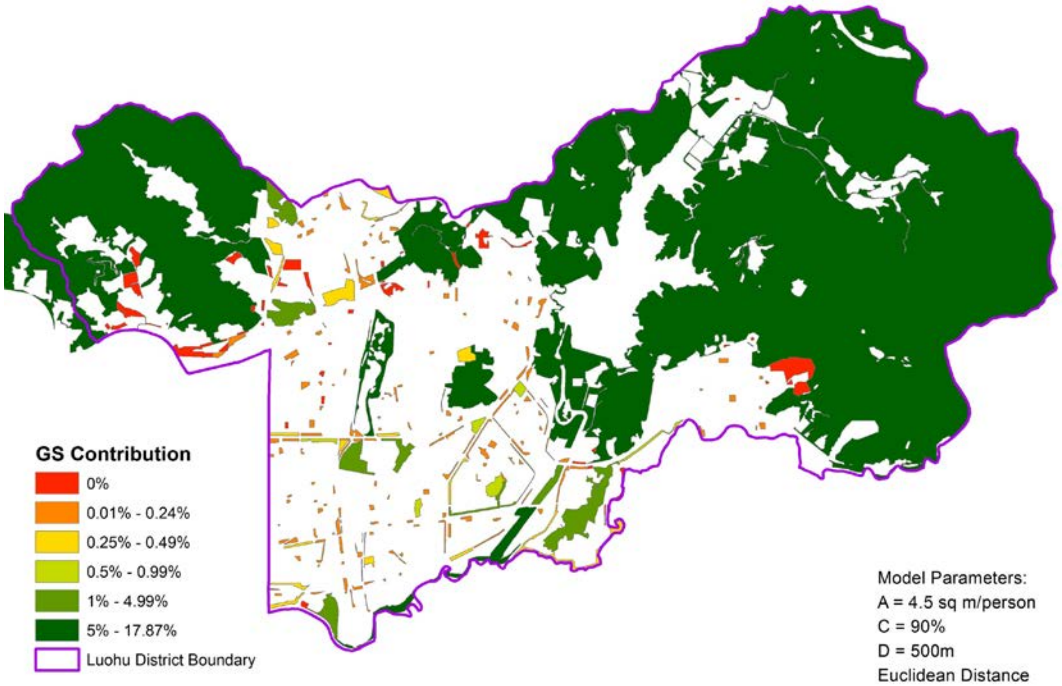

Figure 4-16 Minimal cost - capacitated location-allocation model results: D = 500m, C = 90% with Euclidean distance: A = 4.5

Given that green spaces have different current status which is associated with the cost and potential difficulty in implementation, green spaces were examined and ranked by different types: parks, existing non-park green spaces, vacant land that can potentially be green spaces, potential green spaces but need renewal.

For existing non-park green spaces, top 20 in the results of the three models were examined in Table 4-5, non-park green spaces ranked after 20 were not in the analysis since their demand contribution in all models are very small, usually less than 0.1%. These top 20 non-park green spaces can be categorized into three groups: (1) Green spaces in urgent need. Marked as red in the table, most of these green spaces have high ranks in all three models, and their contribution of serving the public demand is relatively large. The one with ID= 115, though its ranks in A=4 and A=4.5 models are low, it contributes to 0.6% of population demand, and will remain in solutions of later two models, so it is categorized in the first group. (2) Green spaces with lower priority, marked in yellow in the table. Their contribution is roughly consistent with the three models, not too high, but also not too low to be ignored. So construction of these green spaces can follow those in the first group. (3) Green spaces that can be built later, blue records in the table. They did not contribute much or no contribution at all in A = 3.5 model, but their contribution increases when A increases. These green spaces will not help much in meeting current needs, but will be helpful for higher public access objectives of higher demand for each person or higher percent coverage.

Table 4-5 Non-park green spaces in solutions of the three models: *D*=500m, *C*=90% and *A*=3.5,4,4.5

	A=3.5m^2/person		A=4m^2/person		A=4.5m^2/person	
GS ID	Assigned demand(%)	Rank in type	Assigned demand(%)	Rank in type	Assigned demand(%)	Rank in type
134	5.8	1	5.9	1	5.6	1
77	1.6	2	1.7	2	1.7	2
179	1.4	3	1.2	4	1.1	4
211	1.2	4	1.4	3	1.4	3
268	0.9	5	0.8	5	0.7	5
103	0.8	6	0.7	6	0.6	6
115	0.6	7	0.2	22	0.3	16
74	0.4	8	0.4	8	0.3	9
209	0.4	9	0.4	9	0.3	11
309	0.4	10	0.3	12	0.3	14
147	0.4	11	0.4	10	0.3	10
11	0.4	12	0.3	14	0.3	15
82	0.4	13	0.3	15	0.3	17
72	0.3	14	0.3	13	0.3	12
81	0.3	15	0.3	16	0.1	46
181	0.3	16	0.3	17	0.2	19
22	0.3	17	0.2	19	0.2	21
43	0.3	18	0.2	20	0.2	22
188	0.2	19	0.2	21	0.2	24
16	0.2	20	0.2	23	0.2	25
120	0.1	37	0.0	52	0.5	8
90	0.1	39	0.5	7	0.5	7
216	0.0	--	0.3	11	0.3	13

Table 4-6 Vacant lands in solutions of the three models: *D*=500m, *C*=90% and *A*=3.5,4,4.5

	A=3.5m^2/person		A=4m^2/person		A=4.5m^2/person	
GS ID	Assigned demand(%)	Rank in type	Assigned demand(%)	Rank in type	Assigned demand(%)	Rank in type
79	0.1	1	0.2	2	0.2	2
276	0.0	0	0.2	3	0.5	3
280	0.0	0	0.1	5	0.1	5
296	0.0	0	0.0	6	0.1	6
303	0.0	2	1.3	1	1.7	1
310	0.0	0	0.1	4	0.1	4
79	0.1	1	0.2	2	0.2	2

For potential green spaces on vacant land, all the green spaces that are in the solutions of any models are listed below in Table 4-6. All of them do not contribute much when A=3.5m^2/person, but their contribution becomes larger when A increases. So most of them can have low priority, as the second group mentioned above.

There are two exceptions, ID=303 and ID = 276 show a clear pattern of increase in the contribution of meeting demand, especially ID=303 green space can serve 1.7% of total demand when higher green space access (A=4.5m^2/person) is to achieve. It is similar to the third group in the previous section.

Potential green spaces that need urban renewal. Since urban renewal cost is considerably high, the model results in Table 4-7 show that non of these candidate sites are chosen for the first two models, when green space service expectation is higher as *A*=4.5, these green spaces will be in use. As shown in the last model, they were used as least as possible so the their contribution to serve demand is low. These green spaces have low priority for construction.

Table 4-7 Renewal land for green spaces in solutions of the three models: *D*=500m, *C*=90% and *A*=3.5, 4, 4.5

	A=3.5m^2/person		A=4m^2/person		A=4.5m^2/person	
GS ID	Assigned demand(%)	Rank in type	Assigned demand(%)	Rank in type	Assigned demand(%)	Rank in type
102	0.0	0	0.0	0.0	0.1	6
104	0.0	0	0.0	0.0	0.3	2
106	0.0	0	0.0	0.0	0.2	3
127	0.0	0	0.0	0.0	0.2	4
135	0.0	0	0.0	0.0	0.1	7
149	0.0	0	0.0	0.0	0.1	5
222	0.0	0	0.0	0.0	0.3	1

Existing parks are different from the other three types of green space candidates. Since these parks already existing, rather than checking those with high rank and more contribution, it is more interesting to existing parks with low contribution. There are 18 small neighborhood parks not in any of these three models, indicating these small parks are an extra supply for local residents, and residents living in the places near these 18 parks benefit from having more than average amount of green space. For the rest of the parks, since they serve a certain amount of demand, good maintenance is recommended.

Finally, the recommended green space site selections are classified as follows:

For existing parks, most of them have to be kept and well maintained to serve public demand.

For existing non-park green spaces, some are in urgent need to fill the demand gap for large population; some existing green spaces may not be in the lower standard model at A=3.5, but they play important roles in the higher standard model at A = 4 or A = 4.5 to meet higher demand.

For the vacant and renewal land as the candidate sites, similar to existing non-park green spaces, they may serve a lot of people in higher demand models but recently is not in urgent need.

Some of existing green spaces and vacant lands were in the model results, but they would not serve too much demand, both for low and high standard models. According to the model results, they should be built sooner or later but is less important than those serving large demand.

Besides, there are still some candidate sites that have never been chosen in any of the model' solution, even including a small amount of existing parks. For these existing parks and green spaces, they offer extra benefit for nearby residents. For those non-green space candidate sites, the planners or decision-makers do not have to weight them too much in recent green space location plans from the public access improvement perspective.

Figure 4-17 shows the recommended allocation of green spaces, which are classified by their current status and their status in the model solutions, and Table 4-8 reveals the relationship of these classes with implementation strategies.

1) Existing parks that need maintenance
2) Extra existing parks: not in the solutions
3) Extra existing green spaces: not in the solutions
4) Existing green spaces in urgent need
5) Existing green spaces need to be built later
6) Existing green spaces with low priority (low demand)
7) Vacant lands that need to be built later
8) Vacant and renewal lands that have low priority
9) Extra vacant and renewal lands: not in the solutions
10) For the rest: low priority

Table 4-8 Green space classification according to existing status and model results

		Existing parks	Existing non-park GSs	Vacant candidates	Renewal candidates
Strategies	Urgent need		4)		
	Build later	1)	5)	7)	
	Low priority		6)	8)	8)
	No need	2)	3)	9)	9)

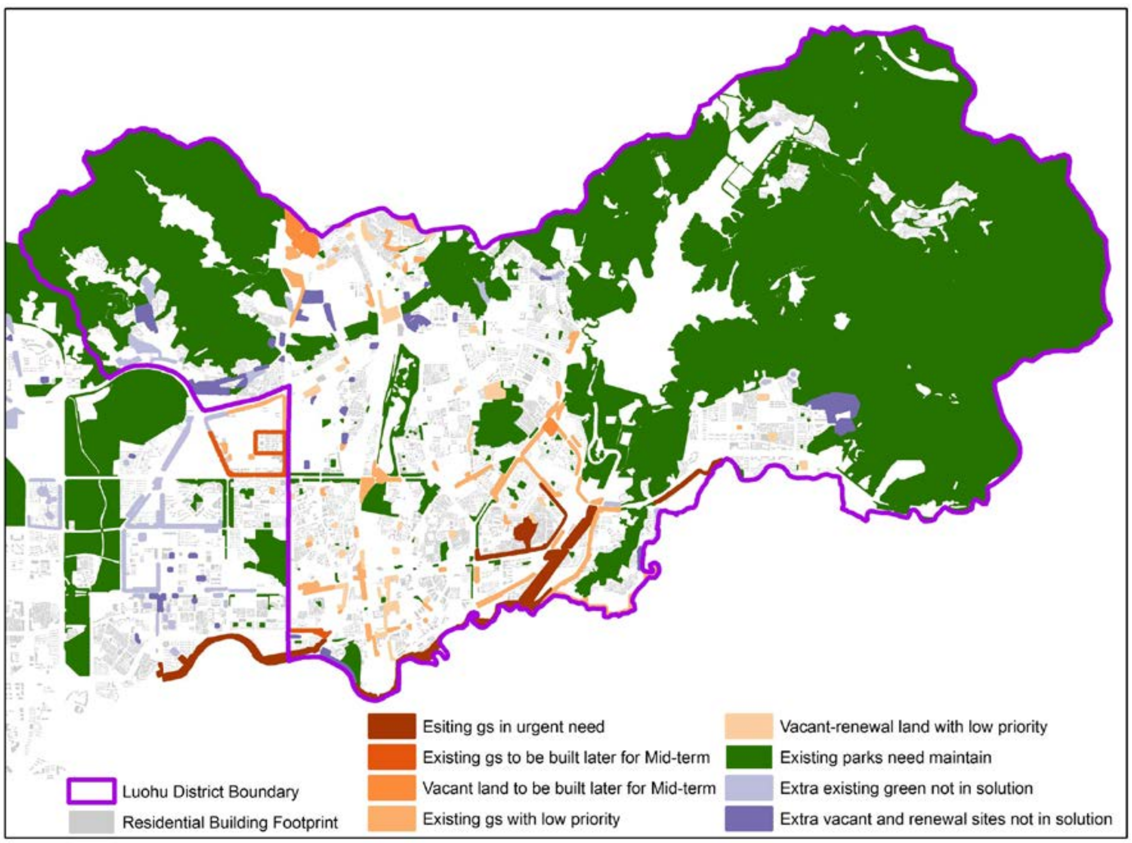

Figure 4-17 Green space location solutions and classification for future implementation

In total, there are 7 existing green spaces that need necessary facilities to open for public recreation use. The adjusted area is about 67 ha. 66 ha of green spaces has to be built sooner or later, class (2) has priority over (4) since it can supply more demand in high standard models, and 39 ha of additional green space are needed, from either vacant land or renewal sites. Since solutions from three models are all involved, from low to high standards, the overall cost of proposed green space location solution will be more than the previous model solution at A = 3.5. The proposed solution, however, takes into account both the low standard that can be achieved in the short term and higher standard that may need longer time to accomplish. The advantage of comprehensively analyzing multiple model results and propose a new solution is that in this new solution, it is possible to distinguish the importance and robustness of the candidates (here, green spaces) across models, so appropriate implementary suggestions can be made for different green spaces.

CHAPTER 5
SUMMARY AND CONCLUSION

The existing and potential green spaces and their service coverage in Luohu District, Shenzhen were evaluated by a combination of location-allocation models with green space planning standards. It was found that though with classical planning standards in an average form to numerically measure the green space coverage, the city has standout results. However, when uneven distribution of population and green spaces are concerned, the figures in some planning standards seem to be too high to achieve. Some areas such as city centers with dense population and limited green spaces always experience a green space shortage, either nearby green spaces are over occupied, or residents have to travel a long distance to visit a green space. In other areas, especially suburban areas, low population is exposed to large amounts of green spaces. Besides, it is not unusual that there are large natural or semi-natural green spaces in suburban or rural areas of a city's jurisdiction. So a city wide average figure does not reflect the shortage of green space in populated areas. On the other hand, most planning standards such as coverage or average area per person can hardly guide a plan actively. The most popular use of these planning standards is to adjust the plan afterward in order to meet certain standard criteria. For example, it is not unusual in planning that, in order to meet an average green space per person standard, the current average green space per person figure is computed for the planning area, then it is compared to the corresponding planning standard, and the gap is calculated, so as the extra amount of green space that is needed. Then planners will find that amount of area for new green spaces so that the planning standard can be met. A contribution of this study is that, for planners and decision-makers a possible approach with location-allocation models was explored in more actively involve such planning standards in location selection process while the uneven distribution pattern of population and green spaces was also taken into account. In such a way, locating new green spaces is not only just for meeting planning standards, but also to promote respect for the equity of public access across the entire interest area.

This study demonstrated that most popular planning standards on green spaces can be incorporated into location-allocation models, such as the demand standard on average green space per person, the green space coverage standard, the distance standard for maximal distance that a green space can serve, and the minimum size of parks in definition. This study also pointed out to planners who may use a similar modeling approach that the figures from these standards may not fit the models well. Since these standards are average or overall counts which ignore the uneven spatial distribution of people and green spaces, as just discussed, when these standards were adopted to location-allocation models for public accessing equity, the meanings change slightly. And since the meanings of these "standards" change, the figures may need adjustment to achieve feasible solutions. For example, when the average green space of $5m^2$ per person is used in a location-allocation model, $5m^2$ does not mean the average, instead, it refers to a person's suitable demand for green space. Apparently, if a study area's average green space meets the standard of $5m^2$ per person, with this $5m^2$ as unit demand in a location-allocation model, a feasible solution for full coverage can hardly be found unless a large amount of new green space is involved. It is surprising that for a city with average green space of $5m^2$ per person, if a location set-covering model is performed for full coverage, the demand for each person as a parameter in the model is much less than $5m^2$.

To apply location-allocation models to green space location study, a few unique problems that relate directly to green space were addressed. First, unlike a typical location-allocation problem of locating facilities such as hospitals, schools, or fire stations, the dimension of a green space cannot be ignored at the scale of pedestrian access study, and since it is relatively large, green space cannot be treated as point as other facilities do in such models. So distance calculation between green space and residential sites is not as simple as the distance between two points, and in this study, an approach for calculating various distances between green space and residential sites as demand points was discussed. Another problem is, as supply features, the service of green spaces is much related to the size of the green spaces, there is a supply limit related to each green space candidate site because of the space. Unlike most of facilities in location-allocation models whose supply are not sensitive to space, models on green space have to involve capacity constraints, as long as people have certain demands for green spaces. Thirdly, this study also argues that the area of a green space has to be corrected before being used as the green space's supply. The correction has to be based on understanding of research subject and related planning regulations. This study focused on public access to green space, so the areas that are not feasible for public use are excluded in area correction. The correction can follow existing planning regulation or approaches. This study simply used slope gradient as a correction factor, other factors may also be applied for correction if applicable.

This study created two models in a sequence as a complete approach for the green space location problem. A maximal covering location model was solved for existing green spaces to examine the green space coverage in the study area. Then the model was applied to all green space candidates, including existing ones and potential ones, to determine how much the coverage would be improved after potential green spaces were added to the model. Of course, potential green spaces are related to green space construction cost. This study revealed that the cost for achieving maximal coverage objective can be huge, so a second model of minimum cost capacitated location-allocation model was structured for the objective of reaching an acceptable coverage with minimum cost. This "acceptable" coverage was selected carefully from first model results, with reference to related planning standards. Since there are various standards on average green space per person with different figures, and also because this concept changes slightly to green space demand for each person in the model, this parameter (A) is unknown unless it is predefined by decision-maker and a specific number is expected. For this unknown parameter, a smaller number than the standard value may make better sense for the model, as discussed. In order to choose proper parameter, the model was run multiple times with different parameter input. Inflection points on a cost-effectiveness curve with cost and corresponding A input helped find the proper green space per person parameters. Three inputs for A were chosen as low demand (or part of short-term goal), mid demand (midterm goal) and high demand (long-term goal). These inputs can be used in related city policy making.

The study provided a solution to gather useful information from multiple model results. To solve a traditional location problem, the basic steps are to establish a model, run the model and implement the model results. But since this green space location problem contained uncertain parameters, different parameter input led to different results, it is not a simple question of which model result should be used and where green spaces should be located based on the specific model result. This study explored an approach of combining results from various models and from them collecting helpful information for possible implementation. With the selected low demand, mid demand and high demand per person input of parameter A, three different solutions for the second model were compared. Each green space, or facility in other studies, was assigned a different amount of demand in each model. The green space's relative contribution to meet demand is calculated, in percentage. Then the contribution in three models for each green space is compared, both by number and contribution rank. Contribution indicated the importance of a green space for certain service goal, and with comparison of contribution across models, implementation suggestions can be made. For example, a green space candidate site with a large and steady contribution to serve the public demand in the solution of all three models, a green space must be located at this site (or if it is an existing park, a suggestion can be made for its maintenance and protection).

This study also made an argument on various distance measures in an urban context and discovered some interesting findings on distance measures in location-allocation model results. The distance measurement results showed these distance measures returned quite different distances estimate between features. When these distances were used in the same model with other parameters fixed, it was not surprising that the model results were significantly different, both for the coverage model and the cost model. However, interestingly, if the approach stated above is used, by examining and comparing green space contributions in the results of a set of models with different parameter inputs one finds, quite a number of green spaces have a similar contribution across the various models. This may suggest that, though these distance measures are very different as are location-allocation model results on objectives, many facility sites (green spaces here) in these model results with different distance measures may have similar relative contribution or relative “allocation” importance.

In summary, this research has applied location-allocation models in green space planning, in combination with related planning standards. In this process, the greens space specific problems have been accommodated for this modeling approach. And the cross analysis of modeling results shows with the combination of multiple models, it is reasonable to make policy suggestions on proper planning indicator (standards) setting and model results implementation.

This study has some limitations. A factor that affects any study, especially data driven modeling, is data limitations of availability and quality. In the study case, though luckily the demand points and green space sites were collected, it took a long time to distinguish residential buildings from all constructions since the types of the buildings are not neatly categorized, the existing green space locations are collected, however, they are not classified or named, so it took much effort to categorize green spaces for cost estimation. The largest data shortage is population estimation. Unlike detailed publicly-available population information in the U.S., such as U.S. Census as detailed as at the block level or ACS population at the block group level, it is extremely difficult for most scholars to collect such detailed population data in China since they are not released for public access. The most detailed data that can be found are 2010 Census population in the sub-districts, and a few of them reported the population count of each neighborhood under their jurisdiction. As analyzed before, the neighborhood is still too large to be the basic unit in such a small-scale study. So population estimate for each demand site has to be roughly estimated, and the precision and accuracy of the model results might be affected by estimation error.

In the future, if more detailed population information is available, the green space location model results can be improved. And further, the results may be more accurate using the more disaggregated data such as building locations as demand points, or using more points along open green space boundaries for distance calculation. But it is a tradeoff which requires either high-performance computers, calculation algorithm improvement, dropping any time-consuming calculations, or more tolerance for time.

Another limitation is that none of distance measures are exactly the real distance. Poor estimate of network distance has been found in analysis. Some of network distances are less than Euclidean distances for the same pair of inputs. This is the network distance calculation mechanism and has been adjusted by the adjusted-network distance approach. The network distance calculation for some other inputs is exaggerated. This overestimation can hardly be fixed unless more detailed street network data are obtained. Both measure and the model results would be much improved if the street network is further refined, which will make the network distance estimate much closer to real travel distance. On the other hand, Euclidean distance is much shorter than the real travel distance in most cases. There is an exception that in the same block, the real travel distance between two points may be much closer to Euclidean distance rather than network distance, since the network distance approach snaps points to the streets and travel is only allowed along streets. So, for best travel distance estimate in an urban circumstance, it would be ideal to calculate adjusted network distance with a refined street network for most input pairs, and for the pairs very close to each other, especially in a block, Euclidean or Manhattan distance can be used. So the best solution to estimate travel distance is a combination of multiple distance measures.

This study used uniform unit construction cost for each type of green space. The construction cost is usually location specific and highly related to park design. It varies in a large range. So the cost solution in the second set of models may be far from real cost. Different cost input may impact model results on green space location selection. The estimated cost used in the models served well for the purpose of the best use of existing green spaces since they cost the least and met the model need. But the estimated cost itself should not be used as the real cost estimation in model implementation, nor it is close to the real cost estimate, unless site sensitive cost is refined for the models.

In the future, if the above problems are addressed, the model results can be more implementable. Given what are available for modeling, the current model results may not work well in the implementation, but this research does what is expected, establish a complex modeling approach in combination with popular planning methods, to identify proper locations of green spaces and provide comment on a green space construction sequence according to their relative importance in the models.

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