Measuring and Optimizing Accessibility to Emergency Medical Services

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Abstract

Emergency medical services (EMSs) undertake the responsibility of providing rapid medical care to patients suffering from unexpected illnesses or injuries and transferring them to definitive care facilities. This research concerns several research gaps that are associated with different EMS trips, real-time traffic conditions, improving EMS efficiency and equalities. This research aims to develop GIS-based spatial optimization methods to improve service efficiency and equality in EMS systems. Specifically, the research intends to achieve the following goals: (1) to measure spatiotemporal accessibility to EMS; (2) to improve EMS efficiency and provision through spatial optimization approaches; (3) to reduce urban-rural inequalities in EMS accessibility and coverage using spatial optimization approaches. The proposed approaches are applied in three empirical studies in Wuhan, China.

To achieve the first objective, the proximity and the enhanced two-step floating catchment method (E-2SFCA) are adopted to evaluate spatiotemporal accessibility. First, the EMS travel time is estimated for the two related trips as an overall EMS journey: one is from the nearest EMS station to the scene (Trip 1), and the other is from the scene to the nearest emergency hospital (Trip 2). Then, the E-2SFCA method is employed to calculate the accessibility score that integrates both geographic accessibility and availability of EMS. Travel time is estimated by using both static road network with standard speed limits and online map service considering real-time traffic.

To achieve the second objective, two facility location models are proposed to improve EMS service coverages for two-related trips (Trips 1 and 2). The first model maximizes the amount of demand covered by both ambulance coverage (EMS station – demand) and hospital coverage (demand – hospital). The second model maximizes the amount of demand that can be served by both ambulance coverage and overall coverage (EMS station – demand – hospital).

To achieve the third objective, two bi-objective optimization models are developed. The two models have the same primary objective to maximize the total covered demand by ambulance. The second objective is to minimize one of the two inequality measures: one focuses on accessibility of uncovered rural people, and the other concerns the urban-rural inequality in service coverage.

For the first empirical study with respect to spatiotemporal access to EMS, different spatial patterns are found for the three trips (two partial trips and the overall trip). Good accessibility to one trip cannot guarantee good accessibility to another trip. In addition, urban-rural

inequalities in EMS accessibility and coverage are observed. Finally, it is observed that real-time traffic conditions greatly affect EMS accessibility, particularly in urban districts. Specifically, the accessibility of EMS becomes poor during the morning (7-9 am) and evening peak periods (5-7 pm).

For the second empirical study in relation to EMS optimization involving two related trips, the results find that the first proposed model can guarantee that more demand to be covered by both ambulance and hospital coverages than the Maximum Coverage Location Problem (MCLP). The second proposed model can ensure that as many people as possible to be served by both ambulance and overall coverage than the work by ReVelle et al. (1976).

For the third empirical study attempting to reduce urban-rural inequality in EMS, the results show that the first bi-objective model can improve EMS accessibility of uncovered rural demand, and the second model can reduce EMS service coverages between urban and rural areas. However, the improvement EMS inequalities between urban and rural areas leads to a cost of a decrease in the total covered population, especially in urban areas.

Regarding policy implications, this research suggests that different EMS trips and traffic conditions should be considered when measuring spatial accessibility to EMS. Spatial optimization research can help improving service efficiency and reduce regional equalities in EMS systems. The work presented in this thesis can aid the planning practice of public services like EMS and provide decision support for policymakers.

Keywords: GIS; Spatial optimization; Accessibility; Service coverage; EMS

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*Authors declaration

“I declare that, except where explicit reference is made to the contribution of others, that this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.”

Chapter 1 Introduction

1.1. Background

A Chinese proverb states: “a storm may arise from a clear sky, while human fortunes are as unpredictable as the weather.” This proverb means that something unexpected may happen anytime and anywhere. As a critical component of healthcare systems around the world, emergency medical services (EMSs) undertake the responsibility of providing rapid medical care to patients suffering from unexpected illnesses or unintentional injuries (e.g., cardiovascular diseases, car accidents) and transferring them to definitive care facilities (e.g., hospitals, emergency departments) (Sánchez-Mangas et al. 2010). Before the outbreak of Coronavirus disease 2019 (COVID-19) pandemic, EMS demands had increased dramatically worldwide. In England, annual EMS demands climbed from 7.9 million to more than 10 million between 2010 and 2018, an average annual increase of 6% (English NHS Ambulance Trusts, 2018). In cities such as New York, United States, EMS responded to nearly 1.5 million incidents in 2017, an average of around 4,000 cases per day, representing a 36% increase from the year 2000 (Citizens Budget Commission. 2018). During the outbreak of COVID-19 pandemic, the EMS demand have increased rapidly around the world. For example, one study found the total EMS calls climbed by 23.3% between 2019 and 2020 in Copenhagen, Demark (Jensen et al., 2020). Similar findings were also reported by Ferron et al. (2021). There is no doubt that a high-quality EMS provision is essential to protect public health and safety.

From a historical perspective, the first known EMS system with specialized vehicles was developed by Napoleon’s army, which operated in the Battle of Spires in 1793 (Skandalakis et al., 2006). Before World War II, many hospitals had offered ambulance services in major cities around the world, such as London (Kouwenhoven and Knickerbocker, 1960). The modern EMS systems were developed in the 1960s, especially after the development of cardiopulmonary resuscitation (CPR), and defibrillation. These new techniques led to a revolution in emergency medical care.

Modern EMS systems can be classified into two major groups: Anglo-American and Franco-German (Dick, 2003). The former provides basic prehospital emergency care on-site and transports patients to hospitals’ emergency departments. The latter provides mobile and advanced on-scene medical care, which intends to deliver the “hospital and medical equipment” to the scene. The Anglo-American EMS system has been widely implemented in countries such as China, the United Kingdom, the United States, Australia, New Zealand, and Canada. The Franco-German system has been adopted in Austria, Finland, Germany, France, Russia, and other countries (Van der Vaart et al., 2011). This study focuses on the Anglo-American EMS system.

A high-quality EMS system often provides service in an efficient and fair way. The efficiency and equality of EMS are often assessed by accessibility or service coverage. Accessibility refers to the ease and speed of action, linked with the distance between demands and suppliers. EMS accessibility often pertains to the distance or travel time of an overall journey consisting of two one-way trips (see Figure 1-1): Trip 1 (EMS station – scene) and Trip 2 (scene – hospital). The overall journey (EMS station – scene – hospital) includes the two one-way trips, and hereafter referred to as the overall trip. In general, all trips can affect the quality of EMS system. Good ambulance accessibility allows patients to receive rapid prehospital medical care, which implies better health outcomes (O’Keeffe et al., 2010; Sinden et al. 2020). As most ambulances are equipped with basic and limited medical equipment, many patients need to transfer to hospitals to receive further and specialized medical treatments. Therefore, good hospital accessibility or overall accessibility is also important as they affect the timeliness of receiving specialized medical care (Ouma et al. 2018; Carr et al. 2018).

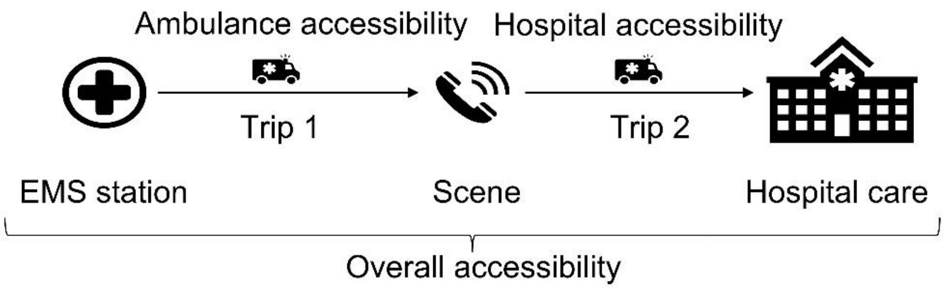


Figure 1-1. Common Procedure of EMS.

Service coverage is defined as the number or proportion of underlying demands located within the service standard for travelling (e.g., maximal distance or travel time). The measurement of service coverage often varies for different trips in various EMS systems. First, many EMS systems worldwide have specific standards for service coverage for Trip 1 (namely ambulance coverage). For example, the UK National Health Service (2017) stresses that 75% of urban emergency calls must be serviced within 8 minutes (hereafter called min) and 95% within a maximum of 19 min after the EMS call coming. In China, the standard varies between different cities, such as 12 min in Beijing or 10 min in the urban area of

Wuhan (Beijing government 2018; Wuhan Municipal Health Commission, 2020). Service coverage in relation to Trip 2 (namely hospital coverage) and service coverage for the overall trip (namely overall coverage) are commonly dictated in EMS provisions. For instance, South Korea defines those patients are underserved by EMS if they require over 30 min to reach local emergency departments or over 60 min to reach regional emergency departments from their residences (Jiang et al., 2021). The National Stroke Center (2021) highlights EMS overall coverage for stroke patients, stating that stroke hospitals should be reachable within 60 min of stroke onset in China.

Poor accessibility and EMS service coverage are common problems for many EMS systems worldwide. The former is often attributed to a high level of the geographic barrier (i.e., long travel distance or travel time) to reaching the services, which affects EMS response times, utilization of services, and health outcomes (e.g., Hung et al., 2009; Branas et al., 2013; Gabrysch et al., 2011). The latter implies that EMS cannot meet many potential demands outside a pre-defined maximal coverage standard. For example, one study reported the inefficient emergency obstetric services in rural Zambia, finding that more than 50% of births were to mothers living more than 25 km from their nearest emergency obstetric facilities, which caused high maternal mortality and low EMS utilization (Gabrysch et al., 2011). Branas et al. (2013) found that the percentage of the population covered by trauma centers within a 60-min service coverage in some US states was much lower than the national average – 71.5%, such as 31.13% in Iowa or 36.03% in Oklahoma.

Inequalities in EMS remain challenges to be addressed in many countries and localities, which have been widely reported in the form of health outcomes, travel distance/time, facility utilization, finances, urbanization speed and other factors (e.g., Jennings et al., 2006; Moore et al., 2008; Aftyka et al., 2014; do Nascimento Silva and Padeiro, 2020; Luo et al., 2020). Inequalities in travel distance/time have been widely documented in particular (e.g., Vukmir, 2004; Gonzalez, 2009; Fatovich et al., 2011; Horeczko et al., 2014). For example, Jennings et al. (2006) found that patients in Victoria, Australia who suffered from out-of-hospital cardiac arrests in urban areas had much lower mortality rates than those in rural regions; this was mainly caused by disparities in distance and travel time to the nearest EMS station. In Lisbon, one study reported that low-income areas generally had a higher number of geographic barriers to EMS than affluent areas (do Nascimento Silva and Padeiro, 2020). The outbreak of COVID-19 has aggravated such inequalities and their implications for healthcare. EMS have undertaken an essential role in the pandemic response but have also suffered much pressure due to inelastic and limited EMS capacity worldwide (Al Amiry and

Maguire, 2021). Improving equalities in EMS is still a significant challenge to various national and local governments and authorities.

This study will use Geographic information systems (GISs)-based methods to evaluate EMS accessibility, and then develop GIS-based spatial optimization approaches to address two problems in EMS planning: the improvement of EMS provision/efficiency and the reduction of inequalities in EMS, taking into account of EMS accessibility and service coverage. The proposed approaches will be applied in empirical studies in Wuhan, China.

1.2. GIS and Public Health Planning

GISs are computer-based systems for integrating, analyzing, managing, and storing spatial data from different resources (Longley and Batty,1997). Traditionally, GIS applications have helped healthcare planners understand the prevalence, etiology, transmission, and treatment of diseases (Rushton, 2003; Richardson et al., 2013). The development of GIS-based techniques has led to a rapid growth in the scope of contributions to social science and healthcare planning criteria (Wang, 2020). Cromley and McLafferty (2011) summarize the roles of GIS in public health into the following eight dimensions:

1. *Mapping Healthcare Information*: An essential function of GIS is the representation of spatial information. Healthcare information is often linked with environmental and social features to identify spatial associations. Mapping is a productive process of viewing, exploring, and analyzing those spatial features. For example, Carlin (2003) used a point map to depict residential locations of health survey respondents in Long Island.

2. *Investigating Spatial Clustering of Health Events*: Public health planning usually involves investigating unusual public health events (e.g., soil pollution or diseases) from a spatiotemporal perspective. GIS can play an important role in exploring the spatial clusters of these events. For example, Devine and Lewis (1994) employed spatial statistical approaches based on GIS to measure the spatial clustering of disease in a population and investigate variations in health outcomes and the prevalence of disease over time.

3. *Investigating Environmental Hazards*: Environmental health problems relate to many agents and cause adverse public health outcomes, often leading to physical, chemical, or biological nature. Human beings are likely to contact these agents through eating, drinking, breathing, or daily physical activities. GIS can aid

environmental authorities in monitoring environmental conditions, assessing environmental quality, evaluating the risks of environmental hazards, and preventing the occurrence of environmental problems. For example, a GIS-based Soil and Water Assessment Tool was employed to analyze the environmental conditions of two sub-watersheds in the Great Lakes Basin because surface run-off and agricultural chemicals increase the risk of environmental problems (Grunwald and Qi, 2006).

4. *Analyzing the Ecology of Vector-Borne Diseases*: Emergency zoonotic diseases such as swine influenzas have increased public awareness of the seriousness of vector-borne diseases linking animal and human groups. The transmission vector is often a living organism, and the distribution area of the vector usually has significant spatial characteristics. GIS applications on vector-borne and zoonotic diseases often attempt to understand and model how humans live with the living vectors (e.g., animals) in a particular ecological system over space and time (e.g., Bretsky, 1995; Rupprecht et al., 1995).

5. *Exploring the Spread and Risk of Infectious Diseases*: The resurgence of an infectious disease often spreads from human to human. This topic has been highlighted in current public health planning under the ongoing COVID-19 pandemic. Transmission factors of infectious diseases are strongly linked with spatial and geographical features, such as land-use change, urbanization, transportation and population mobility, or changes in food and water delivery methods. GIS can help healthcare planners explore the speed of disease spread, analyze the spatial and temporal distribution of the infected population, and investigate the potential impacts on human being (Jennings et al., 2005; Bherwani et al., 2020).

6. *Measuring accessibility to Health Services*: Good accessibility to public services means that demands for such health services (e.g., primary care, emergency care) can be easily met, leading to better public health outcomes. Due to uneven distributions of demands and healthcare suppliers, accessibility to health services usually varies by location. GIS applications can measure accessibility to healthcare services from both spatial (e.g., distance or travel time) and non-spatial (e.g., demographic or socioeconomic status) aspects, helping healthcare planners identify medical shortage areas and improve the deployment and service capacity of health resources (e.g., Wang and Luo,2005; Berke and Shi, 2009).

7. *Spatial Optimization of Healthcare Locations*: The spatial optimization of healthcare facilities is a critical factor affecting accessibility to healthcare services. The approach selected to explore the distribution of health services can affect the identification of underserved regions; it can also influence decisions on where additional medical facilities and staff should be located. GIS applications in public health are commonly used to adjust the locations of existing facilities and seek the best sites for new facilities in order to improve healthcare provision (e.g., Wang and Tang, 2013; McLay and Mayorga, 2013; Enayati et al., 2019).
8. *Exploring and Reducing health-related Inequalities*: Variations in healthcare outcomes exist on the global, regional, and local scales, and such disparities are often attributed to factors such as physical barriers, limited health resources, shortages of funds, and finances. GIS applications have been widely employed to visualize differences in health outcomes (e.g., Krieger et al., 2003), explore relevant factors for causing disparities (e.g., Kamphuis et al., 2008), or use spatial methods to reduce such inequalities from a spatial perspective (e.g., Chanta et al., 2014).

This research focuses on the following three roles of GIS in public health management and planning: (1) measuring accessibility to health services, (2) optimizing healthcare facilities, and (3) reducing health-related inequalities.

1.2.1. Measures of healthcare accessibility

Over the past few decades, many GIS-based metrics have been proposed to assess potential spatial accessibility of healthcare, mainly including proximity-based measures, provider-to-population ratios (PPRs), and gravity models. Distance and travel time are two common indexes of the proximity-based measures. The former is frequently represented by the straight-line or road network distance between locations of demand and service supplier. The latter refers to the time required to travel to seek health service by a transport mode, such as walking, driving, or public transport. The PPR is often calculated as the ratio of the supplier's capacity (e.g., the number of physicians or ambulances) to demands (e.g., population) using data aggregated at certain geographic scales. Gravity-based models integrate the above two methods and account for the spatial interactions between demands and service providers, following a distance/travel time-decay function. The most well-known gravity-based models since the groundbreaking work by Joseph and Bantock (1982) is probably the two-step floating catchment area (2SFCA) (Luo and Wang, 2003) and its extensions such as the enhanced 2SFCA (E-2SFCA) (Luo and Qi, 2009).

All aforementioned types of methods have been broadly employed to measure the quality of EMS sector, with the consideration of accessibility or service coverage (e.g., Tansley et al., 2015; Joyce et al., 2018; Xia et al., 2019). For accessibility, Joyce et al. (2018) employed GIS to measure the travel time to the nearest emergency hospitals between different demographic groups in Ohio State, the United States. They found that deprived communities, elderly, or black people were highly associated with the longer travel times in Ohio State, the United States. For service coverage, Tansley et al. (2015) used GIS to conduct to measure spatial accessibility to emergency services in Namibia and Haiti. They found that around 25% and 50% of the populations in Namibia and Haiti respectively lived in an EMS underserved area where the nearest EMS facility was at least 50 km away.

1.2.2. Spatial optimization of healthcare facilities

Spatial optimization aims to seek the best spatial configuration of facilities/resources or land use activities in relation to certain objectives, usually subject to travel distance/time or cost constraints (Church, 2001). The development of spatial optimization is mainly attributed to the availability of accurate spatial data, progress in optimization algorithms, computer technology, and the evolution of geographical information science.

In recent years, there has been a proliferation in spatial optimization applications in healthcare planning, mainly attributed to the advances in GIS including data collection and mapping, the measurement of distance and travel time, and result visualization (Church 2002, Church and Murray 2009, Murray 2010). First, GIS is a powerful tool for preparing and describing spatial information as input for spatial optimization models through desktop mapping software. For example, data aggregation, which is usually applied in spatial optimization approaches to facilitate model formulation or reduce the problem size, can be easily and quickly achieved through GIS by extracting data at a specific spatial scale.

Second, GIS can help measure the spatial relationship (e.g., in distance or travel time) between healthcare needs and services, which is often an essential component for the location optimization of healthcare facilities. For instance, calculating distance or travel distance is a fundamental function of GIS. Also, the service area of a hospital or clinic can be derived with buffer analysis within a GIS environment.

Third, solutions from spatial optimization models can be depicted in GIS that has powerful visualization capability, like mapping hospital demand and hospital desert areas during the COVID-19 in the United Kingdom (Verhagen et al., 2020). Visualization is essential in describing and understanding objectives, decisions, and model spaces (Densham, 1994) and investigating underlying problems that otherwise cannot be found (Murray, 2005).

Spatial optimization approaches have contributed to the high-quality delivery of healthcare services (e.g., Ndiaye and Alfares., 2008; Shariff et al., 2012; Chanta et al., 2014). Common spatial optimization models that have been applied in healthcare planning can be grouped into two categories: (1) coverage-based models developed by Toregas et al. (1971) and Church and ReVelle (1974) and (2) median and center problems proposed by Hakimi (1964). The former concern the maximal service area of each facility, and the latter focus on (weighted) distance or travel time between demands and their nearest facilities.

1.2.3. Visualization and reduction of health-related inequalities.

This section concerns the roles of GIS in addressing healthcare access inequalities, including (1) identifying the effect of inequalities, (2) visualizing inequalities, and (3) reducing inequalities.

First, GIS plays an essential role in measuring inequalities in healthcare services, especially in identifying such inequalities in the spatial dimension. On the one hand, distance/travel time calculated by GIS can assess the inequality in accessibility to healthcare services by measuring and comparing the shortest distance or travel times between patients and their nearest facilities (Hasnat et al., 2018). On the other hand, healthcare capacity (e.g., number of ambulances in EMS station), demand volume (e.g., the total population), demographic and socioeconomic factors (e.g., race, income) can be linked to geographic locations in GIS, helping explore healthcare inequalities from different aspects (Luo and Wang et al., 2003; Wang and Luo, 2005).

Second, GIS has been used to visualize healthcare-related inequalities by mapping, depicting the spatial distribution of distance/travel time to healthcare service or other accessibility indexes. Clusters of communities with high or low travel times can be highlighted using spatial statistical methods (e.g., Luo et al., 2018). Visualizing inequalities in EMS accessibility can help healthcare planners to find medically underserved areas for further deployment of health resources. Meanwhile, non-spatial factors affecting accessibility to healthcare (such as race, income, education level) can be assessed spatially through GIS application (Wang and Luo, 2005). Geographic locations and non-spatial attributes can be integrated to visualize and identify those with poor accessibility to healthcare services.

Many methods that attempt to reduce health-related inequalities have been incorporated into GIS. For example, classic spatial optimization models (e.g., p-center problem) have been incorporated into GIS software such as ArcGIS or optimization software (e.g., Gurobi package based on R or python modelling language), which can be employed to achieve the goal of reducing inequality by seeking out the locations of new medical facilities or optimizing the locations of existing medical facilities. In addition, some operational studies have adopted GIS functions. For example, Chanta et al. (2014) used a commercial GIS software (ArcGIS 10) to classify urban and rural areas in order to improve rural healthcare accessibility by locating service facilities.

1.3. Case Study City: Wuhan, China

Wuhan is the capital city of the Hubei province and the largest city in Central China; it is also the only sub-provincial city in the six central provinces. The city lies in the confluence of the Yangtze River and the Han River, covering an area of 8,569.15 km^2. Wuhan consists of 13 districts: 7 districts in the urban area and 6 districts in the suburban and rural areas. Since the Chinese economic reform and opening, Wuhan has become the core of the urban agglomeration and the engine of the rise of Central China. In 2019, Wuhan's economic aggregate ranked among the top ten cities in China, and the city achieved a regional GDP of 235 billion US dollars, showing a year-on-year increase of 7.4% at comparable prices. In 2019, the city's per capita GDP was 21,100 US dollars, while the per capita disposable income of Wuhan residents was 6,677.79 US dollars—which is 1,586 US dollars higher than the average level in China—with a year-on-year increase of 9.2% (Wuhan Statistics Bureau, 2020). Specifically, the average disposable income was 7,504 and 3,595.94 US dollars per urban and rural resident, respectively (Wuhan Statistics Bureau, 2020). In 2020, Wuhan's general health expenditure budget was 2.29 billion US dollars, ranking eighth among Chinese cities (Wuhan Municipal Health Commission, 2020 b). In the next few years, Wuhan government plans to build a large number of hospitals and EMS stations to provide people with more convenient public health services.

Wuhan has been experiencing fast population growth and it faces the problem of an aging population. By the end of 2020, the total population in Wuhan reached 11.2 million, with a natural growth rate of 0.25% (Wuhan Statistics Bureau, 2021). Figure 1-2 depicts the spatial variation of population density in Wuhan. Specifically, the urban population accounted for

73.7% of the total population, with an annual increase rate of 0.2%, while the rural population growth ratio was near 0.5%. Due to rapid urbanization and economic achievements, Wuhan has attracted a large number of migrants in recent years. The net migration rates increased by 19.78%, 26.55%, and 18.95% between 2017 and 2019. In addition, Wuhan has seen a severely aging population. By the end of 2018, Wuhan's elderly population (aged over 60) reached 1.88 million, accounting for 21.27% of the total population (Wuhan Civil Affairs Bureau, 2019). Annual growth rates of Wuhan's elderly population have ranged between 0.4% and 0.7% from 2014 to 2018, and the growth rate is likely to increase in the next decade. Due to the sharp increase in population (especially the elderly population), the existing healthcare resources are under great pressure for meeting the rapidly growing demands, resulting in retrogression in the quality of healthcare service and therefore affecting public health outcomes (Wuhan Municipal Health Commission, 2019).

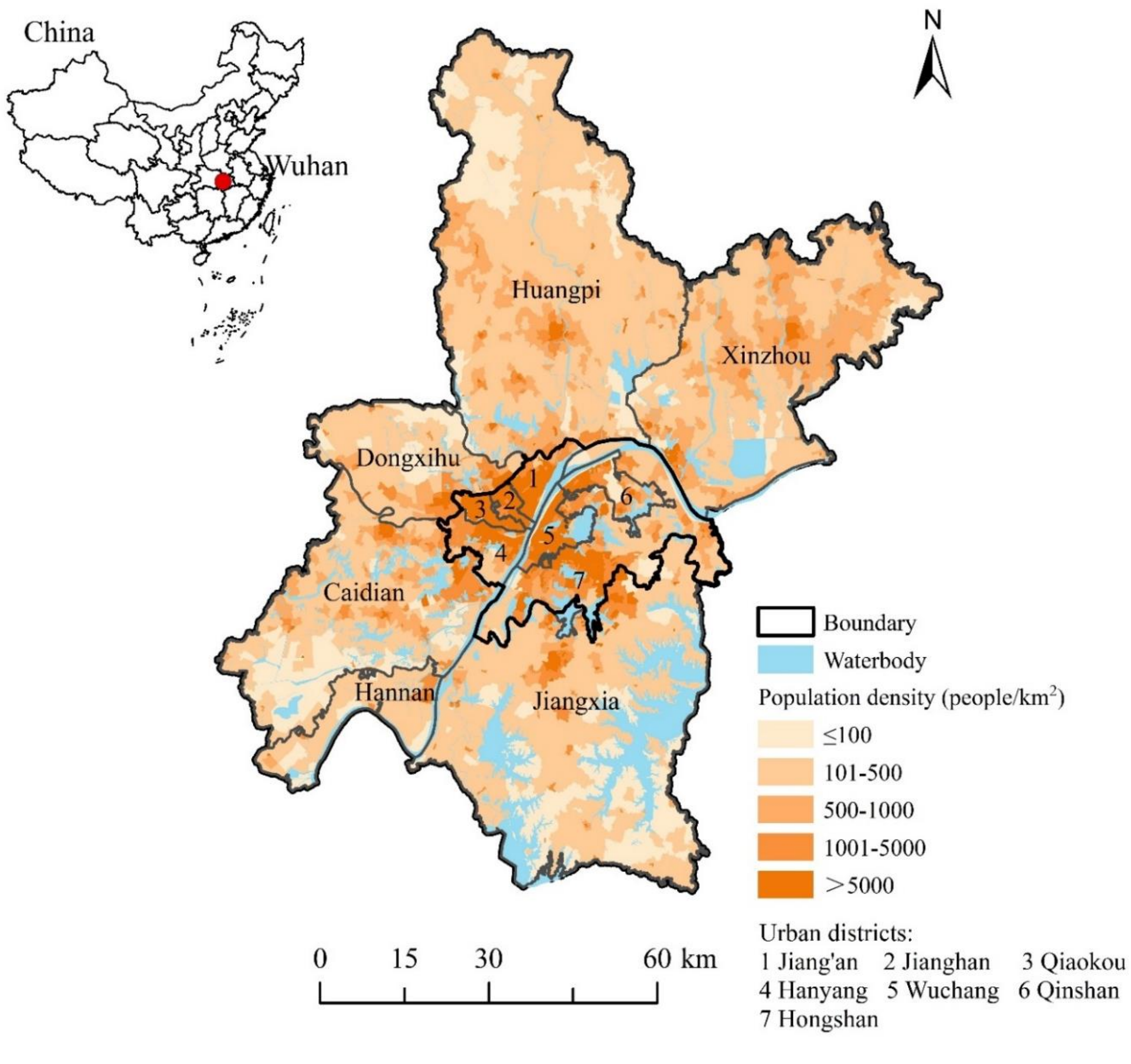


Figure 1-2. Population density in Wuhan.

1.3.1. EMS development in Wuhan, China

EMS in China follows the Anglo-American system. Before the 1980s, the EMS system in China was organized by provincial or local authorities. In 1983, the Association of Emergency Medicine was established to facilitate the development of the EMS system in China, and a national framework was established explicitly to adapt to the local EMS systems. The framework stipulates that regional or local authorities can operate their own EMS departments under the organization of the Ministry of Public Health. In other words, China has built a top-down administrative framework for EMS, with stepwise planning from the central government delivered to the regional and local authorities (Thomas and Clem, 1999). China's EMS system includes three major parts: prehospital care, emergency department (i.e., hospital) care, and the intensive care unit (ICU). The three parts have organized a survival channel from ambulance dispatching to on-scene medical care and then to transportation to definitive in-hospital medical treatment.

The Wuhan EMS system was established in 1958. Before 2000, the efficiency and governance of EMS in Wuhan were still backward (Wuhan Emergency Center, 2017). Since the early 2000s, the local EMS system has started to develop rapidly attributed to a lot of political and financial support from provincial and municipal authorities. Currently, the Wuhan EMS system is a non-profit and well-organized medical unit under the Ministry of Public Health that provides prehospital care, transportation services, and specialized in-hospital medical treatment. It plays an essential role in protecting public health and safety and disseminating knowledge related to emergency care. By the end of 2020, there are 79 EMS stations in total, and a large number of new EMS stations are going to build in the further (Wuhan Government, 2021). Wuhan EMS stations have implemented advanced technologies, such as whole-process computer scheduling, synchronous real-time recording, ambulance GPSs, wireless tracking systems, and video monitoring. In addition, a whole-course dynamic management system for sharing EMS information has been implemented in the EMS command center. Wuhan's EMS system offers purely prehospital care and transportation services, with no inpatient beds for specialized or definitive medical care. At present, there are several operating modes for Wuhan EMS stations: (1) hospital-based stations, (2) independent operating stations, and (3) private operating stations. Some EMS stations are at the same locations as the hospitals, but other stations are established at different sites. After the COVID-19 pandemic in Wuhan, the local municipal government plans to provide more policy and financial support to develop the local EMS system in order to improve the capacity of emergency management (Wuhan Municipal Health Commission, 2020).

1.3.2. Challenges for EMS planning and management

Accessibility and inequalities are two problems faced by many EMS systems worldwide (e.g., Branas et al., 2013; Luo et al., 2018), and there is no exception in Wuhan. Currently, the Wuhan EMS system has two major problems: relatively poor accessibility to EMS and spatial inequality in EMS between urban and rural areas. Thus, the major aim of future EMS planning in Wuhan include: (1) to improve accessibility of EMS and (2) to reduce regional inequalities (Wuhan Municipal Health Commission, 2020 c; Wuhan Government, 2021).

On the one hand, poor EMS accessibility and inefficient provision remain a challenge to Wuhan local authority. With the rapid urbanization and the ageing population in Wuhan, the total population has increased in recent years, resulting in relatively poor accessibility. According to Wuhan Municipal Health Commission (2019), many people are still not encompassed by the EMS service standard especially in suburban and rural areas, which can negatively affect public health and increase the health disparities between urban and rural areas. The COVID-19 pandemic has stressed the urgent need to improve EMS provision efficiency. Wuhan government (2021) plans to provide more EMS resource during the next few years to improve EMS accessibility and service coverage in the whole city and improve the capacity to handle different large-scale emergencies, achieving the goal that the proportion of ambulances to population reach to 1:30,000 (Wuhan Municipal Health Commission, 2020c). In addition, traffic congestion in Wuhan is an additional problem that affects EMS accessibility. In detail, the road density in Wuhan only ranks eighteenth among Chinese cities. However, the total number of private motor vehicles is in the top ten among Chinese cities (China Academy of Urban Planning & Design, 2021). According to Baidu Map (2021), Wuhan is one of the six most congested cities in China. The average traffic speed is only 28.89 km/hour during peak traffic periods, and traffic congestion occurs more frequently in the urban area. Severe traffic congestion will likely reduce ambulances' running speeds and increase the risk of EMS arrival delays, leading to poor health outcomes (Earnest et al., 2011).

On the other hand, the Wuhan Municipal Health Commission (2019) has highlighted that a great challenge to be addressed in the near future is EMS inequalities between different regions within Wuhan, especially between urban and rural areas. The primary reason for such inequalities is related to fast urbanization speed and insufficient EMS resources, such as funding, equipment, training of personnel, or road infrastructure. In the end of 2019, Wuhan Municipal Health Commission (2019) reported that only 11 EMS stations and 30 ambulances were located in rural districts in Wuhan. Although EMS resources have been increased in rural districts in these years, which still cannot meet the larger number of demands. Thus, EMS inequalities impede the service quality of EMS in achieving better health outcomes, and therefore improving equality in EMS within and across regions remains a significant challenge in the near future (Wuhan Municipal Health Commission, 2019).

1.4. Research Aim and Objectives

This research aims to use GIS-based approaches to measure spatial accessibility to EMS and develop GIS-based spatial optimization models for improving service efficiency and equality in EMS systems. Empirical studies will be carried out using the data from Wuhan, China. Specifically, three objectives are to be achieved through this research:

- Research objective 1: to measure spatiotemporal accessibility to EMS using GIS-based spatial analyses.
- Research objective 2: to improve EMS provision/efficiency by developing new facility location models.
- Research objective 3: to reduce regional inequalities in EMS accessibility and service coverage through improving current spatial optimization research.

1.5. Structure of Thesis

This thesis consists of six chapters. The current chapter introduces the background of the proposed study as well as the research aim and objectives.

Chapter 2 reviews relevant literature on applications of GIS approaches in public healthcare management and planning, with a focus on EMS accessibility and optimization. First, various definitions of healthcare accessibility are described and discussed, after which a range of measures for geographic accessibility is examined. Then, common facility location models that have been adopted in healthcare planning are reviewed, primarily including median and coverage models. Finally, the limitations of existing studies are discussed, and the potential contribution of this research is presented.

Chapter 3 focuses on the first research objective—measuring spatiotemporal accessibility of EMS in consideration of two one-way trips (e.g., Trip 1 and Trip 2). The geographic accessibility of EMS was measured by travel time along road networks, which varies across different times of the day. The online map service Baidu Map (https://map.baidu.com/) was used to obtain the real-time travel time between EMS stations, hospitals, and each demand concerned. The empirical results demonstrate the spatial variations in EMS accessibility across Wuhan for the two related trips, as well as the impact of rush-hour traffic on EMS accessibility.

Chapter 4 focuses on the second research objective—improving EMS service coverage in consideration of the EMS overall trip. This chapter proposes two spatial optimization models for siting EMS stations and emergency departments with the goal of improving EMS service coverage with respect to the overall trip. Specifically, the first model is intended to maximize the total number of demands met by the coverage related to Trip 1 and Trip 2. The second model attempts to maximize the total number of demands met by the coverage for Trip 1 and the overall trip. Two proposed models are implemented with the empirical data from Wuhan.

Chapter 5 focuses on the third research objective—reducing regional inequalities in EMS. This chapter develops two bi-objective models for siting EMS stations, attempting to reduce urban–rural inequalities through two means: minimizing the total weighted travel distance between the uncovered rural population and the nearest open stations, and reducing the difference in population coverage between urban and rural areas. With another objective of maximizing total service coverage, the model explores various trade-offs between service coverage and urban–rural inequalities using the empirical data from Wuhan.

Chapter 6 summarizes the major findings as well as the contributions of this research to the fields of health geography and spatial optimization. The findings are discussed in relation to existing literature and public healthcare planning. The limitations of this research and potential areas for further study are also discussed. The thesis finishes by highlighting the policy implications of this research.

Chapter 2 Literature Review

The review discusses three topics relevant to the applications of GIS in EMS planning, including EMS system efficiency and equality, measures of accessibility of healthcare in general and EMS in particular, and optimizing healthcare facility location with GIS-based spatial optimization. Specifically, section 2.1 delves into details of efficiency and equality of EMS systems. The methods for measuring spatial accessibility to healthcare services, as well as their applications in EMS, are covered in section 2.2. Section 2.3 considers a range of classic spatial optimization models and their extensions for location optimization of health facilities and EMS stations. Finally, section 2.4 summarizes the limitations of existing literature and the prospective contributions of this research.

2.1. Efficiency and Equality of EMS Systems

The quality of EMS is often assessed against efficiency and equality. In general, the efficiency of EMS is often evaluated by accessibility and service coverage (e.g., Sayed and Mazen, 2012). The inequality of EMS is attributed to disparities in elements like funding, qualified EMS personnel, geographic barriers, or road infrastructure (Jennings et al., 2006; Carr et al., 2009; do Nascimento Silva and Padeiro, 2020).

2.1.1. Efficiency of EMS

Although efficiency of EMS is related to numerous factors (e.g., governance, organization, training personnel), accessibility to EMS and service coverage are the most common indicators when evaluating the level of EMS efficiency. Service coverage is easily interpreted; it is the proportion of demand covered within the pre-defined service coverage for travelling (e.g., 5 km or 10 min). In general, a well-developed service coverage often represents good accessibility, and vice versa. This section mainly introduces common accessibility measures adopted in the health geography field, particularly those applied to EMS. Then, various planning policies related to EMS accessibility are discussed.

As a multidimensional concept, accessibility to healthcare services often concerns the ability to use healthcare services when and where people are needed (Aday and Anderson, 1981). It assesses and describes the potential relationship between the features of the service delivery systems and the attributes of the healthcare demands (Cromley and McLafferty, 2011). Scholars from various disciplines, including geography, sociology, and public policy, have extensively researched healthcare accessibility. (Joseph and Bantock, 1982; Gulliford and Morgan, 2003; Curtis, 2010; Wang, 2012).

Accessibility to healthcare services can be divided into four categories (see Figure 2-1) depending on utilization (revealed versus potential) and whether adopting spatial dimension (spatial versus non-spatial) (Khan, 1992). From the utilization perspective, accessibility can be divided into revealed and potential. Revealed accessibility refers to the actual use of health services. It is usually relevant to the service utilization or the perceived satisfaction level with the service. Potential accessibility is based on the probable utilization of the service but no guarantee of the actual utilization. Policymakers or planning analysts are often interested in potential accessibility, which can help assess the healthcare delivery and identify feasible strategies for further improvements (Luo and Wang, 2003). From the spatial perspective, accessibility to healthcare services can be differentiated as either a spatial or non-spatial dimension. The former concerns the geographic distance, travel time, or spatial interaction between demand and suppliers. The latter concerns socioeconomic status, demographic characteristics, or the healthcare organization system that might influence the ease of receiving healthcare services. GIS necessarily stresses the spatial dimension of accessibility to healthcare services as the framework of time and geography provides critical insights into individual healthcare decision-making in space and time (Kwan et al., 2015). This study concerns potential spatial accessibility to healthcare services, especially in EMS sector. In addition, some studies also use the term "access" to represent accessibility, which has the same meaning (e.g., Patel et al., 2012). Therefore, the term "access" is equivalent to "accessibility" in this thesis.

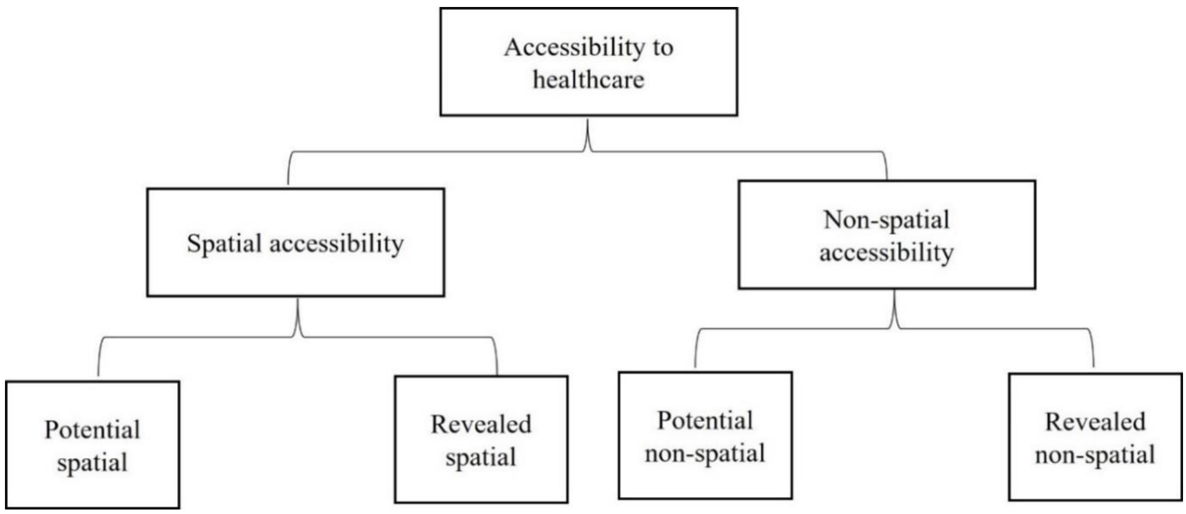


Figure 2-1. Classification of accessibility to healthcare (Khan, 1992).

Regarding EMS, potential spatial accessibility and service coverage are the most critical measures of service efficiency, where the former is the ease and speed of the service action, and the latter refers to the number or proportion of underlying demands that can be encompassed during the service standard. Both measures are often related to the time elapsed by the EMS response process. Specifically, the total EMS response time can include five intervals (see Table 2-1): alarm time, preparation time, arrival time (Trip 1), on-scene time, and transport time (Trip 2) intervals. The alarm time interval and on-scene time are often related to EMS management, the training of personnel, or the physical barriers on the scene (e.g., a high-rise building). The arrival and transport time intervals are highly linked with spatial and temporal factors such as the travel distance/time between original and destination locations, or traffic condition on the route. According to Spaite et al. (1993), the arrival and transport time intervals are the majority components of the EMS response time, accounting for about 70% of the total time spent on average.

Service standards with respect to EMS accessibility and coverage vary across countries and regions over the world. For Trip 1, about 90% of emergency calls must be serviced within 9 min in urban areas (Fitch, 2005). The UK National Health Service (2018) stresses that 75% of urban emergency calls must be serviced within 8 min and 95% in a maximum of 19 min. For Trip 2, South Korea is building an EMS network so then patients can reach their local emergency hospital within 30 min (Jang et al., 2021). For the overall trip, in China, the National Health and Medical Commission (2018) launched the "60-min circle for stroke" project to construct an EMS service coverage that patients could use to reach the nearest stroke hospital within 60-min after stroke onset.

Table 2-1. Five major intervals for EMS response.

Different time intervals	Definition
Alarm time	Time interval between the arrival of an EMS call and the selecting of an ambulance with an EMS team ready to be dispatched.
Preparation time	The time cost of preparing an ambulance with a team after receiving the dispatch decision.
Arrival time interval (i.e., travel time for Trip 1)	Time interval between preparing an ambulance with an EMS team and arriving at the scene of an emergency.
On-scene time	Time spent by the team at the scene of an emergency, including searching the patient, on-scene treatment, and patient removal.
Transport time (i.e., travel time for Trip 2)	Time interval between taking the patient to the ambulance and their arriving at a definitive care facility.

2.1.2. Equality in EMS

Inequalities in EMS include differences in access and experience to such services, which are not only apparent at the national, regional, and local scales, but also common for communities and individuals. First, inequalities in EMS are apparent at a national level, especially between developed and developing countries. Many studies have indicated that healthcare accessibility in developed countries is much better than that in developing countries (Van Doorslaer and Masseria, 2004; Roudsari et al., 2007), which might contribute to the disparity in public health outcomes. Van Doorslaer and Masseria (2004) compared the healthcare services in 21 organization for economic co-operation and development (OECD) countries. They found that high-income countries had better hospital accessibility than relatively low-income countries. The high-income countries often have more EMS resources and better health outcomes than those middle-or-low-income countries. Roudsari et al. (2007) compared the EMS systems in 11 countries, and they found that the group of developed countries had the higher ratio of air ambulance use than the group of developing countries, resulting in faster EMS response time in developed countries.

Second, inequalities in EMS are common within/across regions in relation to accessibility and service coverage. Many studies have indicated that accessibility to EMS in urban areas is better than that in rural regions (e.g., Grossman et al., 1997; Gonzalez et al., 2006; Raatiniemi et al., 2015). First, such inequalities can be represented by travel time. For example, Gonzalez et al. (2006) revealed that the average travel times for ambulance arrival were 11.2 versus 13.9 min in urban and rural settings in Alabama statewide in the USA. Similar findings are also confirmed by Grossman et al. (1997) or Raatiniemi et al. (2015). Second, the urban-rural inequalities can be represented by EMS service coverage (e.g., Aftyka et al., 2014; Luo et al., 2018; Luo et al., 2018; Ahmed et al., 2019). For example, Aftyka et al. (2014) reported that 69.7% and 7.2% of demands in both urban and rural settings of Poland could be covered by the 10-km service coverage for emergency department, respectively, reflecting the notable regional inequality in the service coverage.

Further, healthcare inequalities are also a common issue within communities and between individuals. Such inequalities are often associated with demographic variables (such as age, sex, and race), socioeconomic status (i.e., high income versus low income), and sociocultural barriers (e.g., a linguistic barrier) within neighborhoods and individuals (Wang and Luo, 2005). Regarding EMS, it was found that deprived communities in Lisbon generally had worse spatial accessibility to EMS than affluent communities (do Nascimento Silva and

Padeiro, 2020). Riney et al., (2019) indicated that poor EMS accessibility was highly linked with deprived communities in Hamilton County in the United States. In Chongqing, China, it was reported that EMS provision was more accessible to wealthy residents than to the disadvantaged population with a need for EMS (Liu et al., 2015).

Improving the fairness in accessibility to healthcare services like EMS is an important policy concern in many countries and regions. In the United States, the National Highway Traffic Safety Administration (NHTSA) (2020) established the EMS agenda 2050 Vision, which aimed to build a sustainable, efficient, and equitable EMS system, allowing for timely services available to different groups of people. In England, ensuring that all people can access various healthcare services on an equal footing is one of the primary objectives set out in the national health service (NHS) Operational Planning and Contracting Guidance 2017-19 (NHS England, 2016). To reduce the inequalities in accessibility to EMS, the Scottish government (2022) undertook a comprehensive approach to communications and engagement, guaranteeing that the underserved groups can be involved in further EMS planning. In China, Wuhan Municipal Health Commission (2020) set the goal of improving the EMS equalities. It indicated that residents should be covered by their nearest EMS stations within the 10-min driving time for urban areas or 12-min driving time from rural areas.

There is, however, no widely accepted method to measure inequalities (Marsh and Schilling, 1994). Table 2-2 shows various indexes that could measure and represent inequalities in EMS, mainly including the range, variance, standard deviation, mean absolute deviation, sum of the absolute deviation, semi-deviation and Gini coefficient. These measures have been applied to quantify inequalities in relation to preparation time, arrival time, on-scene time, transport time, or health outcomes (e.g., Vukmir, 2004; Gonzalez et al., 2006; Gonzalez; 2009; Fatovich et al., 2011; Horeczko et al., 2014). The adoption of equality measures usually depends on research target and aim.

Table 2-2. Various socio-economic indexes of inequality measurement in EMS.

Inequality measure	**Definition/Description**	**Relevant studies**
Range	The difference in EMS variable values between their highest and lowest levels	McLay and Mayorga, 2013; Westgate et al., 2016
Variance	The difference in EMS variable values between an influence on each group and the system.	Liu and Duan, 2020
Standard deviation	An index of the amount of dispersion or variation of EMS variables	Wang and Tang, 2013; Doyle et al., 2015
Mean absolute deviation	An index of the mean absolute deviation of n EMS variable values between an effect on each group and the system-wide average effect	Mendonça and Morabito, 2001; Newton et al., 2022
Sum of the absolute deviations	Sum up the absolute deviations of EMS variable values (e.g., distance/travel time) between groups	He and Qin, 2019
Semi deviation	A changeable measure to variance or standard deviation, which only concerns the negative fluctuations	Ogryczak, and Ruszczyński, 2001
Gini coefficient	A degree of inequality index between all pairs of seriocomic status, or other effects	Barbati et al., 2016

2.2. Measuring Spatial Accessibility of EMS

First, this section introduces the data representation of EMS demand and supplier in a GIS environment. Then, three types of spatial accessibility measures are presented: (1) geographic proximity-based methods, (2) the provider to population ratios (PPRs), and (3) gravity-based models. This is followed by a brief overview of other relevant measures.

2.2.1. Spatial representation of EMS data in a GIS environment

In a GIS environment, EMS data can be classified into spatial data – geographic locations of EMS facilities and demands, and non-spatial data – attribute information associated with EMS facilities and demands (e.g., capacity of facility, or demand volume).

GIS-based research tends to use points of interest to represent the locations of service facilities (e.g., Luo and Wang, 2003; Xia et al., 2019) because most of the healthcare facilities (e.g., hospitals, EMS stations) are affiliated with buildings, and their total footprint is often negligible compared with the whole study area (e.g., county, district, city).

Demands can be abstracted into discrete points or areas. First, discrete points are the most common spatial features employed in GIS to represent EMS demands. Many studies used the centroids of geographical and administrated areas (e.g., postcode zones) as the demand locations (Henneman et al., 2011; Ahmed et al., 2019; Hu et al., 2020). Population-weighted centroids of the demand areas were also widely used (e.g., Luo and Wang, 2003; Busingye et al., 2011; Bailey, 2011; Joyce et al., 2018). In some studies, the demand locations are first represented by lattice grids, and the central centroid of each grid is represented as a demand location (e.g., Tansley et al., 2015; Tansley et al., 2016; Deng et al., 2021). In addition, some studies modified historical EMS recorded data as the point dataset to simulate the demand location in the future (Vanderschuren and Mckune,2015). The advantage of using the point representation is that it can facilitate model formulation in spatial analysis and spatial optimization and is also easy to understand. The disadvantage is that not all demands are located in/near such points in the real world, large-scale areas in particular.

Second, demands can be represented by areas, such as neighborhood communities, postcodes, or a continuous space (Yin and Mu, 2012; Van Barneveld, 2016; Murray and Tong, 2007). Each polygon (area) has potential demands distributed within its boundary somehow (e.g., Peleg and Pliskin, 2004; Yin and Mu, 2012; Pulver et al., 2016). For example, Yin and Mu (2012) considered a continuously spatial demand based on polygon-overlay representation in a GIS environment. Specifically, their data preprocessing was handled by GIS overlay operations and the demand polygons/objects were defined and depicted by the coverage areas for the candidate facility locations. The advantage of using the area representation is that it can precisely describe the locations of potential demands. However, it is often computationally intensive and difficult to apply in a GIS environment. Generally, the spatial result might highly depend on how the demand location is represented (Murray, 2005; Tong and Murray, 2009).

Non-spatial data are often organized in a table, which is linked to spatial locations with unique identities (IDs). Non-spatial data of service facilities often relates to the capacity that can be represented by the number of ambulances (Zhu et al., 2021), inpatient beds (Vora et al., 2017), levels of hospital facilities (Lilley et al., 2019), or the modelled capacity index (Rocha et al., 2017). Healthcare demand volume can be obtained from historical records (RoCha et al., 2013; Vanderschuren and Mckune,2015; Hu et al., 2018), population Census data (Henneman et al., 2011; Hu et al., 2020; Hassler and Ceccato, 2021), Global Position System (GPS) (Xia et al., 2019) or questionnaire survey (Panciera, 2016).

2.2.2. Geographic proximity

The geographic proximity approach can be defined as the travel distance/time between an origin and its destination, which is often employed to estimate the geographic barriers between demands and their healthcare suppliers. Three indicators are usually implemented, including Euclidean distance, network distance, and travel time along a road network.

Euclidean distance measures the straight-line distance between a patient location and his/her nearest service provider site. Euclidean distance is appropriate when the researcher works with projected geographical coordinates, as in UTM coordinate systems or the state plane. Some studies also use Euclidean distance when transport network data is unavailable. Euclidean distance is widely used to measure healthcare accessibility (Love and Lindquist, 1995; Parker and Campbell, 1998; Jordan et al., 2004). For example, Love and Lindquist (1995) found that older adults had relatively poor accessibility to healthcare services by calculating the straight-line distance to geriatric health services. Although Euclidean distance is easy to compute, the limitation is that Euclidean distance fails to consider the travelling routes or geographic barriers to the movements. In other words, people rarely move from one location to another location in straight lines.

Network distance refers to the total travel distance involved when traversing a specific traffic network. With the development of remote sensing and mapping technologies, transport network data has become easier to obtain from open sources and is now freely available. Thus, an increasing number of scholars have used network distance to measure accessibility to healthcare services (e.g., Victoor et al., 2014; Kadobera et al., 2012; Apparicio et al., 2017). Apparicio et al. (2008) compared these two types of distance-based metrics and found that Euclidean distance is less precise, especially in underdeveloped areas with poor traffic networks (e.g., rural areas or low-income countries). Network distance is extensively implemented for measuring accessibility to healthcare services (e.g., Henneman et al., 2011; Tansley et al., 2015).

Although distance-based measures are fundamental indicators of geographic accessibility, travel time is more relevant to healthcare service utilization. Estimating travel time always requires an accurate dataset, such as real traffic running data or detailed attribute data (e.g., speeds on classes of roads) for a certain transport mode (e.g., walk, cycling, or driving). Travel time offers a more accurate indication of the geographic barriers to healthcare suppliers than distance-based measures. Many relevant studies have used the travel time-based proximity method to evaluate healthcare accessibility (e.g., Joyce et al., 2018; Reshadat et al., 2018).

Travel time along a road network can be estimated differently. GIS-based tools are commonly employed to measure travel distance/time (e.g., Mao and Nekorchuk., 2013; Dai, 2011; Luo et al., 2018). For estimating the travel time between two locations, the travelling route can be identified to connect the nodes along the road network in a GIS environment. The overall estimated travel time can be represented by the sum of the estimated travel times along all road segments in the travelling route. For example, Mao and Nekorchuk (2013) measured healthcare accessibility using multiple transportation modes (private car and public transit) by setting different travel speeds on the road network. Hu et al. (2020) evaluated the travel time of each road type using a transportation simulation model.

Since the development of the Internet of Things, web-based map services such as Google Maps (https://www.google.co.uk/maps) and other applications (i.e., TripIt (https://www.tripit.com/web)) can estimate travel distance/time using their Application Programming Interface (API) services considering real-time traffic. Recently, an increasing number of studies have employed such services and applications when measuring accessibility to healthcare services (e.g., Wang and Xu, 2011; Tao et al., 2018).

The geographic proximity-based method is overwhelmingly popular to employ in EMS accessibility research. Most of the reviewed studies focus on static travel times, taking into account average speeds or speed limits on different classes of the road or in relation to physical barriers (RoCha et al., 2013; Henneman et al., 2011; Tansley, et al., 2015; Deng et al., 2021). When considering different EMS trips, this method has been widely employed in Trip 1 (e.g., Jezek et al., 2011; Tansley et al., 2016; Hu et al., 2020) or Trip 2 (Rocha et al., 2007; Huang, Meyer and Jin,2016). For example, Joyce et al. (2018) compared the travel time to the nearest emergency hospitals between different demographic groups, which is linked with Trip 1. One study used the geographic proximity method to evaluate the ratio of the population within the 30-, 60-, or 90-min service coverages for stroke medical units in East Tennessee, which is associated with Trip 2 (Ashley et al., 2010).

Two reasons can explain why the proximity method is widely employed by EMS accessibility studies. First, the procedure of the EMS operation is consistent with the rule of proximity, as ambulances are often dispatched from the nearest EMS station and transport the patient to the nearest quantified hospital (Zachariah and Pepe, 1995). Second, distance or travel time is easy to interpret and understand. Thus, policymakers and health practitioners can understand the existing spatial distribution of EMS accessibility through intuitive data descriptions and undertake further EMS planning.

Although the proximity method is widely used in healthcare studies, many scholars still point out its significant shortcomings. This approach might over-weight the effect of geographic barriers because the demand might not be willing to select their nearest service supplier. Factors like scale, popularity, competition and service quality can also affect public choice (Birkin and Clarke, 1999). The use of this approach should rely on customer behavior and service type in different situations. Guagliardo (2004) suggested that the proximity method is suitable for measuring spatial accessibility in rural areas where the choices for consumers are usually limited and where the customers are likely to defer to the closest healthcare facility. This approach is also suitable for emergency services where the demanders are more likely to interact with their nearest facilities, such as EMS or firefighting.

2.2.3. PPRs

The PPRs refer to the estimation of supply-demand ratios within geographically bounded areas. It is a popular approach for measuring potential spatial accessibility from the availability perspective. Specifically, the numerator of the PPRs is associated with healthcare capacity indicators such as the number of physicians, hospital beds, clinics, or ambulances.

At the same time, the denominator of PPRs considers the demand aspect, such as the number of historical users or population within the bounded area (Guagliardo, 2004). This data is always obtained from census, but some are taken from enrolment files from healthcare systems, such as emergency calls or medical insurance enrolment.

As an indicator incorporating availability, a larger number of policy-based studies have applied PPRs to compare the healthcare supply between large-scale service areas or geopolitical regions. Policy analysts have used it for setting the minimum standards of healthcare supply and identifying healthcare shortage areas (Connor et al., 1995; Schonfeld and Falk, 1972; Susi. 2002). Based on the implementation of PPRs, Connor and his colleagues (1995) found that there was an uneven spatial distribution of primary care physicians in rural areas. They suggested that further healthcare planning needs to pay more attention to the healthcare resources in rural regions.

PPRs are also helpful in EMS policy studies because many counties have set up minimum standards for their supplier to demand ratios such as ambulances (1:57,000) in France (Directorate-General for Health & Consumers, 2008) or defibrillators (1:100,000) in China. In general, PPRs are highly intuitive, and the data is readily available from the healthcare departments, and the researchers do not necessarily require GIS-based expertise. In recent years, some studies have employed the PPRs cooperated with other methods in order to measure accessibility to EMS (Baloyi et al., 2017; Fishman et al., 2018; Tew et al., 2021). However, rare of extant studies use the PPRs to measure accessibility to EMS.

The PPRs measurement has some shortcomings. First, it does not incorporate any metrics of distance or travel time costs. Second, PPRs do not consider the patients who seek out services by border crossing, especially in small-scale regions such as postcode areas. Third, spatial variations in healthcare accessibility within border areas are challenging to identify.

2.2.4. Gravity-based models

Gravity-based models were inspired by Newton’s law of gravity. In general, gravity-based models integrate both proximity and PPRs approaches, accounting for the spatial interactions between demands and service providers following a distance-decay role.

Reilly (1931) proposed the first gravity model and applied it to retail planning. He noted that the proximity method only considers travel distance or time between providers and customers, but people might bypass the nearest shop to select other stores with more, better and or cheaper goods, all of which are more attractive to customers. Gravity models can account for both travel costs and facilities' attraction. Reilly's law was further extended by the Huff Model to include multiple service providers in response to a range of problems (Huff, 2003, p.34). The general form of the gravity-based model is as shown in (2.1) and (2.2):

$$A_i^G = \sum_{j=1}^{n} \frac{S_j f(d_{ij})}{V_j} \tag{2.1}$$

where

$$V_j = \sum_{i=1}^{m} D_i f(d_{ij}) \tag{2.2}$$

Where A_i^G represents the index of the gravity model, and a higher value means better accessibility at the location i. S_j is the capacity of the healthcare provider j (e.g., ambulances, EMS staff), and V_j is the potential demand served by the provider j. D_i is the amount of potential demand at location i. The distance decay effect is formulated by $f(d_{ij})$. n and m represent the total number of services (e.g., hospitals or EMS stations) and the total demands, respectively. Therefore, the nature of the above model is the ratio of supply to demand, which follows a distance decay effect.

Regarding their extensions in healthcare accessibility, Joseph and Bantock (1982) improved the gravity model that considered the capacity of the health supply and the amount of demand using a negative exponent distance decay function. An integrated approach composed of a sequence of individual measures was proposed by Khan (1992). He started with a gravity model and then integrated it with a series of new elements in relation to potential spatial accessibility. Congdon (2001) employed a gravity model to quantify the referral flows from residences to emergency hospital services. A hybrid form of gravity model was developed with a consideration of the three thresholds of the distance decay function (Schuurman, 2010). Crooks and Schuurman (2012) provided general guidance in applying the basic gravity models to measure healthcare accessibility.

Inspired by the gravity model and the floating catchment area (FCA), Luo and Wang (2003) proposed the 2SFCA method, which considers the PPRs involving both demands and providers. The FCA is a common approach for spatial smoothing, where the catchment area could be represented by a circle (Immergluck, 1998), square (Peng, 1997), or a fixed distance/travel time range (Wang and Minor, 2002). The 2SFCA method is composed of two steps. The first step (Step 1) is to compute the PPRs or provide-to-demand ratios within a pre-defined distance/travel time standard for each service facility j. The mathematical model of step 1 is as shown in equation (2.3):

$$R_j = \frac{S_j}{\sum_{k \in \{d_{kj} \leq d_0\}} D_k} \quad (2.3)$$

Where d_{kj} is the travel costs from the demand site k to the service location j, while d_0 represents the pre-defined travel costs. D_k is the demand at each site k whose centroid is located inside the catchment ($d_{kj} \leq d_0$), and S_j is the supply capacity of the service location (e.g., ambulances, physicians). R_j is the PPR value based on each service facility j.

The second step (Step 2) involves adding up all PPRs of all of the involved the provider j within the catchment of each demand location i. The mathematical model of Step 2 is shown in (2.4):

$$A_i^f = \sum_{i \in d_{ij} \leq d_0} R_j \quad (2.4)$$

Where A_i^f represents accessibility to the healthcare service at the demand location i - a higher value means the better accessibility. d_{ij} represents the travel time or distance between each demand site i and supply location j.

Recent years have seen a decrease in the application of traditional gravity models involving the measurement of EMS accessibility (e.g., Neutens, 2015). Comparatively, more studies tend to use the special case of gravity models - the 2SFCA method to measure spatial accessibility to various healthcare services. It is because the 2SFCA is relatively simple to compute and easy to intuit. The method has been widely applied in health-related studies such as (Yang et al., 2006; Wang and Luo, 2005; McGrail and Humphreys, 2009a; Xiao et al., 2021), and also broadly employed to measure accessibility to various emergency services, such as EMS stations (Hu et al., 2020; Hashtarkhani et al., 2020) or emergency departments (Huang et al., 2016). The 2SFCA method helps policymakers deploy and plan healthcare resources while considering their long-term availability. For example, this method has been employed to help plan the Chinese National Healthcare Plan (*"Healthy China 2030*") for the patient referral system (Xiao et al., 2021). However, the limitation of the 2SFCA method is the denominator of Equation (2.2) – a dichotomous method that defines a service as only accessible or inaccessible using a cut-off travel time (distance).

Several scholars have attempted to extend the distance decay function in different ways, such as creating a continuously gradual decay within a threshold of travel costs and no effect beyond (Guagliardo, 2004; Dai, 2010; Shi, 2012). The travel distance/ time decay function can also be formulated by a discrete function (Luo and Qi, 2009) or by combining both discrete and continuous functions (McGrail and Humphrey, 2009c). Wang (2012) summarizes the different assumptions for conceptualizing the distance decay rule as part of the interactions between the healthcare demand and providers shown in Figure 2-2. Those functions can be represented by a continuous formulation (e.g., Joseph and Bantock, 1982), a discrete set of choices (Luo and Wang, 2003; Luo and Qi, 2009), or in a hybrid form (e.g., Dai, 2010). In practice, the distance decay function and associated parameters are often determined by analyzing healthcare seeking behaviors as well as healthcare planning criteria. A general 2SFCA model was proposed by Wang (2012), which summarized different conceptualizations of the distance decay function in provider-population interactions. The mathematical formulation of the generalized 2SFCA model is as shown in equation (2.5):

$$A_i = \sum_{i=1}^{n} \left[\frac{S_j f(d_{ij})}{\sum_{k=1}^{m} D_k f(d_{kj})} \right] \tag{2.5}$$

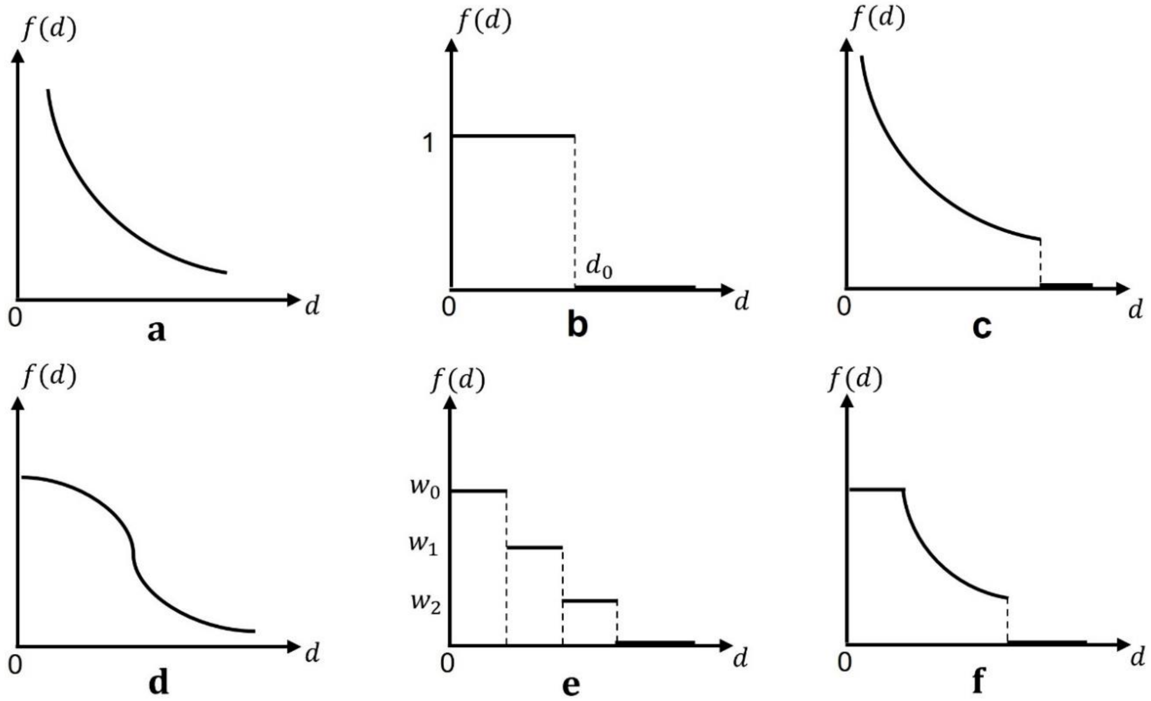


Figure 2-2. Conceptualizing the distance decay functions through the healthcare demand – service supplier interactions: (a) basic gravity function, (b) binary discrete, (c) kernel density, (d) Gaussian function, (e) multiple discrete, and (f) three-zone hybrid (Wang, 2012)

Also, many studies have improved the 2SFCA method from other perspectives, such as considering various transportation modes (Mao and Nekorchuk, 2013; Langford et al., 2006; Tao et al., 2018), demographic factors in the healthcare demand (Ngui and Apparicio, 2011; Hashtarkhani et al., 2020), the potential interaction between supply and healthcare demand (Wan et al., 2012; Delamater, 2013), spatiotemporal factor (Xia et al., 2019), or online healthcare services (Alford-Teaster et al., 2021). For example, Wan et al. (2012) introduced a three-step floating catchment area (3SFCA) method that added an additional step to consider a travel time-based competition scheme to address the problem where previous 2SFCA approaches might overestimate the healthcare demand for some service facilities. Furthermore, the catchment radius can be extended based on the administrative division (e.g., urban or rural) (McGrail and Humphrey, 2009b) or provider and neighbourhood type (Yang et al., 2006).

There are some limitations of those gravity-based methods. First, the coefficient of the distance decay function is usually unknown. Computing the coefficient value typically needs various data on healthcare utilization and the calculation processes can be complex. Second, the obtained results are not intuitively comprehensible and challenging to understand by the public. Thus, the gravity models are difficult to accept in practice. Then, the 2SFCA method may overweight consider the influence of some emergency facilities on users because emergency teams (e.g., firefighting or EMS) are usually dispatched from their nearest facilities. Moreover, the 2SFCA approaches are not suitable for every healthcare system. For example, this method cannot fit the Scottish healthcare system, where patients can only seek healthcare services in their registered public hospitals.

2.2.5. Other methods

There are several other methods to measure EMS accessibility, including the *n*-closest facility method and the kernel density estimation (KDE) approach. Both are occasionally applied to measure potential spatial accessibility to healthcare services. First, the *n*-closest facility method evaluates the average distance/travel time between each demand location and the *n* closest service facilities. From the author's knowledge, studies rarely use this method to measure healthcare accessibility (e.g., Dutt et al., 1986; Apparicio et al., 2007). One problem with the *n*-closest facility method is that it might weight the influence of the nearest service facility less, especially in an emergency. Another problem is that this approach's results are inconsistent with health policymakers' needs because most health policies are concerned about proximity.

Second, the KDE approach is a non-parametric approach for measuring the probability density function of random variables. It is often used to generate a continuous surface for discrete point events. It has been widely used to identify the spatial layouts of all diseases and epidemiological risk distributions. Guagliardo (2004) developed a KDE model to measure healthcare accessibility, including two kernel density raster layers. The former layer represents healthcare providers, and the latter represents the healthcare demand locations. Then, the former layer is divided by another layer to compute a layer with the spatially continuous equivalent of zonal supply-demand ratios, with the index representing the spatial accessibility to healthcare. Spencer and Angeles (2007) applied the KDE through two types of PPRs (population - per facility; population - per physician) to estimate accessibility to healthcare at the national level in Nicaragua. Yang et al. (2006) compared the 2SFCA and KDE methods and suggested that the 2SFCA produced more reasonable accessibility ratios than the KDE method. Based on the 2SFCA and KDE approaches, Dai and Wang (2011) introduced a kernel density 2SFCA method (KD2SFCA), while the main contribution is to use kernel density to simulate the distance decay function. Polzin et al. (2014) improved the KD2SFCA approach by adding weights for different social groups, which makes it better at identifying groups that are less empowered to use healthcare services (Polzin et al., 2014).

The KDE approach has several limitations. First, the accessibility index in boundary areas is less accurate because the bandwidth will stretch beyond the peripheral areas. Second, unoccupied lands such as forests, rivers or big lakes distort the results of the KDE method. Furthermore, the neat circular form of kernels used in healthcare studies does not consider the impact of traffic networks. As a result, KDE is rarely adopted in measuring healthcare accessibility alone.

2.3. Spatial Optimization in EMS Planning

Spatial optimization can be defined as the optimal spatial arrangement science, which combines GIS and mathematical (facility location) models (Church, 2001). Facility location models often use computational and mathematical formulations with one or multi-objective(s) to find optimal solutions to geographic/spatial decision problems under certain constraints. Recent years have seen a proliferation in the applications of spatial optimization approaches in healthcare planning, which often improves healthcare services' capacity, efficiency or equity (Ndiaye and Alfares, 2008; Pulver et al., 2016; Taiwo, 2020). This section will focus on the classic facility location models and various extensions as well as their applications in healthcare planning, especially in the EMS sector.

2.3.1. Classic models

Spatial optimization approaches for healthcare planning can be classified into three groups: coverage, *p*-median, and *p*-center problems. Two classic coverage models are the location set covering problems (LSCP) (Toregas, 1970), and the maximal covering location problem (MCLP) (Church and ReVelle, 1974). The LSCP looks for the minimum number of facilities necessary to serve the entire population with a pre-determined service standard. Given the number of facilities, the MCLP seeks the best locations for such facilities in order to maximize the demand covered by the service. The *p*-median and *p*-center models concern about accessibility to healthcare, where the former considers how to locate a certain number of service facilities so that the total weighted travel cost (e.g., distance or time as geographic barriers) can be minimized. The latter locates a set of facilities, attempting to the maximal geographic barrier between the demand and its nearest facility. The remainder of this section first explains the two coverage models, followed by descriptions of median and center problems.

The LSCP concerns the total number of facilities needed that can represent the total cost of offering emergency services. In the context of EMS, the LSCP aims to cover all demand within the service coverage by locating the minimal number of EMS stations. The planning area can be viewed as the transport network connecting a set of nodes representing the demand locations and potential facilities. Using the following notation:

I, J = set of demand locations and potential facility locations, respectively.

i, j = index of demand locations and potential facility locations, respectively.

S = maximum acceptable service distance or response time standard.

d_{ij} = distance or travel time between i and j.

$N_i = \{(j | d_{ij} \leq S)\}$

$x_j = \begin{cases} 1, & \text{if a facility is locted at node } j \\ 0, & \text{otherwise} \end{cases}$

Toregas (1970) structured the LSCP as the following model:

$$\text{Minimize:} \sum_{j=1}^{n} x_j \quad (2.6)$$

Subject to:

$$\sum_{j \in N_i} x_j \geq 1 \qquad \forall i \in I \quad (2.7)$$

$$x_j \in \{0,1\} \qquad \forall j \in J \quad (2.8)$$

Objective (2.6) minimizes the total number of facilities in needed. Constraints (2.7) guarantee that for every demand location i, at least a service facility j is opened from N_i. Constraints (2.8) define those decision variables. The LSCP is a compact model that involves *n* variables and *n* constraints. This model is important to EMS facility deployment as it can be employed for planning purposes by solving the LSCP over a range of service coverages.

The MCLP maximizes the number of demands that can be served by given facilities with a service standard, which was developed by Church and ReVelle (1974). As an extension of the coverage problem, it addressed one limitation of the LSCP – the number of available facilities is insufficient to cover all demands with a predefined service standard. Using the following additional notation, the MCLP can be formulated as follows:

p = number of facilities to be located

a_i = the total amount of demand at the location i

$$y_i = \begin{cases} 1, & \text{if demand } i \text{ is covered within the service standard} \\ 0, & \text{otherwise} \end{cases}$$

$$\text{Maximize: } \sum_{i=1}^{n} a_i y_i \tag{2.9}$$

Subject to:

$$\sum_{j \in N_i} x_j \geq y_i \qquad \forall i \in I \tag{2.10}$$

$$\sum_j x_j \geq p \tag{2.11}$$

$$x_j \in \{0,1\} \qquad \forall j \in J \tag{2.12}$$

$$y_i \in \{0,1\} \qquad \forall i \in I \tag{2.13}$$

Objective (2.9) aims to maximize the covered demand. Constraints (2.10) decide whether the demand location i is severed within the service coverage or not. The variable y_i could be allowed to equal 1, only if one or more facilities are selected to cover the location i. The total number of facilities to be located is limited by constraint (2.11). The binary integer variables are presented by constraints (2.12) - (2.13). The MCLP is critical to the EMS facility deployment as it could be solved for a given application by changing the number of facilities (p).

Instead of service coverage, p-median and p-center problems concern total travel cost, which is often employed to represent accessibility in EMS planning. Hakimi (1964) proposed the p-median problem (PMP), which, given p facilities, attempts to minimize the total (weight) travel cost (e.g., distance or time) between each demand i and its nearest open facility j. ReVelle and Swain (1970) proposed an integer-linear programming formulation of the p-median problem, which is presented in (2.14) - (2.19):

$$z_{ij} = \begin{cases} 1, & \text{if demand } i \text{ is assigned to facility } j \\ 0, & \text{otherwise} \end{cases}$$

$$z_{jj} = \begin{cases} 1, & \text{if node } j \text{ has been selected for a faiclity and assigns to itselfs} \\ 0, & \text{otherwise} \end{cases}$$

Minimize: $\sum_{i\in I}\sum_{\in J} a_i d_{ij} z_{ij}$ (2.14)

Subject to

$\sum_j z_{ij} = 1$ $\forall i \in I; j \in J$ (2.15)

$\sum_j z_{jj} = p$ $\forall j \in J$ (2.16)

$z_{ij} \leq z_{jj}$ $\forall i \in I; j \in J$ (2.17)

$z_{ij} \in \{0,1\}$ $\forall i \in I; j \in J$ (2.18)

$z_{jj} \in \{0,1\}$ $\forall j \in J$ (2.19)

Objective (2.14) minimizes the total weight travel cost of the demand assignment. Constraints (2.15) enforce that every demand i should be assigned to an open facility. Constraint (2.16) indicates that the total number of facilities to be located is p. Constraints (2.17) guarantee that demand i can be assigned to facility j only if that facility is open. Constraints (2.18) (2.19) define decision variables.

The p-center model was developed by Hakimi (1964) with the intention of easing the worst-off scenario through minimizing the maximal geographic barrier between a demand location and its nearest facility. The p-center problem can be formulated as follows:

Minimize W (2.20)

Subject to

$\sum_j z_{ij} = 1$ $\forall i \in I; \forall j \in J$ (2.21)

$\sum_j z_{jj} = p$ (2.22)

$z_{ij} \leq z_{jj}$ $\forall i \in I; \forall j \in J$ (2.23)

$W \geq \sum_j d_{ij} z_{ij}$ (2.24)

$z_{ij} \in \{0,1\}$ $\forall i \in I; \forall j \in J$ (2.25)

$z_{jj} \in \{0,1\}$ $\forall j \in J$ (2.26)

The objective (2.20) minimizes the maximal travel distance/time or cost between a demand and its nearest open service facility. Constraints (2.21) ensure that each demand i is only assigned to one facility. Constraint (2.22) states that in total p facilities are to be located.

Constraints (2.23) ensure that demand i can be assigned to facility j only if the facility at j is open. Constraints (2.24) states that the maximum geographic barrier between any demand and its nearest open facility (W) must be larger than the distance between any demand i and its closest facility j. Constraints (2.25) and (2.26) define decision variables. The p-center problem is a complex model where the decision variables and constraints increase exponentially with the area size.

All classic models have been widely employed in locating EMS facilities. For example, an existing study employs the MCLP to seek the best sites for the COVID-19 testing facilities in Nigeria (Taiwo, 2020), ensuring the testing facilities can be accessible across the country. Chanta et al., (2014) used the p-center problem to improve EMS accessibility in rural areas. These traditional models, however, fall short of capturing several factors and circumstances. First, traditional models do not consider the busyness or unavailability of each facility. Second, traditional models only involve a single type of facility. However, some services require the cooperation of multiple types of facilities (e.g., EMS stations and emergency hospitals). In addition, the MCLP and p-median problem tend to locate facilities in densely populated areas (e.g., urban regions), leaving fewer facilities in sparsely populated areas (e.g., rural regions), which might cause spatial inequalities in access to such services.

2.3.2. Extensions of classic models

The classic models mentioned above have been extended in many ways to account for the EMS planning practice in reality. Those extensions largely focus on three aspects of a model: (1) demand, (2) service coverage, and (3) objective functions.

(1) Demand

In facility location modeling, demand refers to the underlying population, communities or groups who need the service provided by the facilities. The underlying motivation of facility location modelling is to enhance the service capacity to serve people in need in an efficient and fair manner. It is a pre-requisite and the most important element of the public service sectors.

In an EMS system, the demand is often uncertain or random attributed mainly to the EMS arrival process. Many scholars have attempted to extend the classic models to account for the uncertainties or randomness in the EMS demand. For example, Beraldi et al. (2004) developed a stochastic model considering the demand uncertainty. They assumed that each

EMS facility was able to handle a fixed number of EMS calls in each day, described as the facility capacity. As an extension of the LSCP, the model was further extended by adding probabilistic constraints with a random demand variable to guarantee patient satisfaction with the acceptable level of reliability. Later, a two-stage framework incorporating the demand uncertainty was developed (Beraldi and Bruni, 2009). To the best of my knowledge, Beraldi and Bruni (2009) engaged in the first attempt to implement a two-stage approaches with demand uncertainty in the EMS facility location. Following this idea, the demand uncertainty in the EMS was further extended by Zhang and Jiang (2014) and Zhang and Jiang (2015) by simultaneously minimizing the EMS calls not served on time. The uncertainty or randomness of the EMS demand was also developed by Nickel et al. (2016) and Boujemaa et al. (2017) by considering the discrete probability distributions or various types of ambulances. Currently, the uncertainty or randomness of the EMS demand has been widely implemented in EMS facility location modelling (e.g., Ruslim and Ghani, 2006; Yang et al., 2020). For example, based on the EMS data from the Songjiang district, Shanghai, one study focused on the location-allocation problem of EMS facilities in inner Shanghai city, with the consideration of the uncertainty or randomness of the EMS demand (Yang et al, 2020).

(2) Service coverage

Service coverage is an important component of coverage models (e.g., the LSCP and MCLP) (Schilling et al., 1979; Eaton et al.,1985; Murray et al. 2007). Classic models often require a demand is covered by the nearest facility. However, the nearest facility might not be always available, or there is a probability associated with the availability of a facility. As a result, various forms of service coverage have been proposed to better reflect the service provision in practice, primarily including (1) multiple and backup coverage, (2) coordinated coverage, (3) hierarchical coverage, and (4) probabilistic coverage.

Multiple or backup coverage means that two or more coverages from the same service should encompass demand locations. It intends to address problems where a demand covered by a single facility might be insufficient because one facility might not be capable of offering the quality of service needed to meet a large number of demands. Toregas (1970) observed that some services acted as the backup coverage to fill the gap when the primary coverage was unavailable. Daskin and Stern (1981) proposed a novel backup coverage problem structured using a bi-objective formulation to minimize the number of EMS facilities to cover all demand locations and then to maximize the number of demands covered at least twice. This work was further extended by Storbeck (1982) and Hogan and Revlle (1986). The former aimed to minimize the uncovered demands and to maximize the number of demands covered by at least twice based on the given number of facilities, and the latter introduced a multi-service MCLP that intended to maximize the demands that could be covered by the desired number of facilities. Later, Gendreau et al. (1997) improved the previous work by combining the concepts of double coverage and different coverage radiuses. The multiple coverage problems have cooperated with many variables, such as the operating cost, the additional cost for EMS delay, the workload of EMS stations or the priority (Liu et al., 2014; Su et al., 2015; Liu et al., 2016). The multiple/backup coverage problems have also been employed to deal with the disaster, hazard, or large-scale emergency cases (e.g., earthquake, flood or nuclear accidents) (e.g., Pual et al., 2017; Yang et al., 2020). At present, the multiple coverage problems have been widely employed to EMS sector (e.g., Laporte et al., 2009; Mohamadi and Yaghoubi., 2017). Many spatial optimization studies have applied the Multiple or backup coverage problems to their different planning criteria (Doerner et al., 2005; Laporte et al., 2019).

Coordinated coverage problems consider that coverages are cooperative and coordinated to provide a complete service. ReVelle et al. (1976) was the first to focus on the coordinated accessibility problem which defined the maximum EMS service distance /travel time as the sum of the travel time of two-related EMS trips. Based on the above concept, Branas et al. (2000) introduced a Trauma Resource Allocation Model for Ambulances and Hospitals (TRAMAH) to locate two types of facilities (trauma centers and air EMS stations) with a consideration of different service coverages for different trips. As an extension of the LSCP, Moon and Chaudry (1984) developed a conditional covering model to minimize the number of facilities required to cover all demands. Meanwhile, the model ensures that each demand location is covered by at least one facility, and it guarantees that when a facility j is opened, there must be another opened facility k located within T travel distance/time from the opened facility j. The conditional covering problem has been further extended by many studies (e.g., Hale and Moberg., 2005; Ratick et al., 2008; Paul et al., 2017). All types of coordinated coverage problems have been widely employed in EMS planning practice (Branas and ReVelle, 2001; Branas et al., 2005; Wang and Okazaki, 2007; Rana, 2012; Liu et al., 2016; Bozorgi-Amiri et al., 2017).

Hierarchical coverage problems often consist of at least two types of coverages in relation to hierarchical facilities, such as clinics and hospitals. Moore and ReVelle (1982) introduced a model with respect of successively inclusive services which strives to locate types of facilities in a way so then the facilities in the lower level can be served by the higher-level facilities. Then, an extended hierarchical model incorporating a distance decay function is proposed (Hodgson, 1988), which considered the referral trip. Butler et al. (1992) developed a hospital-based hierarchical model to address multi-level hospital location with considering the referral trip. One study also considered the factor of socioeconomic demand groups with different income levels (Marianov and Taborga, 2001). Previous models were also further extended by several studies (Gerrard and Church, 1994; Galvão et al., 2002; Galvão et al., 2006). For example, Galvão et al. (2006) improved the three-dimension model by adding capacity constraints, especially for the resource-limited and higher level of the hierarchical facilities. Some studies improved the hierarchical coverage problem by adding other variables, such as the fixed and variable costs for facility construction (Ratick, 2008), the risk of disruption (Smith et al., 2009) or the multi-flow nested hierarchical system (Zarrinpoor et al., 2017). A special case of the hierarchical location problem was discussed by Church and Eateon (1987) that involved activities between the levels such as the referral activities in select healthcare systems. (Church and Eateon, 1987). The hierarchical location problem is often implemented in the planning of emergency response facilities (e.g., shelters, hospitals) during hazards or disasters (e.g., Chen et al., 2013; Zhang et al., 2017; Trivedi et al., 2017).

Probabilistic coverage problems involve a non-zero probability that the service facilities might not often be available when needed. In general, the probabilistic coverage problems can be divided into (1) reliable coverage and (2) expected coverage. On the one hand, the concept of reliable coverage was introduced by Chapman and White (1974). That is, whether a demand could obtain a timely service depends not only on the location within the service coverage but also on the probability of a facility being unavailable. The probabilistic coverage location model was improved by ReVelle and Hogan (1988), which aimed to enforce that at least one ambulance was available for each demand with a given level of reliability. One study also considered two types of service facility with a minimum level of reliability (ReVelle and Marianov, 1991). To estimate the busyness fraction depending on each facility, Marianov and ReVelle (1994, 1996) developed two approaches incorporated with the queueing theory. The model was further extended by several studies (Harewood, 2002; Galvão, 2005; Shariat-Mohaymany et al., 2012).

On the other hand, the expected coverage problem incorporates the likelihood that a facility would be unavailable or busy. The first expected coverage problem was introduced by Daskin (1982, 1983). They proposed an expected coverage model (MEXCLP) to maximize the expected coverage by locating a fixed number of vehicles, considering the nature of facility availability. Differing from the reliable coverage problem, the works by Daskin (1982, 1983) have counted the service coverage as providing a benefit rather than needing a minimum coverage reliability threshold. The MEXCLP and its further extensions (Bianchi and Church, 1988; Daskin et al., 1988) consider three major assumptions: the fraction of unavailability is (1) the same for all facilities and already known; (2) is independent of each facility; (3) is independent of each ambulance. Later, ReVelle and Hogan (1989) developed a maximal availability model (MALP) It considered how to optimize the spatial layout of EMS stations, thus the maximal number of demands could be provided α-reliable coverage. The expected coverage was then developed by considering the different types of ambulances as in the work of Mandell (1998) and McLay (2009). A variant of MEXCLP called the adjusted MEXCLP (AMEXCLP) was developed by (Restrepo et al., 1989), which integrated the corrective factor from a hypercube model (Larson, 1974) and a queuing theory (Larson, 1975) to simulate the expected coverage with a predetermined plan. Goldberg et al. (1990) improved the MEXCLP by considering the stochastic travel times to scenes and their priority level. Many studies further improved the expected coverage problem (e.g., Ingolfsson et al., 2008; Van den Berg and Aardal, 2015; Van den Berg et al., 2016). Recent years have seen a proliferation in the application of involving EMS in location planning (e.g., Ball and Lin,1993; Sorensen and Church, 2010; Lei et al., 2014).

(3) Objective functions

The objectives of classic models have been extended to account for three characteristics of EMS systems: system efficiency, service inequality, and the trade-off between efficiency and inequality.

Improving system efficiency is the mainstream of facility location modelling, which is mainly achieved in two ways. The first type of approach is often the extension of the LSCP, which aims to minimize an index that obstructs system inefficiency. Early extensions of the objective often considered equipment needed (e.g., ambulances) or both facility and equipment. For example, Schilling et al. (1979) developed a spatial optimization model that aimed to minimize the total amount of all types of equipment needed in the system (such as basic and advanced emergency vehicles). Unlike the traditional LSCP and early extensions, some studies intend to minimize other indexes that might obstruct EMS systems, such as financial costs, or uncertainties. For example, Beraldi et al. (2004) developed a deterministic EMS location model to minimize the total EMS financial costs, including the opening and assignment costs. Similar works are also conducted by several scholars (e.g., Beraldi et al., 2009; Zhang and Jiang 2014; Su et al., 2015; Nickel et al., 2017). Differently, some studies aimed to minimize or enforce various uncertainties within an acceptable level, such as the likelihood of EMS delay or random travel time (Ingolfsson et al., 2008; Zhang and Jiang, 2014; Zhang and Jiang, 2015).

The second type of approach to improve EMS efficiency is to maximize an index that represents system efficiency, which is often the extension of the MCLP. Early extensions improved the objective of the MCLP by considering more than one coverage (Hogan and ReVelle,1986; Gendreau et al., 1997), the expected coverage (Daskin, 1983), or different facilities or equipment (Bianchi and Church, 1988). For example, Bianchi and Church (1988) developed a Location and Equipment Emplacement Technique (FLEET) problem, which aimed to maximize the amount of demand covered by an equipment by locating service facilities and allocating emergency vehicles. Moore and ReVelle (1982) introduced a hierarchical coverage model that aimed to minimize the uncovered demands by any level of health service (i.e., clinic or hospital). Unlike the objective of the classic MCLP and previous extensions, which only involved the covered demand, current extensions also consider the maximal positive outcomes from other perspectives, such as survivals. For example, Erkut et al. (2008) developed a maximal survival model by maximizing the expected number of survivals. Similar work is also represented by Knight et al. (2012).

Many objectives are developed to improve equality in healthcare services by minimizing disparities in the influences or outcomes such as travel distance/time/costs. The frequently used objectives of equality measures often minimize the variance (e.g., Wang and Tang, 2013), the range (e.g., McLay and Mayorga, 2013), the mean deviation (e.g., Newton et al., 2022), or the Gini coefficient (Drezner et al., 2009), and among many others. For example, Wang and Tang (2013) developed a quadratic spatial optimization model that aims to minimize the variance of 2SFCA scores across demand locations by optimizing the spatial locations of service providers. Newton et al. (2022) developed a generalized equality model for minimizing the mean absolute deviation of spatial effect in the siting of EMS stations. Drezner et al. (2009) developed an equitable spatial optimization model to reduce the Gini index in relation to facility location analysis.

Trade-off between efficiency and equality is also considered by some EMS location studies, which can be achieved by adding equitable constraints or using multi-objective models. On the one hand, some studies are committed to adding equity constraints, guaranteeing that the systems can maintain minimum levels of equitable services (ReVelle and Hogan, 1989; Ball and Lin, 1993; Gendreau et al., 1997; McLay and Mayorga, 2013). For example, a reliability model was developed by Ball and Lin (1993), which incorporated equitable constraints, leading to the result that every demand location has an acceptable opportunity to accessibility an available ambulance. On the other hand, EMS location models can balance efficiency and equality through objective functions where one or more objectives are relevant to improving equality (Chanta et al., 2014; Khodaparasti et al., 2016). For example, Khodaparasti et al. (2016) introduced a bi-objective model where the primary objective was to maximize the total efficiency index assigned to the EMS stations and the secondary objective proposes maximizing the equality performance system.

2.4. Research gap

GIS-based spatial approaches have been widely employed in EMS such as measuring spatial accessibility to EMS and optimizing spatial layout of EMS facilities. However, there are four research limitations or challenges that remain to be addressed.

The first research limitation is that, in general, the travel time in existing EMS accessibility studies is usually estimated with fixed speed limits for different types of roads, transportation models and land-use types, such as 70 miles/hour on highways and 30 miles on local roads for driving (e.g., Cudnik et al., 2012; Dekamater et al., 2012; Mao et al., 2013), or estimated by transportation simulation models (e.g., Hu et al., 2020). Such methods often ignore the real-time traffic, which can greatly affect the travel time of ambulances (e.g., Earnest et al., 2011). In particular, the travel time in urban areas during peak and off-peak hours can be very different (Luo et al., 2020). If an ambulance is delayed during the peak hour due to traffic congestion, it might have a huge impact on the patient's health. Therefore, the consideration of traffic conditions during peak hours has strong practical significance.

The second research limitation is that most studies have only considered a one-way trip (Trip 1 or Trip 2). Although this is common to general healthcare-seeking behavior (e.g., primary care, general hospital), it is not suitable for EMS, which often includes two related trips. Even if the work by Vanderschuren and McKune (2015) considered both trips when evaluating spatial accessibility to EMS, they employed static road networks with speed limits to estimate travel time for ambulances. In fact, both EMS trips (i.e., Trips 1 and 2) are important to survival rates and patients' outcomes. Therefore, it is necessary to consider the two related EMS trips when evaluate accessibility to EMS.

The third research limitation related to service coverage with respect to two related EMS trips. Most EMS location optimization work only considered the service coverage for one of the two related trips, either for Trip 1 (Van den Berg et al., 2016) or for Trip 2 (Salman and Yucel, 2015). Similarly, it is not suitable for EMS because it typically entails two related trips, both of which are critical to saving lives. Therefore, it is necessary to consider service coverages for two related trips to guarantee the overall EMS provisions.

Finally, how to reduce inequalities in EMS through location optimization of EMS facilities remains a great challenge. In particular, few studies of EMS location optimization have focused on the urban-rural inequalities in EMS although such inequalities have been well documented (e.g., Jennings et al., 2006; do Nascimento Silva and Padeiro, 2020). Compared with the inequalities between communities or individuals, regional inequalities in EMS have received less attention, especially between urban and rural areas. However, achieving regional healthcare equality, is a critical goal of national or regional policies (e.g., Wuhan Municipal Health Commission, 2019; the State Council of China, 2012). Thus, reducing regional inequalities in EMS has strong policy implications.

The thesis intends to fill the four research gaps mentioned above. The first and second research limitations will be addressed in Chapter 3. The last two research gaps will be covered by Chapters 4 and 5, respectively.

2.5. Chapter summary

In summary, this section finds that efficiency and equality are two important factors that worldwide EMS systems have widely concerned. According to the review on GIS-based methods, the geographic proximity and 2SFCA method are widely employed in measuring accessibility to EMS. In spatial optimization, classic models and their various extensions have been also broadly employed in EMS sections, which can be discussed based on three perspectives: EMS demand, service coverage and objective functions. Finally, four research gaps are presented, which will be addressed in this thesis.

Chapter 3 Measuring Spatiotemporal Accessibility to EMS

This chapter aims to measure spatial and spatiotemporal accessibility to EMS with a consideration of two-related trips and real-traffic conditions. The proximity and E-2SFCA methods were adopted to measure both spatial and spatiotemporal accessibility. In addition to traditional methods using standard speed limits on the road network, real-time traffic conditions are considered when calculating accessibility measures. An empirical study is carried out with the data from Wuhan, China.

3.1. Introduction

Accessibility to healthcare is a multifaceted term. From the utilization aspect, revealed accessibility concerns the actual use of health services. Potential accessibility focuses on the probable utilization of the service but does not guarantee the actual utilization of the services. From a spatial aspect, geographic accessibility often refers to travel distance/time between healthcare providers and demands or consider their potential spatial interaction (Joseph and Bantock 1982). The non-spatial perspective mainly focuses on factors that could influence the easiness of healthcare acquisition, such as demographic, socioeconomic status dimensions (Donabedian, 1973). Of interest in this study is potential spatial accessibility and its variations over space and time, accounting for two-related EMS trips.

Many GIS-based methods have been employed to measure potential geographical accessibility to healthcare services, which can be classified into three major categories: proximity-based measures, PPRs, and gravity-based approaches, including the traditional gravity models and 2SFCA-based methods.

However, most relevant studies concern static travel times (e.g., average travel times) or focus on a one-way EMS trip (e.g., Trip 1 or Trip 2) from an EMS station to a scene or from the scene to a hospital (see Figure 1-1 in Chapter 1). Although two-related trips and real-time traffic conditions are important to EMS provision (e.g., O'Keeffe et al., 2010; Earnest et al., 2012; Carr et al., 2018), the spatial variations in EMS accessibility caused by real-time traffic conditions (e.g., non-peak verse peak hours) with respect to two-related trips are often ignored.

The aim of this chapter is to measure spatial and spatiotemporal accessibility to EMS, accounting for two related EMS trips and real-time traffic conditions. An empirical study is carried out in Wuhan, China. Specifically, three objectives are to be achieved in this chapter: (1) to measure spatial accessibility to EMS with standard/predefined speed-limit (static); (2) to measure spatiotemporal accessibility to EMS with a consideration of real-time traffic conditions; (3) to compare spatial patterns of ambulance accessibility (Trip 1) and hospital accessibility (Trip 2). Two approaches are employed to measure accessibility to EMS: the proximity approach – measuring EMS travel times, and the E-2SFCA approach – considering spatial interactions between demands and suppliers.

This chapter is organized as follows. Section 3.2 reviews existing studies on EMS accessibility. Section 3.3 describes the data and methods employed in this research. Section 3.4 presents the results of spatial and spatiotemporal accessibility of EMS in Wuhan. Section 3.5 discusses the major findings and associated policy implications.

3.2. Background

This section first reviews the influence of Trip 1 and Trip 2 on health outcomes in the context of EMS. Then, the impacts of traffic condition on accessibility to EMS are discussed. Finally, limitations of existing study are summarized, followed by highlighting the chapter's aim and objectives again.

Trip 1 plays a critical role in improving health outcomes for EMS demands. Short travel time for Trip 1 means patients is likely to obtain early on-scene medical treatment, resulting in favorable healthcare outcomes. Many studies have found that Trip 1 is associated with out-of-hospital cardiac arrest (OHCA) (Cummins et al.,1991; O'Keeffe et al.,2010; Sladjana et al.,2011). For example, O'Keeffe et al. (2010) reported that a 1-min reduction in travel time for Trip 1 could improve the chances of survival by 24% from cardiac arrest. Similar results were also indicted by De Maio et al. (2003), Heidet et al. (2020) and Park et al. (2021). Short travel time for Trip 1 is also crucial to EMS demands with other illnesses or injuries (Sánchez-Mangas et al.,2010; Mahama et al., 2018). In addition, Trip 1 is vital to favorable healthcare outcomes regarding different illnesses or injuries (Wilde, 2012; Gauss et al., 2019). For example, a cohort study found a linear association between the travel time for Trip 1 and all-cause deaths in-hospital, so that mortality risk would increase 18% for each 10-min increase in travel time for Trip 1 (Gauss et al., 2019).

The importance of Trip 2 has been highlighted by numerous scholars (Haegi, 2002; Ouma et al., 2018; Carr et al., 2018). Short travel time for Trip 2 means patients is likely to receive early advanced and specialized medical treatments in hospitals. Many studies have indicated that Trip 2 is important to trauma patients (Newman, 1997; Higgs, 2004; Rammohan et al., 2013; Mucunguzi et al., 2014). For example, more than 50% of deaths in the UK resulting from road accidents happened at the scene or in the EMS vehicle, that is, prior to getting comprehensive and specialized medical care in hospitals (Higgs, 2004). Some studies have reported that short travel time for Trip 2 is also crucial to the health outcomes of infants and mothers (Nesbitt et al., 1990; Chay et al., 2009). For example, Chay et al. (2009) reported that the post-neonatal mortality was highly associated with short travel time to the hospital, and investment in improving geographic accessibility to healthcare facilities could have a long-term effect on health outcomes for infants and mothers. Further, short travel time for Trip 2 is also important to cardiac arrest patients (Langhorne et al., 1993; Rhee et al.,2000; Pajunen et al., 2005). In general, reducing travel time for Trip 2 is crucial to help patients receive in-hospital specialized medical treatments on time, therefore resulting in favorable healthcare outcomes.

The variation in real-time traffic conditions can greatly affect EMS accessibility. Congested traffic conditions are likely to cause ambulance delays, and patients might not be served on time, thereby influencing patients' health outcomes. Many studies have found that ambulance travel time or accessibility scores were significantly reduced during traffic peak hours (Earnest et al., 2011; Hu et al., 2020; Fraser et al.,2020). For example, Earnest et al. (2011) found that Singapore's short EMS travel time was significantly associated with uncongested traffic, such as during off-peak hours or weekends. Some studies found that the estimated travel time was often shorter than the actual travel time recorded because uncertainties in reality, like congested traffic conditions, were not always considered in the estimation (Neeki et al., 2016). In addition, the change in weather, lights and sirens were also associated with EMS travel times (Fleischman et al., 2013). Therefore, understanding the spatiotemporal influence of the traffic condition is crucial to help healthcare planners to maintain an accessible EMS system during rush hours, ensuring that patients can get relatively good EMS accessibility even if traffic flows are large.

Two major limitations in current studies on EMS accessibility remain to be addressed. One is that the EMS travel time is usually measured by a static travel speed. Although it might be suitable for places where traffic conditions are often stable, it might not be applicable to measure accessibility in densely populated areas, such as metropolises. Even if the culture that traffic gives way to an EMS vehicle is adhered to in some countries, not all areas follow this role. China always meets this problem that ambulances are difficult to priority pass-through traffic because some drivers lack the awareness to give way to ambulances. Moreover, drivers are sometimes difficult to give way to ambulances due to extremely overcrowded roads that do not have extra space for giving way to ambulances. Thus, traffic flow is an essential factor in influencing the quality of EMS and survival rates, while good traffic condition usually leads to better health outcomes. Nowadays, dynamic traffic condition can be already estimated through online map services like Google Maps (https://www.google.com/maps). Many studies have employed online map services in measuring accessibility to healthcare services (Tao et al., 2018; Wang and Xu, 2011).

Another limitation is that, in general, only one-way trips are considered when measuring EMS accessibility, either Trip 1 (Hu et al., 2020) or Trip 2 (Bailey et al., 2011; Rocha et al., 2017). This is problematic as EMS includes two related trips and both trips play important roles in saving lives. Some people might be reached easily by ambulances but spend a long time to reach their nearest hospitals, and vice versa. Although the work by Vanderschuren and McKune (2015) considered both trips, they used the static travel time to measure EMS accessibility.

As can be seen from the above discussion, involving real-time traffic and two-related trips is crucial to better understanding and improving EMS accessibility from a spatiotemporal perspective.

3.3. Methods

3.3.1. Study area and data

Wuhan consists of 13 districts, with 6 in the rural region and 7 in the urban area. The EMS response times set by local government for urban and rural areas are different: 10 and 12 min, respectively (Wuhan Municipal Health Commission, 2020). In this empirical study, residential locations are employed in representing locations of demands (i.e., patient origins), which is frequently used to assess healthcare accessibility due to the lack of actual health data (Wang and Xu, 2011; Balamurugan et al. 2016; Hu et al., 2020). EMS stations and hospitals are used as locations of EMS providers.

Specifically, the dataset employed include 3,493 local communities in Wuhan (often called *Shequ* in China; 1,172 and 2,321 in the urban and rural areas), 79 EMS stations (54 in the urban area) and 72 EMS care facilities (equal to general hospitals in Wuhan; and 53 in the urban area). Shequ is the lowest administrative geographical unit in China, covering a certain spatial area where residents have close social interaction. The finest geographical scale at which census population data are available is Shequ. In our dataset, there are 2,880 ($people/km^2$) per shequ on average in Wuhan. The number of ambulances based at each station in Wuhan is not available. Therefore, we presume that all EMS stations have an equal number of ambulances (usually two to three). In China, the hospital is a hierarchical system that is categorized into three groups: Level I, II or III. Level III hospitals have the highest medical capacity, but Level I hospitals have the lowest medical capacity. As Levels II and III hospitals are the main EMS care facilities in China, our study only includes hospitals for these two levels (74 hospitals above Level II). Overall, the EMS demand is represented by the total population of each shequ. The two types of providers are represented by EMS stations and hospitals.

All data adopted here are from free and open databases. Specifically, the location of providers was collected from Baidu Map (https://map.baidu.com/), the largest and most well-known web-based map service in China. The population data, capacity of hospitals and road network were obtained from the Geographical Information Monitoring Could Platform (http://www.dsac.cn/) and Hubei Institute of Land Surveying and Mapping (http://dzj.hubei.gov.cn/chy/).

Figure 3-1 (a) depicts the related spatial and population density information in Wuhan. It is evident that the rural region is less densely populated than the urban area. Seven urban districts account for 51.9% of the total population but only cover 20.5% of the overall area. Among the 13 districts, Jianghan has the highest population density (19,380 people/km^2), but Jiangxia has the lowest population density the lowest density (485 people/km^2). In the urban area, only the northeast of Hongshan is relatively sparsely populated. In the rural area, most population concentrates around town centers where local EMS is provided. It is thus not surprising that most EMS stations and hospitals are located in the urban region. For example, eleven EMS stations and nine hospitals are located in Jiangan, even though this district occupies only 9% of Wuhan’s total area. In contrast, rural districts have fewer numbers of EMS stations and hospitals, even though their total area accounts for more than three-fourths of Wuhan. For example, only two EMS stations and three hospitals are located in Xinzhou, but this district accounts for 21% of Wuhan’s total area. Therefore, it that EMS stations and hospitals are spatially unevenly distributed, especially between urban and rural areas. Figure 3-1 (b) presents the different road types in Wuhan, and the figure shows that the urban road network is significantly more developed than the rural road network. Densely populated areas tend to have better road networks around them, and vice versa. For example, the road network in the northwest boundary of Wuhan is less developed, and this area also has small population density.

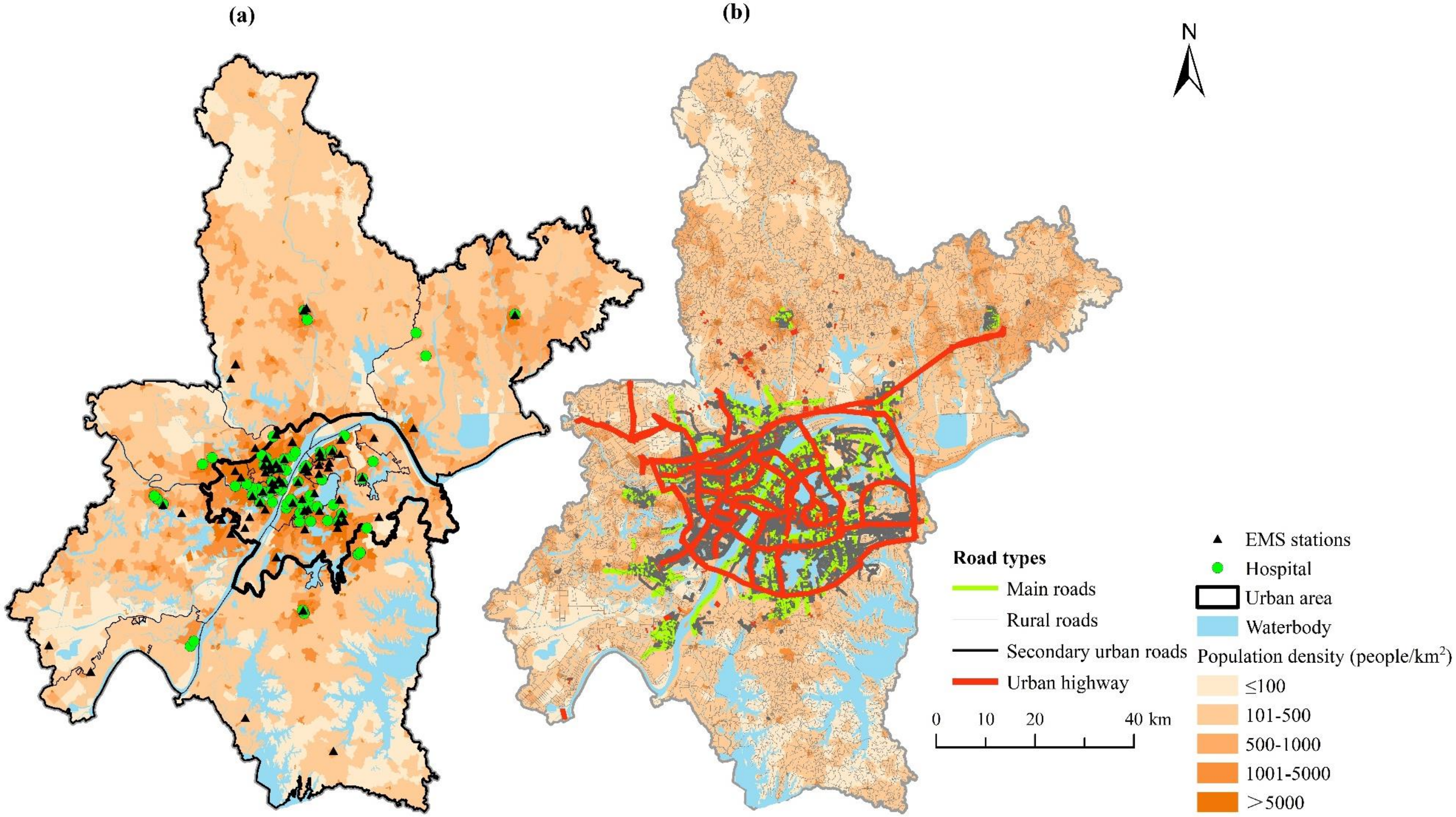


Figure 3-1. Study area in Wuhan (a) EMS locations and population density; (b) different road types.

3.3.2. Measuring accessibility to EMS

Two types of measures are employed: the proximity and E-2SFCA approaches. Both are based on estimated travel times, obtained from (1) calculation using static road network with average speeds on different road types, and (2) online map service considering real-time traffic conditions.

The framework of analysis is described in Figure 3-2. First, average, and real-time traffic travel times are estimated in relation to two trips (i.e., Trips 1 and 2) involved in one EMS journey (i.e., overall trip). The demand location is represented by the centroid of each shequ.

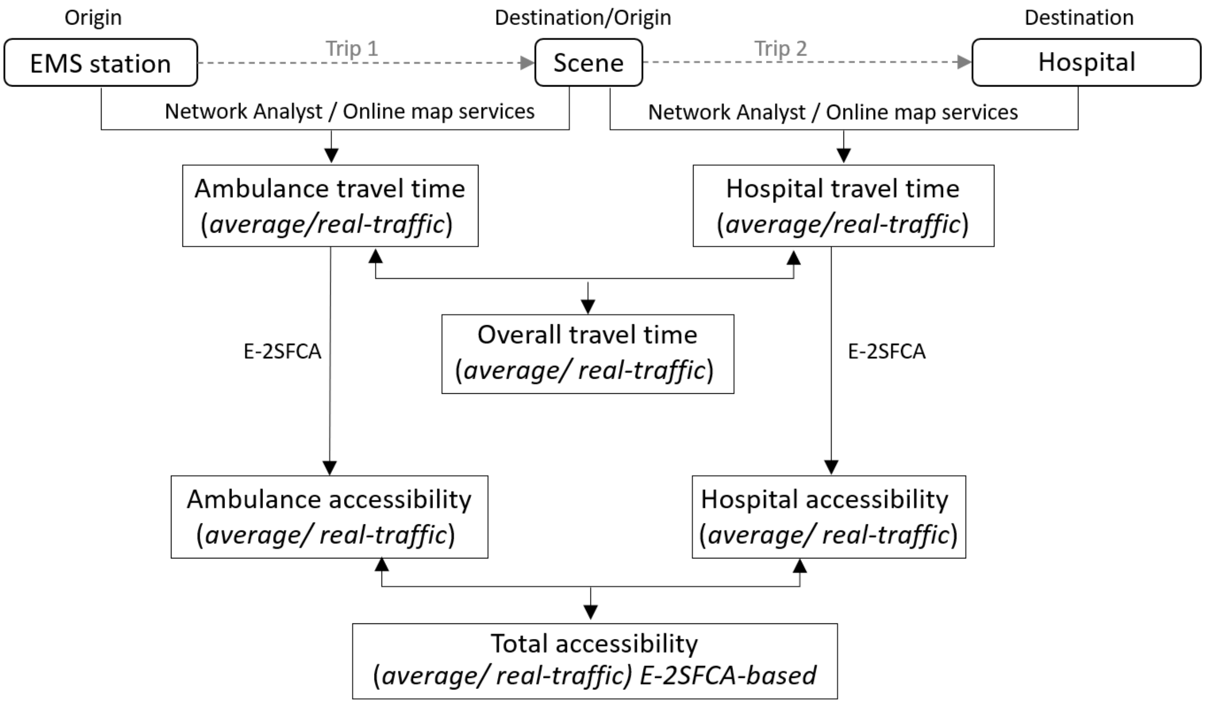


Figure 3-2. Analysis Framework of Spatial / Spatiotemporal Accessibility to EMS.

The average (static) travel times are based on 2020 Wuhan Road network dataset. This is implemented with the network analyst extension in ArcGIS (version 10.7). The road network contains the average speed on each type of road, and Wuhan has four road classes (see Table 3-1). The average speed on the urban highways is 60 km/hour, which is the fastest road class, including urban high-speed roads and ring roads. The average speeds on main roads and secondary urban roads are between 40-55 km/hour. The average speed on rural roads is lowest, only 30 km/hour. In general, traffic conditions on the urban highway and rural roads are stable, but on main roads or secondary urban roads are often unstable, which means the traffic congestion occurs more frequently here. The distribution of road network in Wuhan has been shown in Figure 3-1.

Table 3-1. Average travel speeds on different road types.

	Types	Average Speed (km/h)	Speed Stability
Urban area	Urban highways	60	Stable
	Main roads	55	Unstable
	Secondary urban roads	40	Unstable
Rural area	Rural roads	30	Stable

To estimate real-traffic travel times, Baidu online map service (https://map.baidu.com/) is employed here, which contains the most updated road network in China and accounts for real traffic flows. Java scripts (see https://github.com/WeicongLuo/PhD_thesis_Chapter_3) were developed to call Baidu Map's Application Programming Interface (API) for route planning (https://lbsyun.baidu.com/products/products/direction). It is worth noting that all API services provided by Baidu Map run in the BD-09, which is a geographic coordinate system used by Baidu Maps. Therefore, the coordinated system of the demand and provider locations should be transferred into the BD-09 geographic coordinate system during the estimation process.

Based on the estimated travel times, the E-2SFCA model then uses to combine accessibility and availability. The estimation of travel time is implemented for traffic peak and off-peak periods. Two traffic peak periods (7:30–8:30 and 17:30–18:30) and one off-peak period (21:00– 22:00) are involved. They are based on the traffic off-peak/peak intervals stipulated by Wuhan Traffic Management Bureau. As traffic congestion occurs mainly during weekdays, the estimation of EMS travel time was processed at the five consecutive working days between September 5th – 10th, 2021. During those days, there were no large-scale events that would impact traffic and weather was good.

There are two steps in the E-2SFCA. The first stage is to calculate the supply-to-demand ratio for each EMS facility (EMS station or hospital) within a predetermined journey time, divided by a discrete distance-decay function (Luo and Qi, 2009). The distance-decay function is then used in the second step to add up the PPRs of all EMS facilities within the specific travel time of each demand site. The E-2SFCA model extends the 2SFCA by dividing the total travel times into various time zones, each with a set weight that accounts for the influence of travel time decay. The E-2SFCA is employed in this situation because EMS often requires a minimum service standard, such as 10 or 12 min, which can be used to specify various service coverage zones. Using the following notation:

i, j, k:	the index of EMS stations, hospitals and scenes (population locations), respectively;
E_i, H_j:	the supply capacity at the ith EMS station and the jth hospital, respectively;
P_k:	the population at location k;
t_{ik}, t_{jk}:	the travel time from the ith EMS station to the kth population location, and from the kth population location to the jth hospital, respectively;
r , T_r , w_r:	the index of travel time zones, the rth time zone and its associated weight, respectively.

the definition of E-2SFCA in the context of this research can be formulated as in (3.1) - (3.3):

$$R_i = \frac{E_i}{\sum_r \sum_{k\in(t_{ik}\in T_r)} P_k w_r} \qquad R_j = \frac{H_j}{\sum_r \sum_{k\in(t_{jk}\in T_r)} P_k w_r} \tag{3.1}$$

$$A_k^E = \sum_r \sum_{i\in(t_{ik}\in T_r)} R_i w_r \qquad A_k^H = \sum_r \sum_{j\in(t_{jk}\in T_r)} R_j w_r \tag{3.2}$$

$$A_k = A_k^E + A_k^H \tag{3.3}$$

where the PPRs for the EMS station i and the hospital j are computed, represented by R_i and R_j, respectively. Besides, accessibility scores of the demand location k are calculated, represented by A_k^E for Trip 1 and A_k^H for Trip 2. Then, they are derived by summing up the corresponding weighted R_i and R_j. Finally, the sum of A_i^E and A_i^H is calculated to represent the overall accessibility (A_k) at the demand location k. A higher value of accessibility score indicates better accessibility.

Due to the lack of accurate ambulance data, it is presumed that all EMS stations have an equal number of EMS vehicles; that is, $E_i = 2$ for all EMS stations i. The number of inpatient beds in each hospital is employed to represent the medical capacity of hospital H_j, ranging from 50 to 3,300. Three time zones are used in this study ($r \in [0,10]$, (10,12] and $(12, +\infty)$ min) since Wuhan has approved two criteria for EMS response times: 10 min for urban districts and 12 min for rural districts. The value of w_r is then determined based on those three time zones. Specifically, $w_r = 1$ when the travel time t_{ik} or t_{jk} is less than 10 min. If the travel time t_{ik} or t_{jk} is between 10 and 12 min, the weight of w_r reduces with the increase of t_{ik} or t_{jk}, which follows the Gaussian function applied in studies on healthcare access (see Dai, 2011). $w_r = 0$ if the travel time t_{ik} or t_{jk} is beyond 12 min.

As the different E_i and H_j scales adopted in this study, the values of A_k^E and A_k^H should be standardized by Equation (3.4) before being employed Equation (3.3) to obtain A_k. In Equation (3.4), A_k^E or A_k^H is represented by v, and the standardized value is v'. After the standardized process, the values of A_k^E and A_k^H have a range between 0 and 1+σ. The parameter σ is employed to distinguish areas with standardized 0 score and areas with no accessibility score. Equation (3.4) represents the 'relative accessibility' in comparison with the maximum and minimum values. In detail, a local community has the best access within the study area if it has a score 1+σ. In this study, the value of σ is defined as 0.01. A higher score means better accessibility to EMS. If the A_k^E or A_k^H equals to 0 in an area, it means this area cannot access to the nearest EMS station or hospital within the pre-defined longest travel time threshold (i.e., 12 min), and v' would equal to 0, representing the poorest accessibility to EMS.

$$v' = \begin{cases} 0 & \text{if } A_k^E \; or \; A_k^E = 0 \\ \frac{v - v_{min}}{v_{max} - v_{min}} + \sigma & \text{otherwise} \end{cases} \tag{3.4}$$

3.4. Results

3.4.1. Spatial accessibility of EMS

(1) Proximity-based spatial accessibility

Figure 3-3 describes spatial patterns of estimated travel times for three trips: Trip 1, Trip 2 and the overall trip. Regarding two related EMS trips, the average and median travel times in urban districts are much smaller than the values in rural districts. However, travel times in rural districts have higher ranges of interquartile. According to the median depicted in Figure 3-3, among those urban districts, more than 98% population in Jianghan could reach the nearest ambulance or hospital within 10 min driving time (i.e., urban service coverage standard). Qiaokou has the shortest average travel times for trip 1 (3.1 min). Jianghan has the shortest average travel times for Trip 2 and overall trip, which are 2.4 min and 5.7 min, respectively. Meanwhile, more than 95% population in Jiangan, Qiaokou, Qinshan and

Wuchang could reach the nearest ambulances or hospitals within 10 min driving time. The average travel times in those districts were within 5 min for one-way trips (i.e., Trip 1, or Trip 2) and within 10 min for the overall trip. In comparison, EMS accessibility in Hongshan is the poorest among other urban areas. Only 78.2% of the population in Hongshan could reach the nearest ambulances or hospital within 10 min, and 77.5% of the people could complete the overall trip within 20 min. Hongshan has the highest average travel times among urban districts, 8.8 min for Trip 1, 10.4 min for Trip 2 and 19.2 min for the overall trip. Meanwhile, Hongshan has more extensive interquartile ranges than other urban districts.

When considering EMS travel times for the six rural districts, Dongxihu has the shortest average travel times for all trips, 23.5 min for Trip 1, 21.1 min for Trip 2, and 44.6 min for the overall trip. In Dongxihu, 38.8% and 72.2% of the population could reach the nearest EMS stations and hospitals within 12 min (i.e., rural service coverage standard), and 74.5% of the people could complete the overall trip within 24 min. The highest average travel time for Trip 1 is in Huangpi (42.0 min), where only 24.9% of people could reach the nearest ambulances within 12 min. The second-highest average travel time for Trip 1 is 35.0 min in Hannan, where only 46.9% of people can be served by their nearest ambulances within 12 min. As for Trip 2, the highest average travel time is in Jiangxia (55 min), where 23.1% of the population could arrive at their nearest hospitals within 12 min. the second-highest average travel time for Trip 2 is in Huangpi, where the average travel time is 43.9 min, and only 24.6% of the population could be served by their nearest hospitals within 12 min. For the overall trip, the highest average travel time is in Huangpi (86.0 min), and 19.9 % of the population could complete the total journey within 24 min. Then, the second-highest average travel time for the overall trip is in Jiangxia (85.8 min), and 21.4 % of the population could complete the overall journey within 24 min.

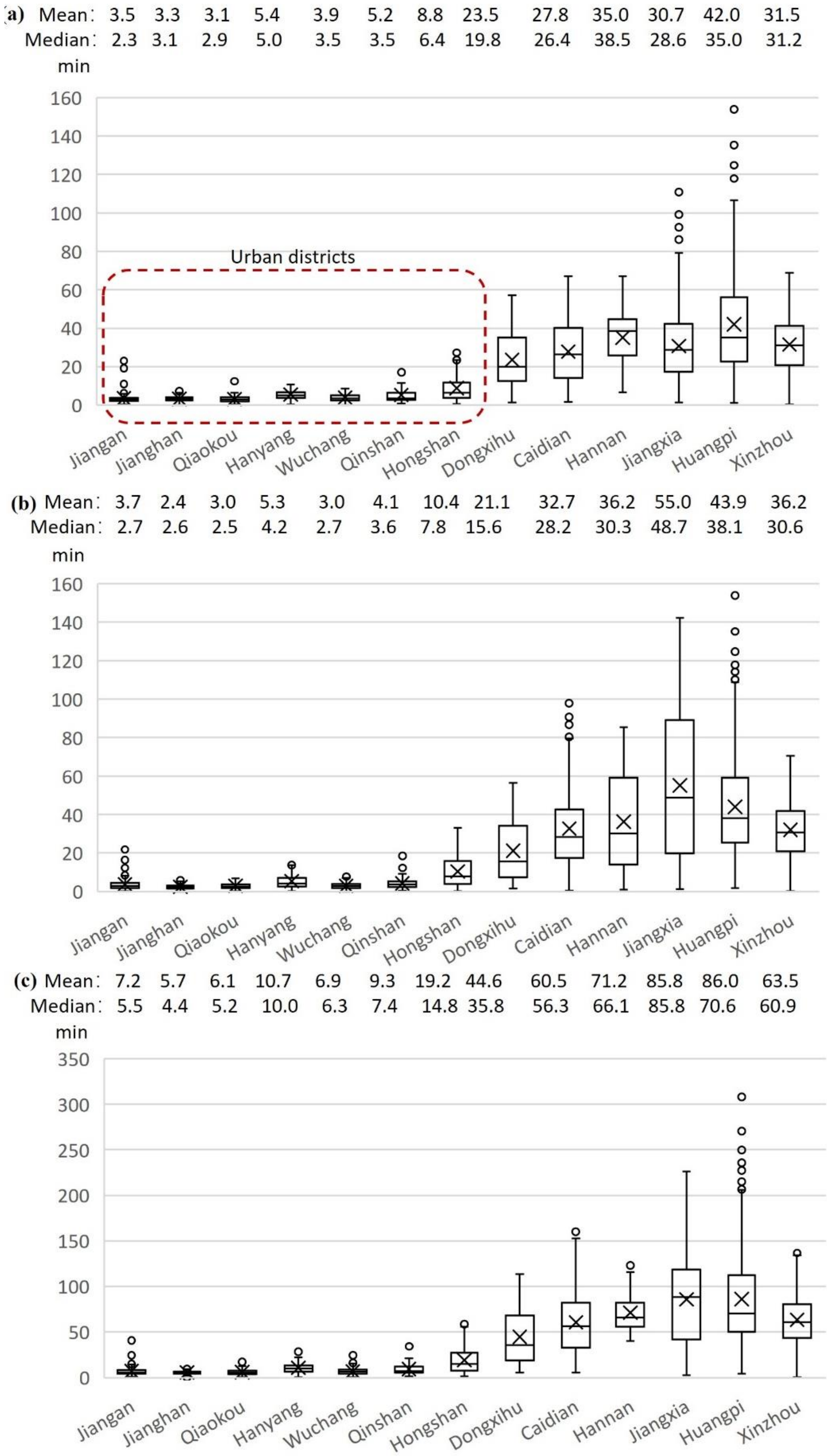


Figure 3-3. Boxplots of the estimated average travel time of different districts: (a) Trip 1 (EMS station to Scene); (b) Trip 2 (Scene to Hospital); (c) overall trip (EMS station to Scene to Hospital).

Comparing EMS accessibility between urban and rural districts, Figure 3-4 presents that the average urban travel times are shorter than the average travel time in rural areas in relation to all trips. Specifically, the average travel times in the urban areas are 5.05 and 5.07 min for Trip 1, and Trip 2, respectively. However, the average travel times in the rural areas are 33.39 and 39.18 min for Trips 1 and 2, which are 28.34 and 34.11 min higher than the urban values, respectively. For the overall travel time, the urban average value is 10.12 min, but the rural average is 72.57 min, with a one-hour difference. For Trip 1, about 94.4% of patients living in urban districts could reach to EMS vehicles from their closest EMS stations within 10 min, but only 28.2% of people living in the rural districts could reach their nearest ambulances within 12 min. For Trip 2, around 93.6% of urban patients could be transported to their nearest emergency hospitals within 10 min, but 32.3% of rural patients could reach their nearest ambulances within 12 min. For the overall trip, around 93.5% of urban patients could complete the overall trip within 20 min, but 30.3% of rural people could finish the overall trip within 24 min.

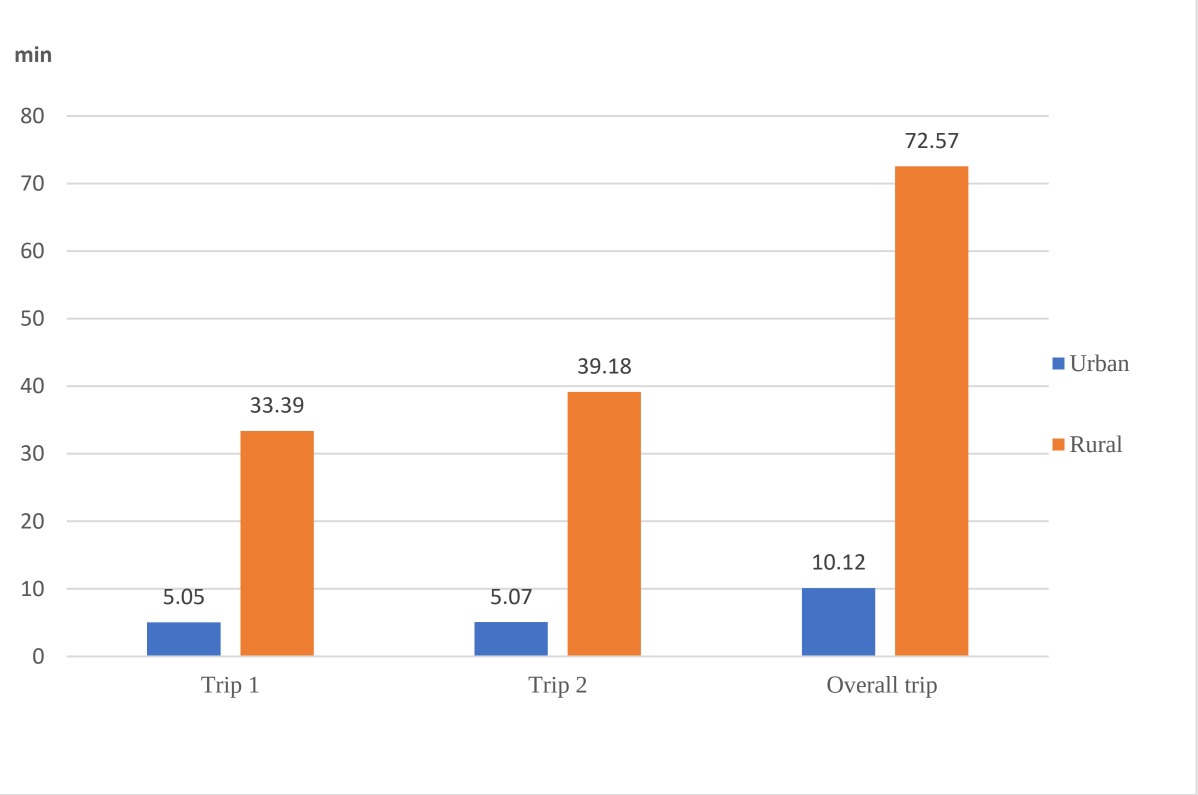


Figure 3-4. Average travel times for different trips between urban and rural areas.

The spatial patterns of average travel times are described in Figures 3-5. In general, EMS travel times for all trips increase from the central urban areas toward rural areas. Most shequs in the central urban areas have relatively good EMS and hospital accessibility (i.e., Trip 1 or Trip 2 ⩽10min, the EMS response standard in the urban area) as well as overall accessibility (i.e., Trip 1 + Trip 2 ⩽ 20 min). The urban shequs with relatively poor ambulance accessibility (i.e., Trip 1 > 10min) are clustered in the south and the east of Hongshan (see Figure 3-5 (a)). The urban shequs with relatively poor hospital accessibility (i.e., Trip 2 > 10min) are located in the south, the east and the north of Hongshan (see Figure 3-5 (b)). For the urban area with relatively poor overall accessibility (i.e., the overall trip > 20 min), those shequs are mainly distributed in the south, the east and the north of Hongshan (see Figure 3-5 (c)). Among the urban groups, the community with the longest travel time for Trip 1 is Kuailin shequ located in the east of Hongshan, where local residents need to take 29.62 min to reach an ambulance. The urban community with the longest travel time for Trip 2 is Jintang shequ, located in the south of Hongshan. Local residents need take 33.6 min to reach the nearest hospital. In urban areas, the longest travel time for the overall trip is Kuailin shequ located in the east of Hongshan, where local residents need take about one hour to complete the overall EMS trip.

In contrast, most shequs in rural districts have relatively poor ambulance and hospital accessibility (i.e., Trip 1 or Trip 2 >12 min, the EMS response standard in the rural area) as well as poor overall accessibility (i.e., Trip 1 + Trip 2 > 24 min). Except for some areas close to EMS stations or hospitals, most rural shequs could not be served by the ambulance or hospital services within the 12-min time standard. Specifically, those rural shequs with relatively good ambulance accessibility are mainly clustered in the middle and southwest of Huangpi, the middle and the southwest of Xinzhou, the north and the south of Jiangxia, the west of Hannan, the north of Caidian and the east of Dongxihu (see Figure 3-5 (a)). Areas with relatively good hospital accessibility are mainly clustered in the middle of Huangpi, the middle and east of Xinzhou, the north of Jiangxia, the east of Hannan, and the north of Caidian east Dongxihu (see Figure 3-5 (b)). Rural shequs with relatively good overall accessibility are mainly clustered in the middle of Huangpi, the middle of Xinzhou, the north of Jiangxia, the north of Caidian, and the east of Dongxihu (see Figure 3-5 (c)). When we consider an individual community, the area with the longest travel times for Trip 1 and Trip 2 are in Yaoshan shequ that is located in the northwest of Huangpi district, with 322 residents. Those local residents are estimated to spend more than two hours to reach the nearest EMS station or hospital and they might need five hours to complete the overall EMS trip.

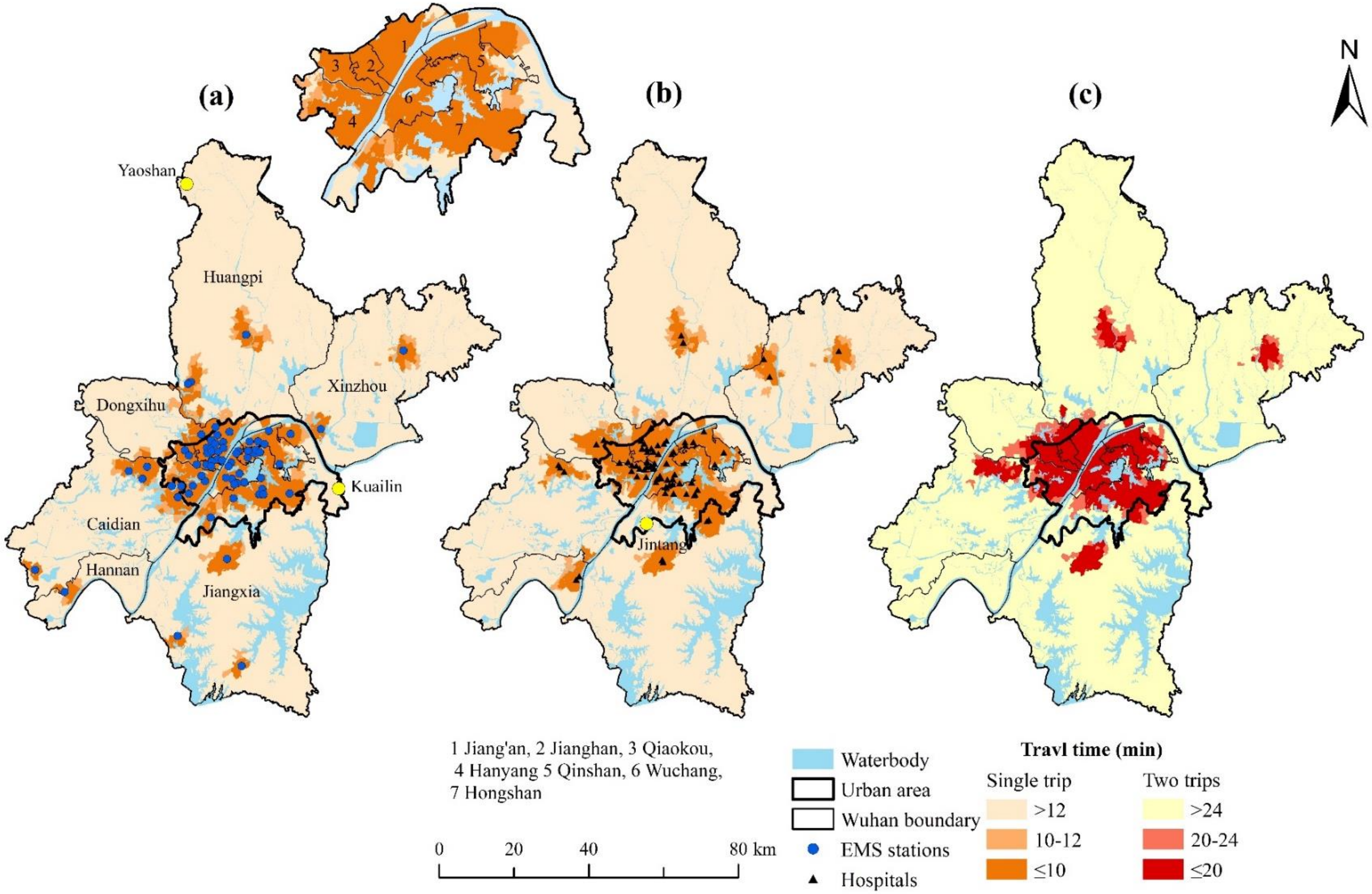


Figure 3-5. Trave time zones for different trips: (a) Trip 1; (b) Trip 2; (c) overall trip.

Figures 3-6 (a) (b) depict the areas (in grey) that are distributed in various travel time zones for Trip 1 and Trip 2. The highlighted shequs have relatively good ambulance accessibility (Trip 1 ≤ 10 min) but relatively poor hospital accessibility (Trip 2 >12 min), and vice versa. Figure 3-6 (a) shows that 206 shequs with 457,657 population can be reached at their nearest EMS stations within 10 min but are more than 12 min away from the closest hospitals. It is because those areas are near to EMS stations but far from hospitals. Spatially, those shequs are located mainly in the south of Jiangxia, the west of Hannan, the southwest and northeast of Caidian, the south and northeast of Dongxihu, the southwest of Huangpi, the southwest of Xinzhou, and the southwest and the northeast of Hongshan. Taking Qinlin shequ (located in the south of Hongshan) as an example, the travel time for Trip 1 is only 2.18 min, but 21.77 min for Trip 2. It means that local residents are within easy reach of an ambulance, but they would find that it is difficult to reach an emergency hospital. Figure 3-6 (b) shows that 199 shequs with 318,076 population can reach their nearest hospitals within 10 min but cannot find the nearest EMS stations within 12 min. It is because those areas are near to hospitals but far from EMS stations. Geographically, those shequs are mainly distributed in the east of Hannan, the southeast and the northwest of Caidian, the middle of Dongxihu, the middle and the east of Huangpi, the west of Xinzhou, the north of Jiangxia, the northwest of Qinshan, and the west of Hanyang. Taking Haijing shequ as an example, which is located in the east of Dongxihu and with more than 10,000 residents, the travel time for Trip 2 is only 1.45 min, but 14.55 min for Trip 1. It means that local residents are likely to reach the nearest hospital quickly, but they are difficult to access from the nearest EMS station. The above results confirm that it is necessary to consider the two-related trips in an EMS journey, which is still the weakness of extant studies on EMS accessibility.

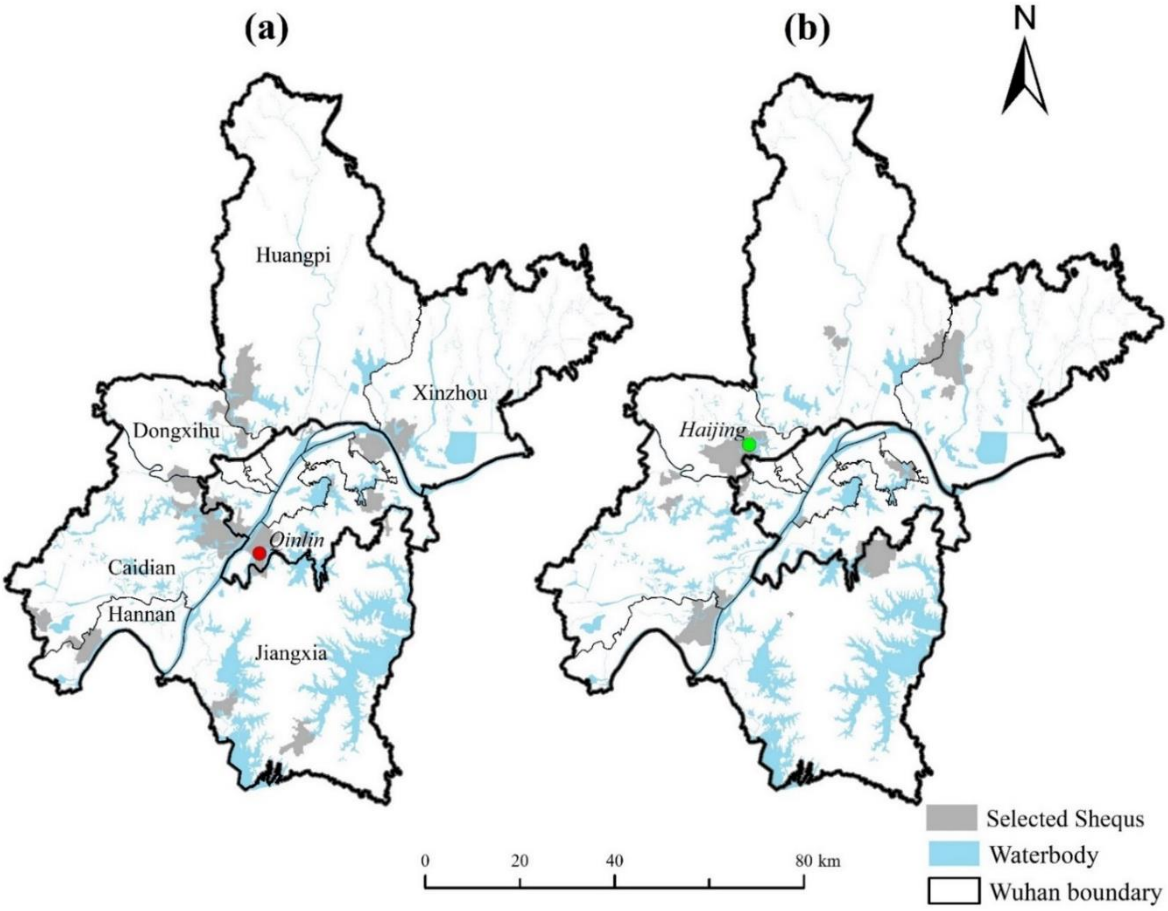


Figure 3-6. Locations of the Shequ within different travel time zones: (a) Trip 1≤10min, Trip 2 > 12 min; (b) Trip 1 > 10min, Trip 2≤12 min.

(2) E-2SFCA-based spatial accessibility

Based on the E-2SFCA, spatial variations in accessibility scores in relation to different trips are depicted in Figure 3-7. Given the range of scores for different trips, the majority of values are relatively low, with more than 75% of the values for Trips 1 and 2 having a score lower than 0.15 for a single trip and 0.3 for the overall trip. The range of ambulance accessibility (Trip 1) and hospital accessibility (Trip 2) is between 0 and 1.01 (0 means poorest accessibility). The range of overall EMS accessibility is between 0 and 1.59. Average and median accessibility scores of districts are also presented in Figure 3-7. It is not surprising that seven urban districts have the higher average accessibility scores than suburban and rural districts. For ambulance accessibility, Qinshan has the highest average score (0.17), and more than 70.5% of the shequs in Qinshan have at least a 0.15 ambulance accessibility score. The second-highest average score is in Jiangan (0.11), and more than 56% of local residents lived in the shequs with at least 0.15 ambulance accessibility score. Xinzhou has the lowest average ambulance accessibility score (0.01), and only 13.9% of the local shequs have at least a 0.15 ambulance accessibility score. Huangpi has the second-lowest average ambulance accessibility score (0.02), and only 21.3% of the local shequs have at least a 0.15 ambulance accessibility score. For hospital accessibility, Jianghan has the highest average score (0.21), and more than 68.3% of the shequs have at least a 0.15 hospital accessibility score. The second highest average hospital score is in Qinshan (0.20), and more than 66.7% of residents lived in shequs with at least a 0.15 hospital accessibility score. Huangpi has the lowest average hospital accessibility score (0.02), and only 16.8% of the local shequs have at least a 0.15 hospital accessibility score. Jiangxia has the second-lowest average hospital accessibility score (0.02), and only 17.1% of the local shequs have at least a 0.15 hospital accessibility score.

For overall accessibility, Qinshan has the highest overall accessibility score (0.37), and more than 65.8% of the shequs in here have at least a 0.30 overall accessibility score. The second-highest average overall score is in Jianghan (0.31), and more than 57.6% of residents lived in shequs with at least a 0.3 overall accessibility score. Huangpi has the lowest average overall accessibility score (0.04), and only 14.5% of the local shequs have at least a 0.3 overall accessibility score. Xinzhou has the second-lowest average overall accessibility score. Only 18.3% of the local shequs have at least a 0.3 overall accessibility score. In general, the above results indicate that Qinshan and Jianghan have relatively high accessibility scores among all districts, but Huangpi and Xinzhou have relatively low accessibility scores for all trips.

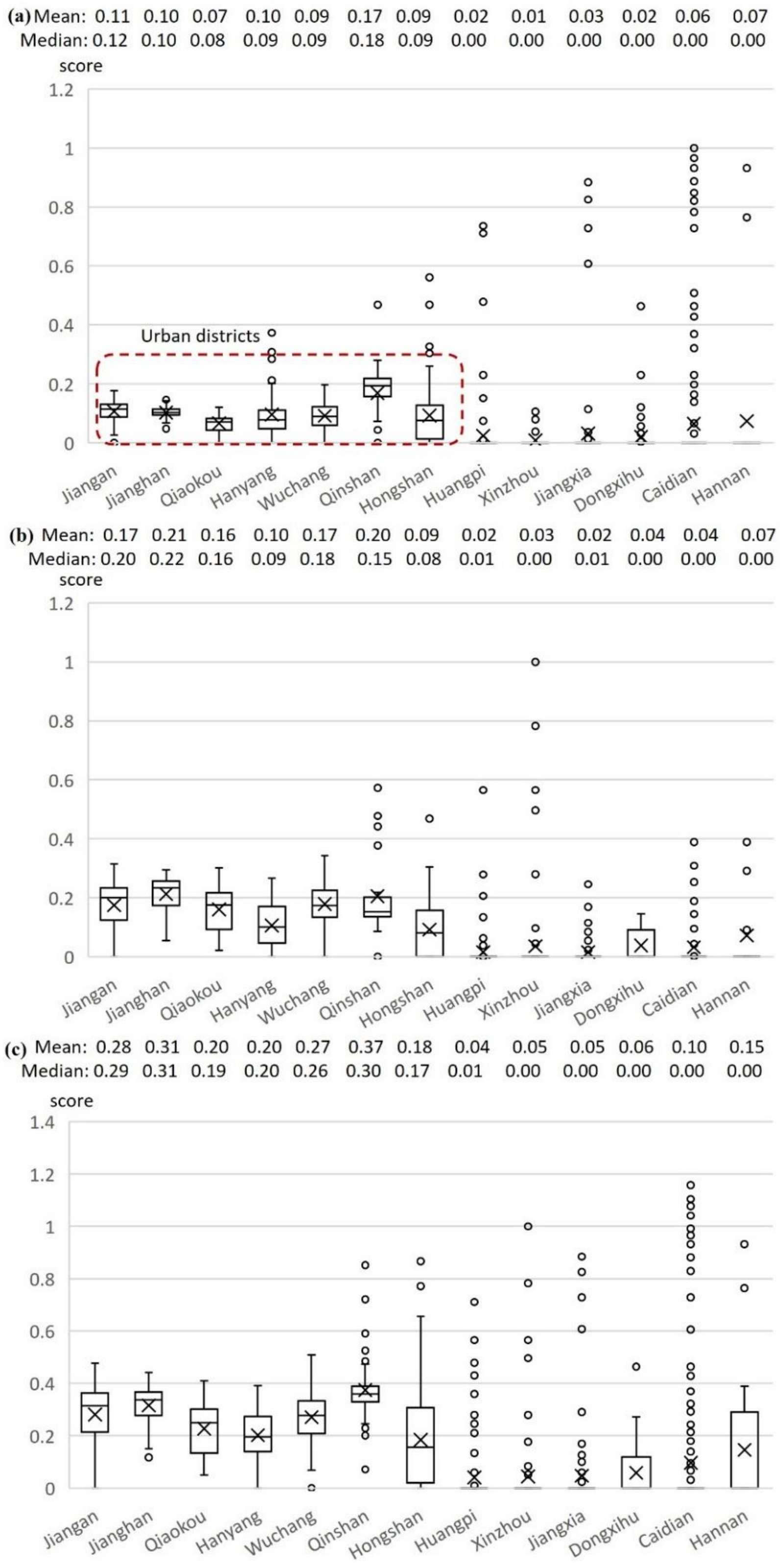


Figure 3-7. Boxplots of E-2SFCA score: (a) Trip 1(EMS station to Scene); (b) Trip 2 (Scene to Hospital); (c) overall trip (EMS station to Scene to Hospital).

Figure 3-8 indicates that the urban area has a higher average accessibility score than that of the rural area with respect to each trip. In detail, the average ambulance score (i.e., Trip 1) is 0.1 in the urban but 0.03 in the rural area. The average hospital score (i.e., Trip 2) is 0.15 in the urban area and 0.03 in the rural area. For the overall trip, the urban average score is 0.26, but the rural average score is 0.06, with a 0.2 difference. In other words, the urban area has better EMS accessibility than that in the rural area regarding all trips.

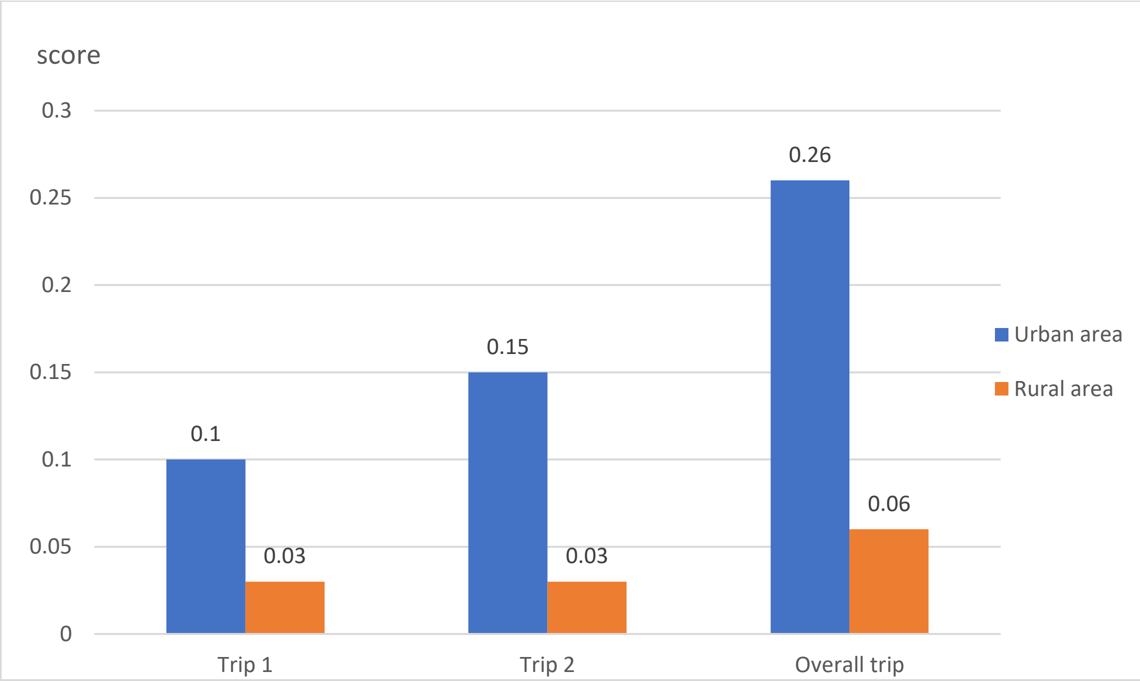


Figure 3-8. Average travel times for different trips between urban and rural areas.

Figures 3-9 describe spatial variations of accessibility scores in Wuhan, where shequs with the estimated travel time more than 12 min for Trip 1 or Trip 2 are left blank; that is A_k^E=0 or A_k^H=0. The reason for using 12 min as the threshold is that it is the secondary standard of EMS response time in Wuhan (for rural area). Those blank areas mean patients are difficult to reach the ambulance or hospital within 12 min in those shequs. Then, the E-2SFCA accessibility score for one-way trips (i.e., Trip 1 and Trip 2) higher than 0.15 and score for the overall trip higher than 0.3 are defined as “relatively good accessibility”.

The urban districts have better EMS accessibility of all trips than rural areas. Specially, about 73% of urban shequs have relatively good EMS and hospital accessibility, and 70% of urban shequs have good overall EMS accessibility. Comparatively, only 18%, 17.5%, and 15% of rural shequs have relatively good ambulance accessibility, hospital accessibility, and the overall accessibility, respectively. Among the urban region, the central urban area (i.e., the west of Wuchang or the east of Jiangan) has better EMS accessibility related to all trips than the peripheral urban areas (i.e., the southwest or northeast of Hongshan). For rural districts, only shequs near EMS stations or hospitals have either relatively good ambulance or hospital accessibility. It is worth noting that the shequ with the highest ambulance accessibility score is located in the southeast of Caidian, and the shequ with the highest score of hospital accessibility is sited in the west of Xinzhou. Both shequs are distributed in the rural areas. Those areas have less potential demand and near to providers, where are the major reasons for the highest accessibility score.

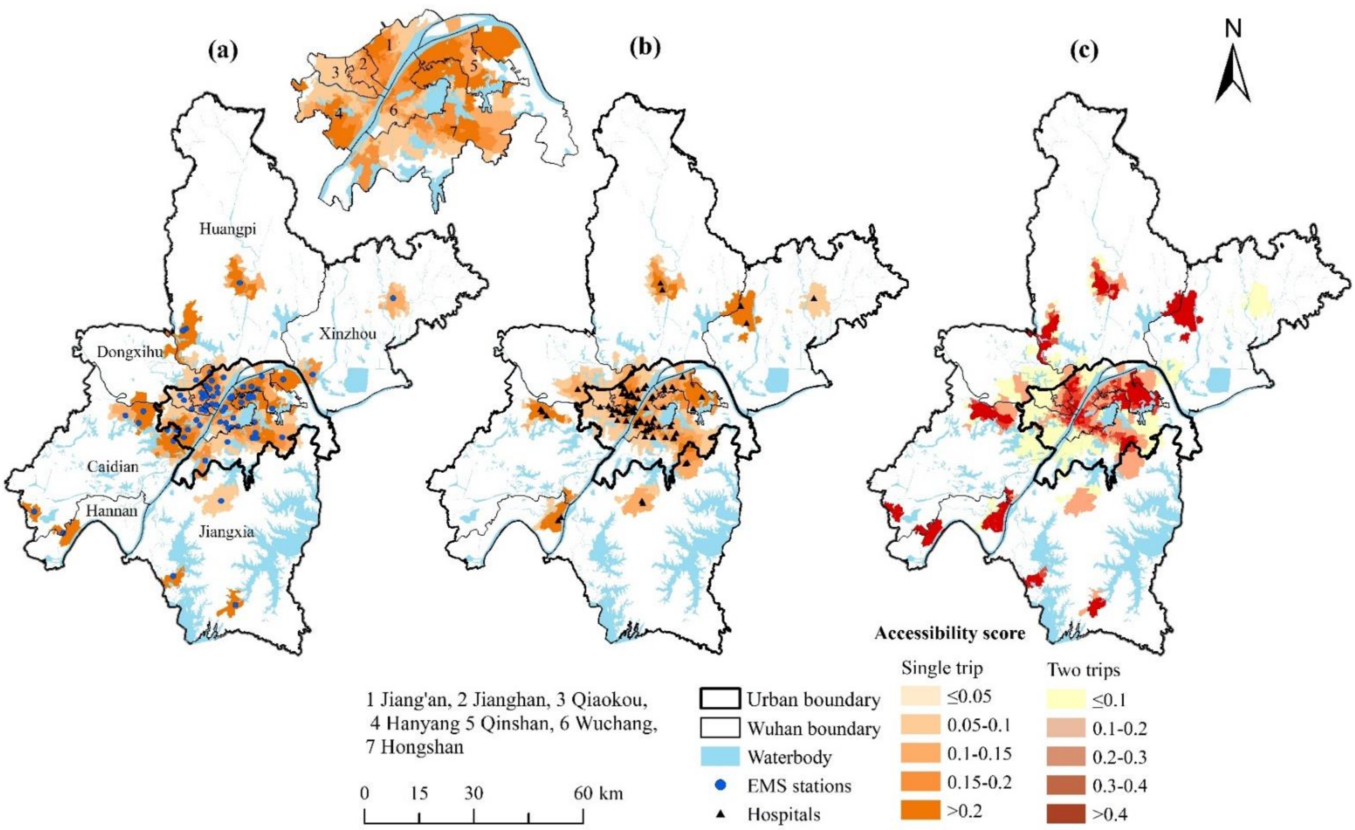


Figure 3-9. E-2SFCA accessibility score for single and overall trips: (a) ambulance accessibility; (b) hospital accessibility; (c) overall accessibility

Figures 3-10 (a) (b) underlines areas with different accessibility for the two single trips based on the E-2SFCA scores. The shequs are highlighted if they have relatively good ambulance accessibility with a score higher than 0.15, and also have relatively poor hospital accessibility with a score of 0, and vice versa. Figure 3-10 (a) shows that 79 shequs with a 168,427 population have relatively good ambulance accessibility but relatively poor hospital accessibility. Geographically, those shequs are mainly distributed in the south and southwest of Jiangxia, the west of Hannan, the west and northeast of Caidian, the north of Dongxihu, and the southwest of Huangpi, the southwest of Xinzhou, and the southwest, middle, and north of Hongshan, respectively. Taking Zhangwan shequ (located in the east of Caidian) as an example, the ambulance accessibility score is 0.158, but the hospital accessibility score is 0, which means the shequ has relatively good ambulance accessibility, but poor hospital accessibility. In contrast, Figure 3-10 (b) shows that 56 shequs with 106,215 people have relatively good hospital accessibility but poor ambulance accessibility. Those shequs are distributed in the middle and east of Huangpi, the west of Xinzhou, the north of Jiangxia, the east of Hannan, the southeast and north of Caidian, the east of Dongxihu, respectively. Taking Sungang shequ (located in the west of Xinzhou) as an example, the hospital accessibility score (A_k^E) is 0.5, but the ambulance accessibility score (A_k^H) is 0.

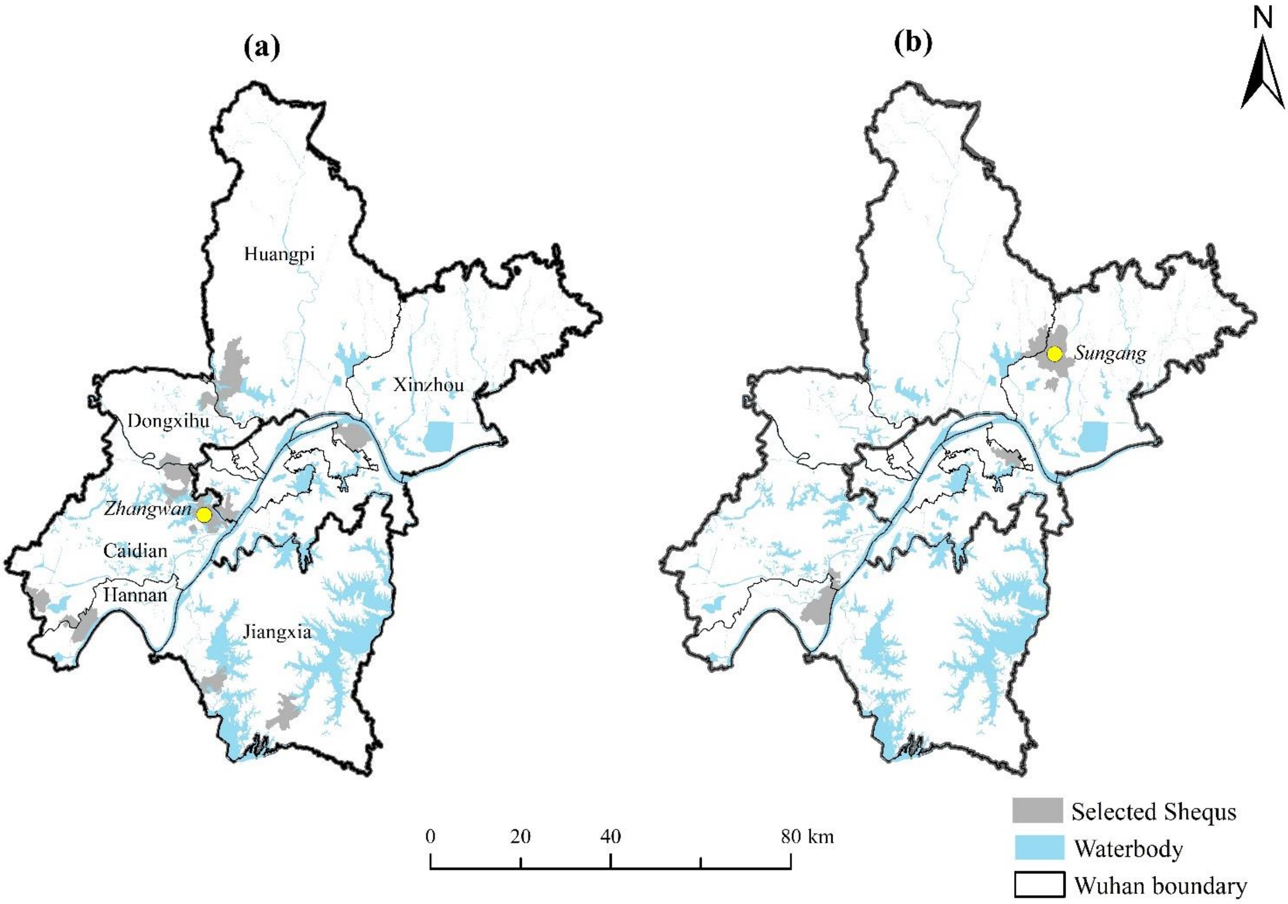


Figure 3-10. Locations of the Shequs within different travel time groups for Trip 1 and Trip 2; **(a)** $A_k^E \leq 0.15$ and $A_k^H = 0$; **(b)** $A_k^H \leq 0.15$ and $A_k^E = 0$.

3.4.2. Spatiotemporal accessibility of EMS

(1) Proximity-based spatiotemporal accessibility

Based each time period of the day (morning or evening peak period; off-peak period), travel times on the five estimated weekdays were averaged for each shequ. Figure 3-11 presents the statistical information of the estimated travel times for different EMS trips. In general, travel times for both morning and evening peak periods are precisely similar, but they differ from the travel times for the off-peak period. Compared with the values for off-peak hours, travel times for morning and evening peak hours have higher median and average values.

It is not surprising that the average travel time for the same trip is generally higher during the peak hours than that in off-peak periods. For example, the average travel times for Trip 1 are 21.7 min and 21.5 min during the morning and evening peak hours, respectively. However, it only takes 19.1 min during the off-peak period, with a more than 2-min reduction. Besides, the average travel time for Trip 2 is 23.4 min and 23.3 min during the morning and evening peak hours, respectively, but it only takes 21.1 min during the off-peak period. Finally, the travel time for the overall trip during two peak periods is between 44-45 min on average, which is 4-5 min higher than that in the off-peak period.

For the overall trip, 57.7 % and 65.1% of the total population could complete the whole EMS journey within 20 min and 24 min at the off-peak period, respectively. During traffic peak hours, these proportions are notably decreased. Meanwhile, the median travel time for the overall trip is 38.1 min at the off-peak hours, but the values would increase over 40 min during morning and evening traffic peak periods. According to Figure 3-11, the average travel time for Trip 1 is lower than the average travel time for Trip 2 during all periods of a day. For example, the average travel time for Trip 1 is 19.1 min at the off-peak hours, which is 2.0 min higher than the travel time for Trip 2 at the same time.

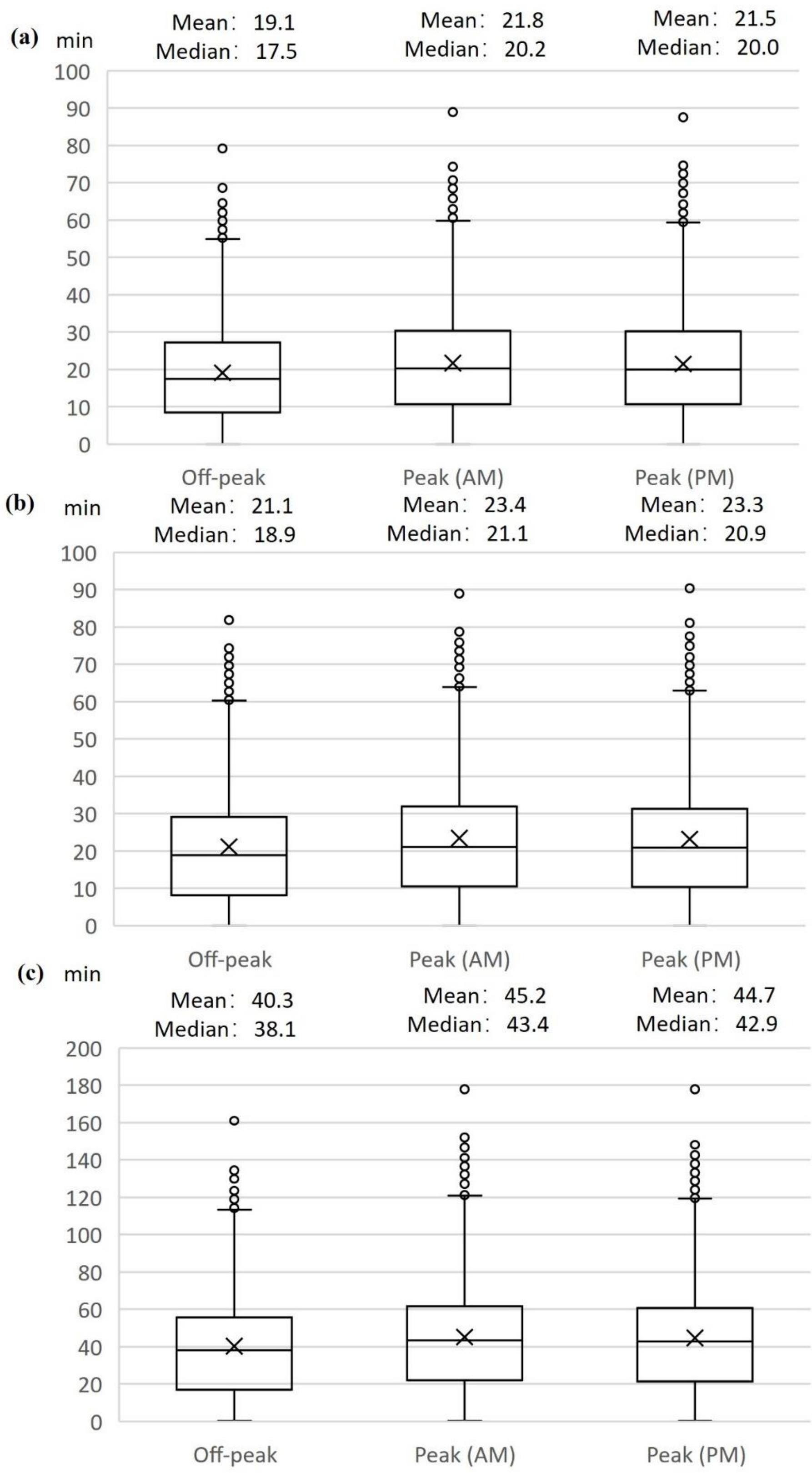


Figure 3-11. Boxplots of travel times in different time periods: (a) Trip 1; (b) Trip 2; (c) overall trip.

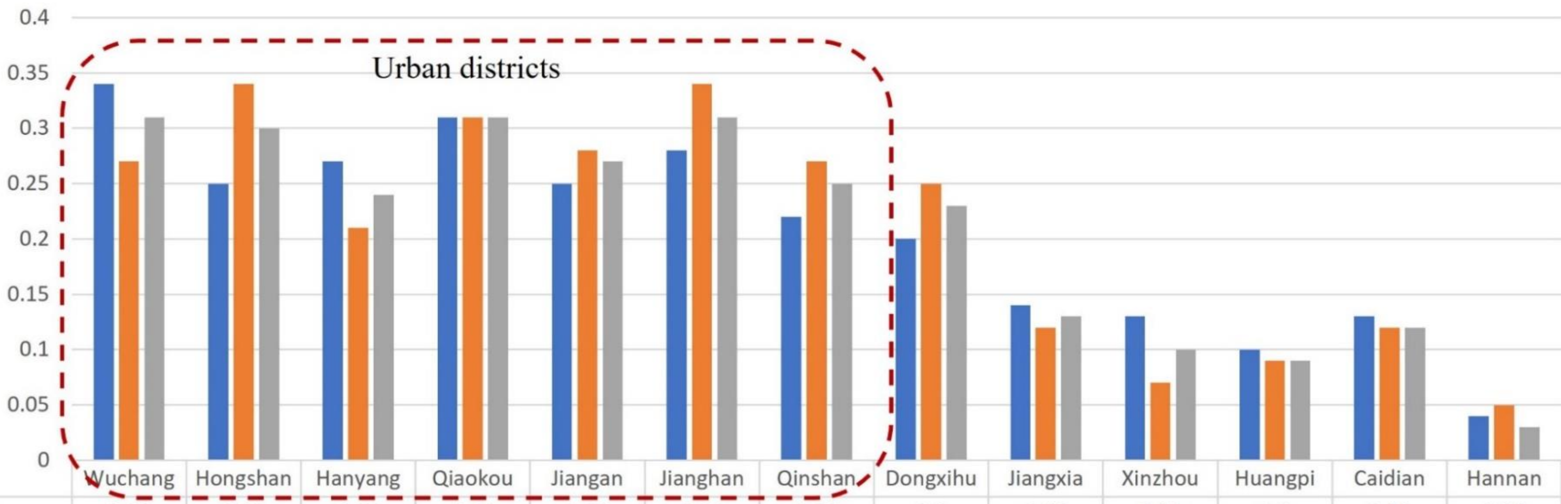
Table 3-2 shows that the average travel times in urban areas are significantly less than in rural areas value for any trip during any time of a day. During the off-peak period, the average urban travel time for Trip 1 or 2 is around 9 min, and the average travel time for overall trip is about 18 min. However, the rural average travel time for Trip 1 or 2 is over 20 min, and over 50 min for the overall trip. Urban-rural differences in EMS travel time are 15.4 min for Trip 1, 18.4 min for Trip 2 and 33.8 min for the overall trip. Average travel times for all trips are increased during traffic peak periods. For example, compared with the travel time at the off-peak period, the average value for Trip 1 is increased by 2.2 min in the urban area, and 2.8 min in the rural area during the morning peak hours. The similar findings also occur during the evening peak period.

Table 3-2. Average travel times during between peak and off-peak hours.

	Time	**Urban (min)**	**Rural (min)**
Trip 1	Off-peak	8.9	24.3
	Morning peak	11.1	27.1
	Evening peak	11.0	26.9
Trip 2	Off-peak	9.0	27.4
	Morning peak	11.3	29.6
	Evening peak	11.2	29.3
Overall trip	Off-peak	17.9	51.7
	Morning peak	22.4	56.7
	Evening peak	22.2	56.2

Temporal traffic variation ratios are calculated by equation (3.5). A high value of temporal traffic variation ratio means the large difference of travel times between peak and off-peak hours. The traffic peak hours have a notable influence on EMS accessibility in those places. A low value of temporal traffic vitiation ratio means the traffic peak hours have a minor influence on EMS accessibility. Difference in travel times between peak and off-peak hours is slight. Figure 3-12 shows the temporal traffic variation ratios for different trips. The average ratios for seven urban districts are significantly higher than the values for rural districts. The average ratios for seven urban districts are higher than 0.2, but the average ratios for five of six rural districts are lower than 0.2. For Trip 1, Wuchang and Qiaokou have the highest and second-highest variation ratios. For Trip 2. Hongshan and Jianghan have the highest variation ratio, followed by Qiaokou, where the variation ratio is 0.03 lower than the highest level. As for the overall trip, Wuchang and Qiaokou have the highest variation ratio, followed by Hongshan, where the variation ratio is 0.01 lower than the highest level. In contrast, the variation values for rural areas are much lower than those in the urban districts. The lowest ratios for all trips are pointed to Hannan, which mean traffic condition during peak hours have very slight impact on this district. The variation ratios for Huangpi are also less than 0.1 for all trips. The highest variation ratios among rural districts are Dongxihu, and its variation ratios for all trips are higher than 0.2. Due to higher temporal traffic variation ratios in urban areas, real-time traffic conditions have stronger impact on EMS accessibility in urban areas than in rural districts.

$$\frac{[\text{Average peak hour traveltime}]-[\text{off peak hour traveltime}]}{[\text{off peak hour traveltime}]} \tag{3.5}$$



	Wuchang	Hongshan	Hanyang	Qiaokou	Jiangan	Jianghan	Qinshan	Dongxihu	Jiangxia	Xinzhou	Huangpi	Caidian	Hannan
Trip1 variation ratio	0.34	0.25	0.27	0.31	0.25	0.28	0.22	0.2	0.14	0.13	0.1	0.13	0.04
Trip2 variation ratio	0.27	0.34	0.21	0.31	0.28	0.34	0.27	0.25	0.12	0.07	0.09	0.12	0.05
Trip Overall variation ratio	0.31	0.3	0.24	0.31	0.27	0.31	0.25	0.23	0.13	0.1	0.09	0.12	0.03

Trip1 variation ratio Trip2 variation ratio Trip Overall variation ratio

Figure 3-12. Temporal traffic variation ratios for different trips.

Spatial variations of the average travel times for peak and off-peak periods are presented in Figures 3-13. In general, most areas with good ambulance accessibility, hospital accessibility (i.e., travel time for Trip 1or Trip 2 $\leqslant$10 min), as well as overall accessibility (i.e., travel time for the overall trip $\leqslant$ 20 min) are clustered in the central part of the urban region. The east part of the urban region has relatively poor accessibility for all trips (i.e., travel time for Trip 1or Trip 2 >10 min; travel time for the overall trip > 20 min). As for rural districts, in addition to some areas near to EMS stations or hospitals, most shequs have travel times more than 12 min for Trip 1 or Trip 2, and over 24 min for the overall trip. It is worth noting that the number of shequs with good EMS accessibility decreases dramatically during morning and evening peak hours, especially in the central part of the urban region. Some shequs (e.g., the south of Hongshan) might have relatively good ambulance accessibility during off-peak hours but have relatively poor ambulance accessibility during the morning or evening peak hours. For example, Lianxishi shequ, located in the south of Wuchang, could reach an ambulance within 7 min during off-peak hours but more than 16 min during traffic rush hours. Besides, some areas have relatively good hospital accessibility during off-peak hours but have poor hospital accessibility during peak hours. For instance, Yudai shequ, located in the southeast of Qiaokou, could reach the nearest hospital within 6 min during off-peak hours but more than 17 min during peak hours. As for the overall travel times, Hudian shequ, located in the middle Hongshan district, could complete the overall trip within 10 min in the off-peak hours but more than 20 min during the peak hours. It is worth noting that some shequs might take an extremely long travel times during any time of the day. For example, Liujiashan shequ, is estimated to take 79 min to receive the nearest ambulance and more than 88 min on getting to the closest hospital.

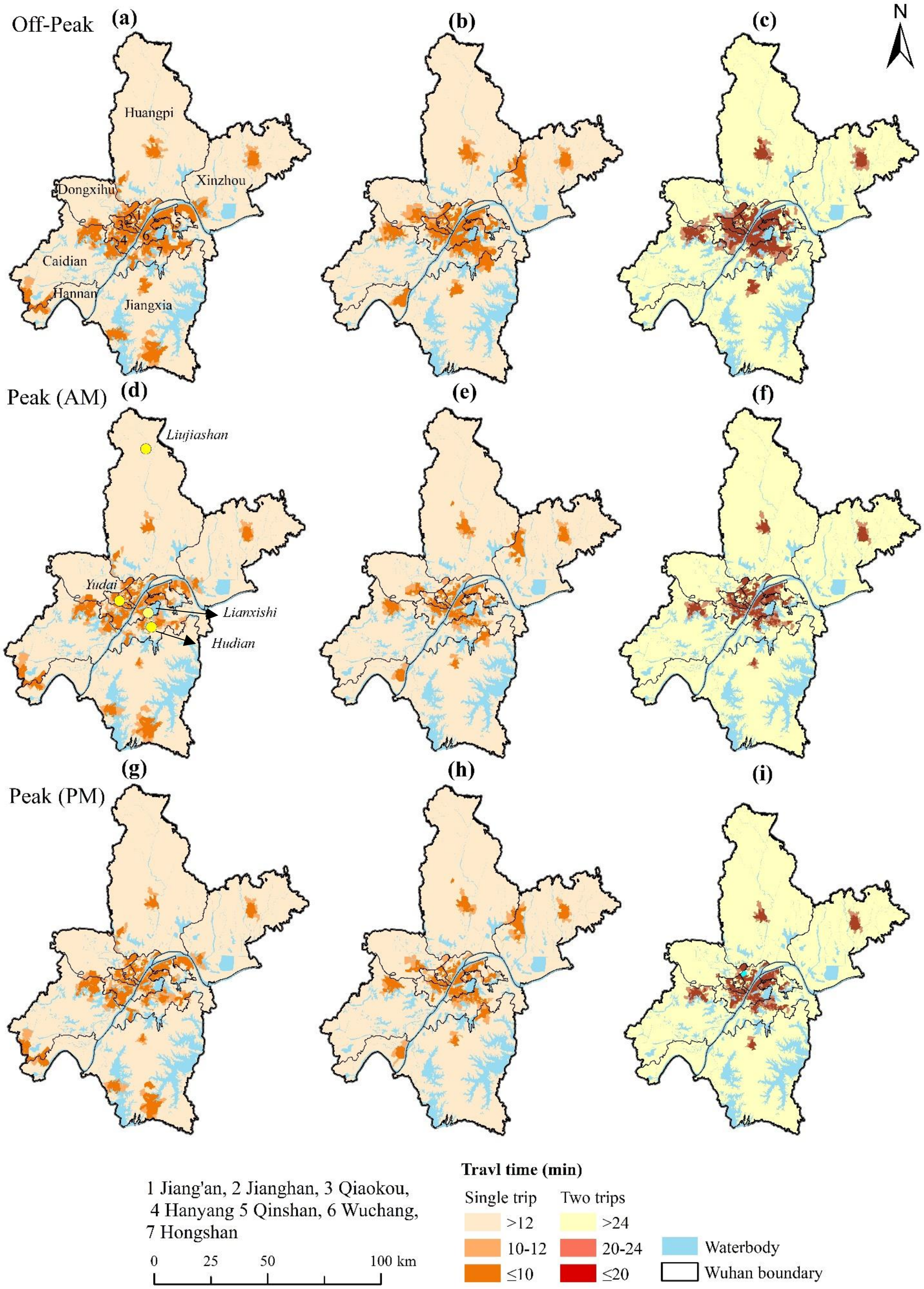


Figure 3-13. Average travel time for single and overall trips at different times of the day; *Off-peak period*: (a) Trip 1, (b) Trip 2, (c) overall trip; *Morning peak period*: (d) Trip 1, (e)

Trip 2, (f) overall trip; *Evening peak period*: (g) Trip 1, (h) Trip 1, (i) overall trip).

Figures 3-14 depict shequs (in grey) with different levels of travel times for Trip 1 and Trip 2, which highlight the shequs that have relatively good ambulance accessibility (Trip 1 $\leqslant$ 10 min) and poor hospital accessibility (Trip 2 > 12min), and vice versa. Figure 3-14 (a) shows that 188 shequs with the 603,874 population can reach their nearest EMS stations within 10 min, but more than 12 min to reach the closest hospitals during the off-peak hours. Those areas are mainly distributed in the southwest of Hongshan, the south of Jiangxia, the west of Hannan and Caidian, and the south of Xinzhou. Figure 3-14 (b) shows that 173 shequs with the 508,635 population can reach their nearest EMS stations within 10 min, but it takes more than 12 min to reach the closest hospitals during the morning peak hours. Those shequs are mainly distributed in the south of Jiangxia, the east of Hannan, the east and northeast of Caidian, the southwest and the northeast of Hongshan. Figure 3-14 (c) describes 168 shequs with the 501,555 population that have relatively good ambulance accessibility and poor hospital accessibility at the evening peak hours. Those shequs are mainly distributed in the south and southwest of Jiangxia, the east of Hannan, the east and northeast of Caidian, the southwest and the northeast of Hongshan.

Figures 3-14 (d) (e) (f) highlight shequs with relatively good hospital accessibility (Trip 2 $\leqslant$ 10 min) and poor ambulance accessibility (Trip 1 > 12 min). In detail, Figure 3-14 (d) finds 187 shequs with the 770,824 population can arrive at their nearest hospitals within 10 min but cannot reach the nearest EMS stations within 12 min during the off-peak hours. Those shequs are sited in the south of Hongshan, the east of Hannan, the southwest and northeast of Caidian, the middle of Dongxihu, and the west of Xinzhou, respectively. Figure 3-14 (e) depicts 166 shequs with the 570,824 people have relatively good hospital accessibility and poor ambulance accessibility at the morning peak hours. The spatial distribution of those shequs is similar to the layout at off-peak hours. Figure 3-14 (f) indicates that there are 170 shequs with the 603,212 residents with relatively good hospital accessibility and poor ambulance accessibility at the morning peak hours. The spatial distribution of those shequs is similar to the layout at off-peak hours. Overall, the above results show that good ambulance accessibility cannot guarantee good hospital accessibility, nor overall accessibility during any time of the day, and vice versa.

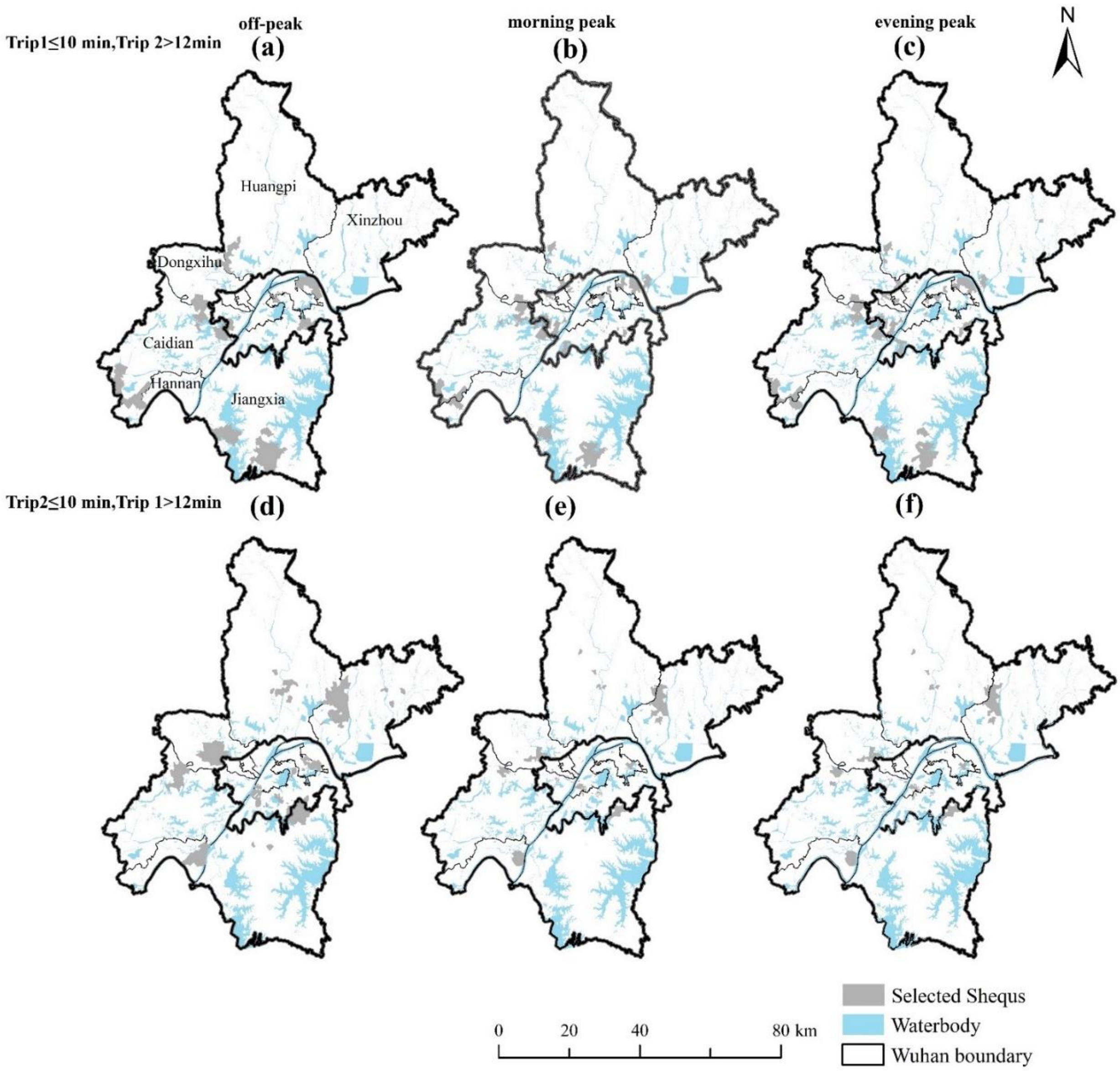


Figure 3-14. Locations of the Shequs within different travel time zones for Trip 1 and Trip 2; Trip 1 ≤10min and Trip 2> 12min; (a) off-peak periods, (b) morning peak periods, (c) evening peak periods; Trip 1>12 and Trip 2≤10min; (d) off-peak periods, (e) morning peak periods, (f) evening peak periods.

(2) E-2SFCA-based spatiotemporal accessibility

Variations in the average E-2SFCA values between peak and off-peak periods are depicted by Figure 3-15. As the range of the E-2SFCA score is between 0 and 1.01 for Trip 1 or Trip 2, most of the scores are relatively small, with only less than 25% of shequs with a score of more than 0.15 for a single trip and 0.3 for the overall trip. In other words, most E-2SFCA scores are less than 0.15 for ambulance accessibility and hospital accessibility and less than 0.3 for the overall accessibility during any time of a day. Among the time periods, the highest average and median scores are at the off-peak hours, indicating the best EMS accessibility in relation to all trips occurs during this period. Similar to the variations in travel times, there are evident disparities in accessibility scores between off-peak and peak hour periods. In general, average accessibility scores for all trips at the off-peak period are higher than that in peak hours. Comparing two traffic peak hours, the morning peak period has higher accessibility scores for all trips than those in the evening peak hours. The median values for all trips are 0 because at least 50% of shequs are not within the12-min travel time catchment for Trip1 or Trip 2 based on the estimation of Baidu online map service.

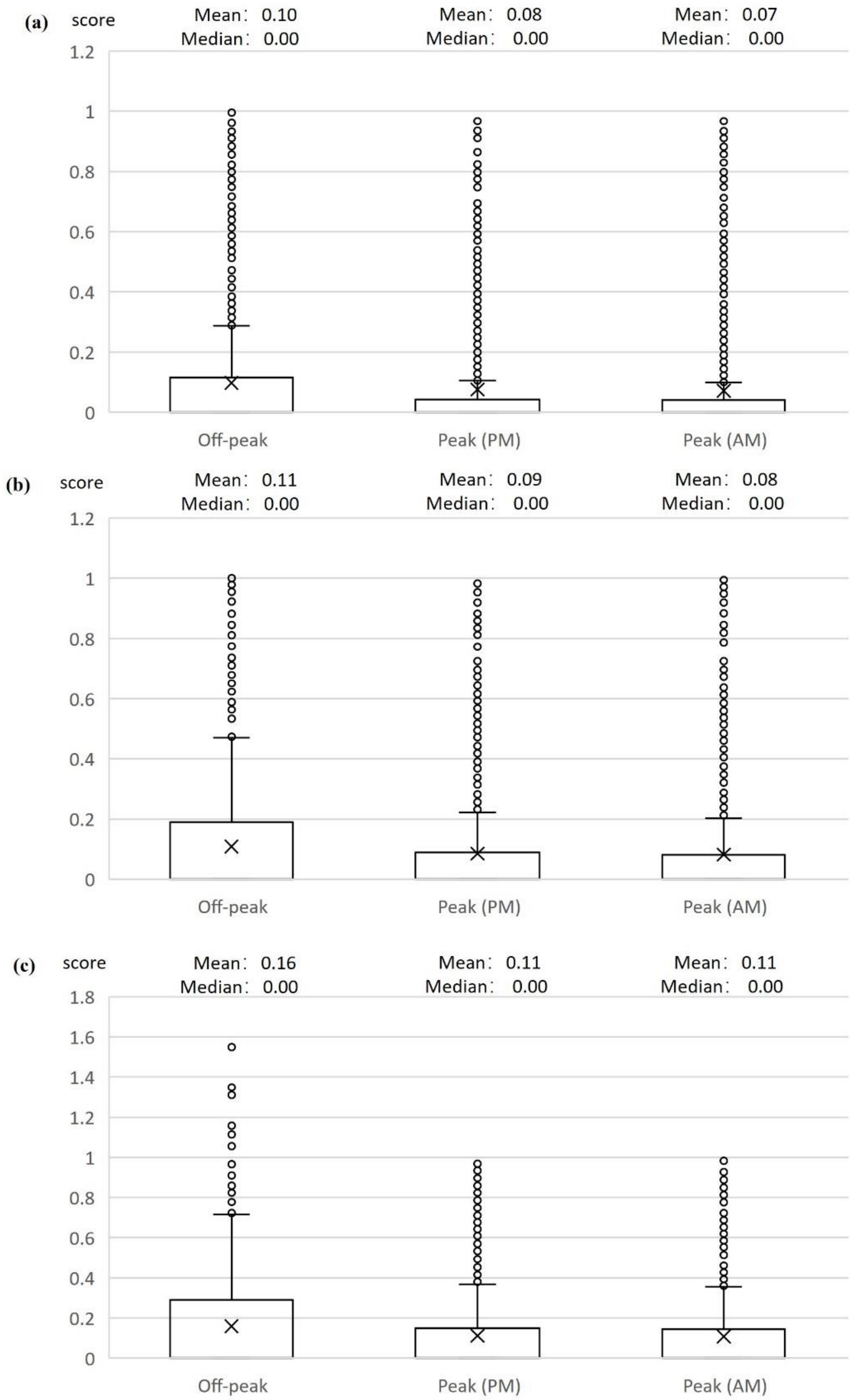


Figure 3-15. Boxplots of E-2SFCA score in different time periods: (a) Trip 1; (b) Trip 2; (c) overall trip.

Table 3-3 shows that urban-rural differences in average E-2SFCA scores decrease during peak periods. At the off-peak hours, the urban-rural average difference is 0.07 for ambulance accessibility score, 0.08 for hospital accessibility score and 0.13 for overall accessibility score. However, the urban-rural difference reduces during traffic peak hours. The urban-rural difference in average scores for morning peak hours is 0.06 for ambulance accessibility score, 0.06 for hospital accessibility score, and 0.13 for the overall accessibility score. The urban-rural differences for the evening peak period are 0.05 for ambulance accessibility score, 0.06 for hospital accessibility score, and 0.10 for overall accessibility score. This is because scores in urban areas drop significantly during peak periods, while scores in rural areas remain comparatively stable. In other words, real-time traffic conditions have stronger impact on urban EMS accessibility rather than rural EMS accessibility.

Table 3-3. Average accessibility scores during between peak and off-peak hours.

		Urban	Rural
Ambulance accessibility score	Off-peak hour	0.13	0.06
	Morning peak hour	0.11	0.05
	Evening peak hour	0.10	0.05
Hospital accessibility score	Off-peak hour	0.14	0.06
	Morning peak hour	0.11	0.05
	Evening peak hour	0.11	0.05
Overall accessibility score	Off-peak hour	0.25	0.12
	Morning peak hour	0.21	0.11
	Evening peak hour	0.20	0.10

Figure 3-16 shows spatiotemporal variations in average E-2SFCA accessibility scores for all trips during various day periods. Shequs with travel time more than 12 min for Trip1 or Trip 2 are left as blank, and the E-2SFCA scores higher than 0.15 as "relatively good accessibility" for single trips and more than 0.3 as "relatively good accessibility" for the total trips. Most urban shequs and some rural shequs have relatively good ambulance accessibility, hospital accessibility and the overall accessibility, especially during off-peak hours. Among shequs in Wuhan, Qiaoliang shequ in the middle of Hongshan, has the highest ambulance accessibility score, representing the best ambulance accessibility. The highest hospital accessibility and overall accessibility scores are pointed to Tazihu shequ in Jiangan, indicating the best hospital accessibility and the overall EMS accessibility.

When comparing EMS accessibility between traffic peak and off-peak periods, it is clear that the number of shequs with relatively good accessibility is highest during the evening off-peak hours, and the number of shequs with relatively good accessibility decreases during the morning and evening off-peak hours. It is worth noting that most shequs have a sharply decrease in accessibility scores for all trips during the morning and evening peak hours, especially in the central urban area. Comparatively, only some urban shequs in Qinshan and Hongshan districts, some shequs along the Yangtze River and most shequs near to EMS facilities have consistently good EMS accessibility for two single trips and the overall trip ($A_k^E, A_k^H \geq 0.15$ and $A_k \geq 0.3$) during anytime of a day. For instance, Taoyuan shequ in the east of Qinshan district has good overall accessibility scores at any time interval. Urban districts are most impacted by real-time traffic conditions, especially in the east of Yangtze River, Wuchang and Hongshan. For example, Shengjun shequ in Wuchang district has an excellent overall accessibility score (0.412) at the evening off-peak period, but the score decreases to 0.10 during the morning and evening peak hours.

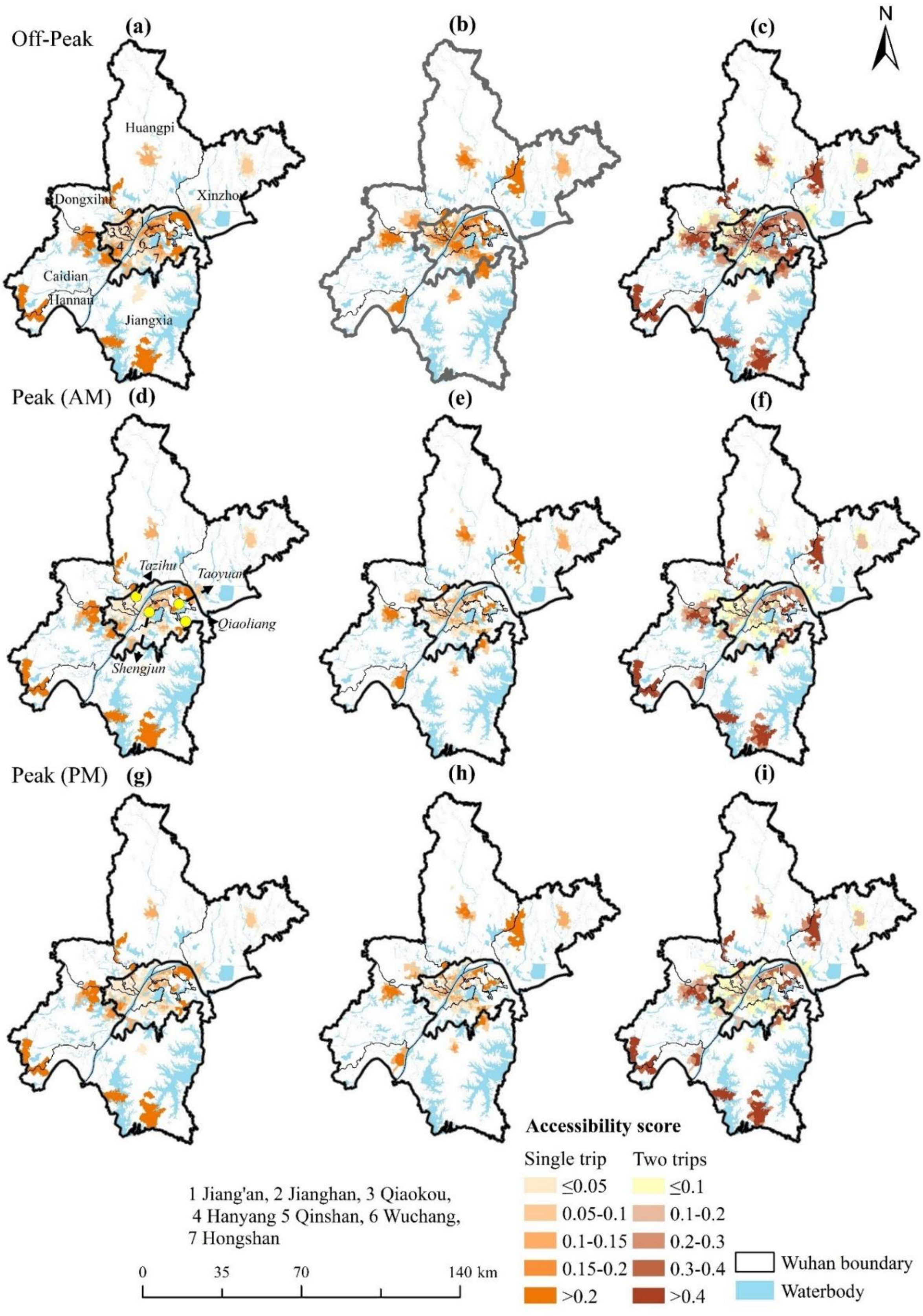


Figure 3-16. E-2SFCA accessibility score for single and total trips at different times of the day (*Off-peak period*: (a) ambulance accessibility, (b) hospital accessibility, (c) overall accessibility; *Morning peak period*: (d)ambulance access, (e) hospital accessibility, (f)

overall accessibility; *Evening peak period*: (g) ambulance accessibility, (h) hospital accessibility, (i) overall accessibility).

Figures 3-17 underlines shequs (in grey) with different accessibility for the two single trips based on the E-2SFCA scores during off-peak hours. That is, if a highlighted shequ has relatively good ambulance accessibility ($A_k^E \geqslant 0.15$), while this shequ has relatively poor hospital accessibility with a blank score ($A_k^H = 0$), and vice versa. Figures 3-17 (a) (b (c) mark the shequs with relatively good ambulance accessibility and poor hospital accessibility. In detail, Figure 3-17 (a) shows that 112 shequs with the 325,315 population have relatively good ambulance accessibility but poor hospital accessibility during the off-peak hours. Those areas are mainly distributed in the south and southwest of Jiangxia, the west of Hannan, the southwest and northeast of Caidian, the south boundary and north of Dongxihu, the southwest of Huangpi and the northeast of Hongshan districts. Figure 3-17 (b) shows that 101 shequs with the 152,386 population have relatively good ambulance accessibility but poor hospital accessibility during the morning peak hours. Those shequs are mainly located in the south of Jiangxia, the west and northeast of Caidian, the northeast of Hongshan. During the evening peak hours, 100 shequs have relatively good ambulance accessibility but poor hospital accessibility (see Figure 3-17 (c)). Those shequs are mainly distributed in the south and west of Jiangxia, the west of Hannan, the west and northeast of Caidian, and the northeast of Hongshan. Figures 3-17 (d) (e) (f) highlight the neighborhoods with relatively good hospital accessibility but poor ambulance accessibility. In detail, Figure 3-17 (d) shows 93 shequs with the 216,457 people having relatively good hospital accessibility ($A_k^H \geq 0.15$), but relatively poor ambulance accessibility ($A_k^E = 0$), during the off-peak hours. Those areas are chiefly located in the east of Hannan, the north of Caidian, the east of Huangpi, the west of Xinzhou, and the north Jiangxia. Figure 3-17 (e) depicts 72 shequs with the 268,703 people who have relatively good hospital accessibility but relatively poor ambulance accessibility during the morning peak hours. Those shequs are mainly located in the east of Hannan, and the west of Xinzhou. Figure 3-17 (f) depicts 81 shequs with the 294,057 people having relatively good hospital accessibility but relatively poor ambulance accessibility during the evening peak hours. The spatial distribution of those shequs is similar to the spatial layout discussed before. Overall, good ambulance accessibility cannot guarantee good hospital accessibility, nor the overall accessibility during any time of the day, and vice versa.

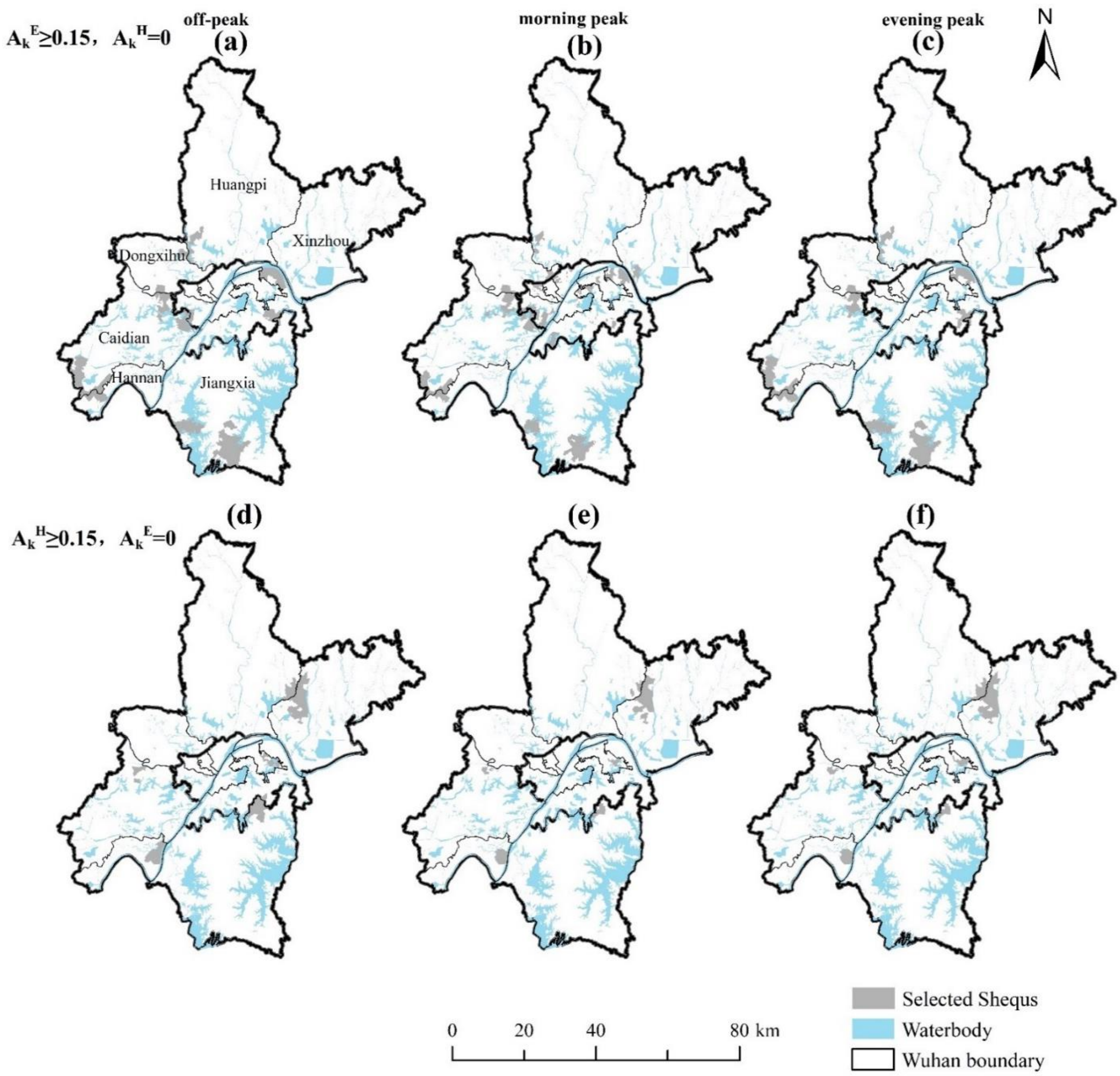


Figure 3-17. Locations of the Shequs within different travel time zones for Trip 1 and Trip 2; A_i^E≥0.15 and A_i^H=0; (a) off-peak period, (b) morning peak period, (c) evening peak period; A_i^E≥0.15 and A_i^H=0; (d) off-peak period, (e) morning peak period, (f) evening peak period.

3.5. Discussion

The results highlight the importance of incorporating two-related EMS trips (Trip 1 and Trip 2) in evaluating EMS accessibility, endorsed by the empirical findings of extant studies using actual EMS data. On the one hand, the importance of ambulance accessibility (Trip 1) has been widely documented by numerous studies (e.g., O'Keeffe et al., 2010; Serbia et al., 2011; Heidet et al., 2020). Good ambulance accessibility means patients are likely to obtain early on-scene medical treatment, resulting in favorable healthcare outcomes. On the other hand, hospital accessibility (Trip 2) also plays a vital role in affecting EMS health outcomes, which a large number of extant studies have reported (e.g., Higgs, 2004; Ouma et al., 2018; Carr et al., 2018). Good hospital accessibility means patients are likely to receive early advanced and specialized medical treatments in hospitals. According to the empirical results based on the proximity and E-2SFCA approaches, many areas have relatively good ambulance accessibility and poor hospital accessibility, such as the southwest of Hongshan, the south of Jiangxia and the southwest of Xinzhou. Residents in those areas might easily reach ambulances but might have difficulty reaching hospitals. In contrast, the results also find that some areas have relatively good hospital accessibility and poor ambulance accessibility, such as the middle of Dongxihu, the north of Jiangxia, and the west of Xinzhou. Demands in those areas might easily reach emergency hospitals but might have difficulty finding ambulances. Hence, healthcare planners and local authorities need to coordinate the EMS planning framework between EMS stations and emergency hospitals, ensuring that patients reach ambulances and emergency hospitals as quickly as possible.

Besides, the empirical results indicate that regional inequalities in EMS accessibility between urban and rural areas. The results show that the urban districts have better EMS accessibility in relation to all trips. The urban-rural inequalities in accessibility to EMS are common problems many countries/regions face, whcih many studies have reported (e.g., Grossman et al., 1997; Nordberg et al., 2004; Gonzalez et al., 2009; Masterson et al., 2015). Uneven distribution of EMS facilities is one of the major reasons for urban-rural inequalities in EMS accessibility. We can take Jiangan and Jiangxia and Jiangan districts as an example in the empirical study. Jiangan is an urban district located in the central urban areas, and Jiangxia is a rural district located in the south part of Wuhan. Jiangxia covers 23% of the area of Wuhan, but only 3 EMS stations and 4 hospitals are located inside the district. The lack of EMS resources leads to poor accessibility in Jiangxia. In comparison, 12 EMS stations and 8 hospitals are distributed in Jiangan, which maintain good EMS accessibility during any time of a day. It is clear that Jiangxia needs more EMS resources to improve local accessibility and thus bringing better health outcomes for local residents. Hence, urban-rural inequalities in accessibility to EMS remain challenges for local authorities and decision-makers, while reducing such inequalities in accessibility is necessary for the further EMS planning contexts.

Further, real-time traffic condition during peak hours is found having a notable impact on EMS accessibility, especially in urban areas. This finding is consistent with many studies using actual EMS running data (e.g., Earnest et al., 2011; Fleischman et al., 2013; Fraser et al., 2020). EMS delays are associated with congested traffic, peak hours, bad weather (e.g., raining, snowing), etc. Unlike the general healthcare-seeking behavior (e.g., primary healthcare, hospital), patients can seek healthcare during off-peak hours. Emergency medical cases might happen anytime and anywhere, but patients require immediate medical care. Thus, the temporal variation in traffic conditions is necessary to consider in accessibility to EMS. According to the empirical study, shequs in Wuhan are likely to have longer travel times and lower E-2SFCA scores for a same trip during morning and evening traffic peak hours. In general, traffic conditions during peak hours have a stronger impact on EMS accessibility in urban areas rather than in rural areas. It is because traffic congestion occurs more frequently in the urban road network. Thus, local authorities should take appropriate measures to reduce the impact of peak traffic on EMS accessibility, such as the traffic light controlling system.

Online map services are valuable tools to measure spatiotemporal accessibility to public services such as EMS. Due to the timeliness of rescue in emergency events, the most approved indicator of EMS accessibility is travel time. There are various advantages of using web-based map service to evaluate accessibility to EMS. First, the travel time can be directly computed from web-based application without implementing GIS, and no need to prepare relevant datasets such as road networks. Second, online map services usually provide updated road network information, resulting in more precise travel times in the estimation. Third, dynamic traffic conditions are often contained in web-based map services, thus providing more accurate travel time estimation. However, many online map services are only free for a certain subset of origin-destination (O-D) pairings; for additional O-D pairs, a payment is necessary. For example, Google Maps offers just 10,000 free OD calculations every month for each account and charges $5 for each additional group of 1,000 computations. In comparison, Baidu Map offers 30,000 free OD calculations every day for each user and additional free calculations for academic pursuits. A monthly payment of USD 2800 is required for the limitless computations service offered by Baidu Map.

The proximity-based and E-2SFCA approaches present different spatial variations in EMS accessibility. The results from the proximity-based approach show that the majority of shequs with good EMS accessibility of all trips are distributed in the central part of the urban area. The results from the E-2SFCA model display that some rural areas have better EMS accessibility than urban areas. Urban areas often have a tremendous potential demand, which might offset the advantages of having more nearby EMS stations and hospitals. However, although some rural areas are surrounded by only one EMS station or one hospital, those areas have a much smaller population, therefore sharply increasing the likelihood of better EMS accessibility. The proximity-based technique is simple to compute and understand. Therefore, it can be used to plan EMS in the short term or to make decisions about emergency services in real-time. As it takes into account both supply and demand factors, the E-2SFCA technique is more suited for long-term EMS planning to address large-impact catastrophes, pandemics, or planning blueprints. It is also important to keep in mind that both of the methodologies utilized here can be applied in different contexts, even though this empirical study uses Wuhan as a case region. In many parts of the world, such as Wuhan, the estimated travel time based on current traffic conditions can be typically derived through web-based map services, such as Google Maps. Meanwhile, the input parameters of the 2SFCA (e.g., inpatient beds) can be also employed in other places. With a similar dataset, the methods described in this paper can be applied to evaluate EMS accessibility outside of China anyplace in the world.

As for policy implications, the results can reflect public healthcare policies on EMS planning and management. First, this chapter finds that good ambulance accessibility cannot guarantee good hospital accessibility nor the overall accessibility, and vice versa. For example, the south of Jiangxia has relatively good ambulance accessibility, but poor hospital accessibility. Hence, this study suggests healthcare planners and relevant authorities need develop a collaborative system between EMS stations and emergency hospitals, ensuring patients can be rapid served by both ambulance and hospital services. Besides, we find the significant urban-rural inequalities in EMS accessibility, which meet the concerns of Wuhan EMS planning document that aims to improve the rural EMS system (Wuhan Municipal Health Commission, 2019). For example, when considering static/average travel times for Trip 1, the urban and rural average values are 5.05 and 33.39 min, with a 28.34 min difference. It is suggested that the EMS system in the rural areas should be further developed. In particular, facility location models can be used to investigate the best spatial layouts for locating EMS facilities when healthcare resources are limited so that EMS facilities can reach as many patients as possible under pre-defined constraints related to accessibility standards (i.e., 10- or 12-min travel time for Trip 1). Accordingly, the improvement of accessibility to EMS can be achieved by relocating some existing EMS stations that are usually easy to adjust their locations. Likewise, similar methods such as the LSCP can be employed for obtaining the minimum number of new stations to locate, which are needed for a geographical unit if any patient is required to be served by an EMS vehicle from the nearest EMS stations within a pre-defined travel time. Further, effective measures are needed to mitigate traffic impact, especially in the central area of the urban region because traffic congestion occurs more frequently in the urban areas.

The study in this chapter has some limitations. First, this study uses residential locations as scenes due to the lack of real-world EMS-run data. However, emergency cases also frequently occur in other sites, such as workplaces and highways. Thus, it is necessary to involve other scenes to measure EMS accessibility, such as locations with high risk of traffic accidents, or historical records of EMS calls. Second, patients with specific severe diseases (e.g., stroke and trauma) can only access specialized hospitals, but this research only considers general hospitals. Hence, examining EMS accessibility regarding specialized healthcare facilities would help understand existing services for those specific diseases. Third, online map services that estimate travel time might lack precision because we cannot adjust the locations of demands and service facilities or visualize those selected routes. All computations are conducted in a black box from API services. Finally, considering the off-peak and peak hours analyzed above, it may be possible for two EMS trips (Trips 1 and 2), one occurring during off-peak hours and the other during peak hours, or vice versa, which might be impacted by the EMS and on-site rescue time again.

Regarding future research, first, if the real-world EMS-run records are available, they would be employed for validating the EMS travel time predicted by GIS and online map services to improve the accuracy of the estimation of EMS accessibility. In addition, the accessibility measures can be improved by adding and integrating the on-scene accessibility time if those data are available. Second, various EMS on-scene times can be predicted from historical EMS records in the real world for different types of diseases (Spaite et al., 1993) to be integrated with EMS travel times in obtaining disease-specific accessibility measures. Finally, a future study can be carried out to identify how patient outcomes, such as morbidity and mortality, are related to accessibility to EMS using these proposed approaches.

3.6. Chapter Summary

Two spatial accessibility measures (i.e., the proximity and E-2SFCA) were employed to estimate spatial and spatiotemporal accessibility to EMS. The ArcGIS Network Analyst and Baidu online maps were employed to estimate average and traffic-based travel times, respectively. There are three major findings of this chapter. First, an area with good ambulance accessibility cannot guarantee that this area also has good hospital accessibility, and vice versa. Second, this chapter finds the urban-rural inequalities in EMS accessibility for Trip 1, Trip 2 and the overall trip. Urban districts generally have less travel times and higher E-2SFCA scores than those in suburban and rural areas. Third, traffic conditions during peak hours can significantly decrease EMS accessibility, especially in urban areas. EMS accessibility decreases sharper in the urban areas than in the rural areas during the peak hours.

This chapter adds to the literature by accounting for two-related trips in measuring EMS accessibility. According to the empirical study, good ambulance accessibility cannot necessarily guarantee good hospital accessibility or overall accessibility, and vice versa. Thus, we urge the need to account for both related trips in evaluating EMS accessibility. Healthcare planers are necessary to build a collaborative system for EMS stations and emergency hospitals. Besides, the existence of urban-rural inequalities in EMS accessibility has been clearly presented by both methods. Reducing such inequalities is necessary for future EMS planning and remains a challenge to governments and local authorities. In addition, online map services are usually valuable tools that can be employed in the studies of accessibility to public service.

Chapter 4 Improving EMS Service Coverage Through Spatial Optimization

This chapter aims to improve EMS service coverage through spatial optimization approaches. Specifically, two optimization models are developed to improve service coverages in relation to different EMS trips. The two proposed models ensure that as many people as possible can be served by ambulance and hospital services within the service standard (e.g., time thresholds). The proposed models are applied in an empirical study in Wuhan, China, to seek the best locations for EMS stations and emergency hospitals simultaneously. Two scenarios are explored. First scenario (Scenario 1) assumes that all existing facilities remain open, while the second scenario (Scenario 2) allows to relocate some of the current facilities. The work presented in this chapter can help the planning practice of public services like EMS systems, where the collaborative work between different types of health services is essential.

4.1. Introduction

Service coverage, an important indicator of quality of EMS provision, refers to the amount potential demand that can be covered with a pre-defined service standard *S*, often represented by travel distance or time. Accordingly, the service coverage relating to Trip 1, Trip 2 and the overall trip can be considered as: (see Figure 4-1).

- Ambulance coverage (i.e., Trip 1 ≤ S_{trip1})
- Hospital coverage (i.e., Trip 2 ≤ S_{trip2})
- Overall coverage (i.e., Trip 1 + Trip 2≤ $S_{overall}$)

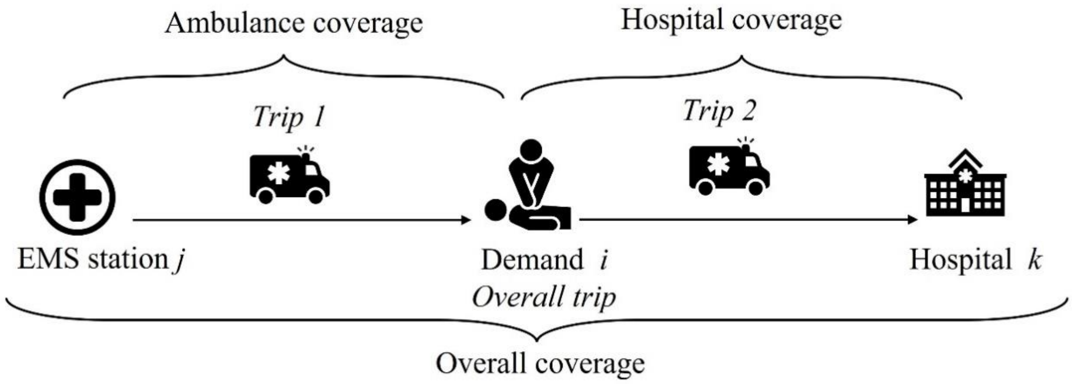


Figure 4-1. Different EMS service coverages.

Service coverages involving different trips are employed in EMS systems across the world. First, most EMS systems throughout the world have specific standards for ambulance service coverage. For example, the U.K. National Health Service (NHS) (2018) stresses that 75% of urban emergency calls must be serviced within 8 min, and 95% must be occur within a maximum of 19 min. In China, the ambulance standard varies in different cities, such as 12 min in Beijing and 10 min in the urban area of Wuhan (Beijing government 2020; Wuhan Municipal Health Commission,2020). Second, rather than ambulance coverage, hospital coverage or overall coverage is often employed in some countries, such as the 30 min of emergency hospital coverage in South Korea (Jang et al., 2021) or the 60 min of overall coverage for stroke patients in China (National Stroke Center, 2021). Coordinating the distribution of those service coverages is essential to improving overall EMS provision, ensuring that patients can quickly receive pre-hospital and in-hospital treatment.

Service coverages are linked with the timeliness of receiving ambulance and hospital services, which affect healthcare outcomes for EMS demands (Rogers et al., 2005; Chay et al., 2009; Sladjana et al., 2011; O'Keeffe et al., 2010; Rammohan et al.,2013; Mucunguzi et al.,2014; Gauss et al.,2019). As discussed in Chapter 3, short travel time for Trip 1 does not necessarily guarantee equally short travel time for Trip 2 or the overall trip; the converse is true as well. Improving overall EMS provisions that ensures reliable access to both ambulance and hospital remains a challenge for many governments and local authorities.

This chapter focuses on the challenge of improving overall EMS provisions, accounting for different coverages involved to multiple EMS trips. In fact, service coverage is highly dependent on the spatial layout of EMS facilities, which has been widely studied by spatial optimization that combines operational research and GIS to find the optimal locations of facilities. In spatial optimization, classic coverage models include the LSCP (Toregas et al., 1971) and MCLP (Church and ReVelle, 1974). These models and their extensions have been widely adopted in numerous applications in locating EMS facilities (e.g., Church and Eaton 1987; Gerrard and Church 1994).

Several facility location models have been developed and adapted to address the coverage problem related to different trips or types of facilities. ReVelle et al. (1976) were the first to suggest that EMS location modelling should consider two related trips (i.e., Trip 1 and Trip 2). Branas et al. (2000) attempted to coordinately locate EMS helicopter depots and hospitals (i.e., trauma centers), taking into account ground-based hospital coverage (demand – trauma center) and air-based overall coverage (helicopter depots – demand – trauma center), ensuring the maximal number of demands that can be encompassed by at least one coverage. In addition, multiple coverage standards have been proposed for a single type of facility, namely the double standard model (e.g., Hogan and Revelle, 1986; Gendreau et al., 1997; Su et al., 2015; Laporte et al., 2019). Similarly, different types of facilities can have different coverage standards. For example, basic EMS units *verse* advanced EMS units, the coverage standard of advanced EMS units is often larger than that of basic EMS units (Brotcorne et al., 2003; Liu et al., 2014; Liu et al., 2016). In addition, multiple coverage from several facilities have been considered in some studies, namely the conditional covering problem or a double set covering problem (e.g., Moon and Chaudry,1984; Lotfi and Moon, 1997; Rana, 2012). Moreover, referral coverage (e.g., clinic–hospital) or hierarchical service coverages (e.g., demand–clinic and demand–hospital) are also extended by several studies on coverage models (e.g., Moore and ReVelle.,1982; Eitan et al.,1991; Galvão et al.,2006).

The main limitation of existing studies is that the extant facility location models seldom seek to coordinately locate EMS stations and hospitals, though a completed EMS journey involves two one-way trips. Some exceptions include the studies by ReVelle et al. (1976) and Branas et al. (2000), which used the overall coverage to include two related one-way trips. Although the two studies attempted to maximize the overall coverage, they could not guarantee the expected ambulance coverage. In other words, they could not guarantee that all patients could be reached by an ambulance with the service standard.

To this end, this study aims to propose two facility location models to improve overall EMS provision by coordinately locating EMS stations and hospitals, accounting for service coverages for different EMS trips. One proposed model involves both ambulance and hospital coverages, and the other considers ambulance and overall coverages. The major contribution of this study lies in the two proposed models that aim to improving overall EMS provisions, ensuring that as many people as possible can be reached quickly by both ambulance and hospital services.

This chapter is organized as follows. Section 4.2 reviews relevant studies and particularly coverage models in EMS/hospital location optimization. The proposed spatial optimization models are presented in Section 4.3. Section 4.4 introduces the empirical study and illustrates the results, where the results from different models are compared. This chapter ends with a discussion of major findings and policy implications of the empirical study.

4.2. Background

A broad range of facility location models has been developed for the service coverage, which can be classified into two main categories: the LSCP (Toregas et al., 1971) and the MCLP (Church and ReVelle, 1974). Detailed descriptions of the above models, including mathematical formulations and common solution approaches, can be found in Chapter 2. The remainder of this section will briefly review multiple coverages, different trips, and facility types involved in coverage-based models.

Toregas (1970) observed that some public services need multiple coverages when the primary coverage was busy or unavailable. The multiple coverage problem was proposed by Daskin and Stern (1981) as a bi-objective formulation. The primary objective minimizes the number of EMS facilities required to cover all demands and then the secondary objective maximizes the demands encompassed by at least two coverages based on a given minimum number of EMS facilities. This problem was further developed by Hogan and ReVelle (1986). Later, Gendreau et al. (1997) proposed a double standard model (DSM) that combined both the concept of double coverage and different coverage radiuses. The multiple coverage problem is also cooperated with the operating cost, the additional cost for EMS delay, the workload of EMS stations or the various priority levels (Liu et al., 2014; Su et al., 2015; Liu et al., 2016).

Various trips are another factor that researchers have focused on facility location modelling. Moon and Chaudry (1984) developed a conditional covering problem (CCP) with a consideration of the trip between the demand and the nearest emergency station, and an additional trip between different EMS stations. ReVelle et al. (1996) extended the CCP model to site facilities in such a way as to maximize the number of facilities that are themselves covered by another facility. The consideration of the additional trip between different facilities is often employed in dealing with large scale disasters, hazards, or terrorist attacks that the local service might paralysis and need such support from other areas/cities (Lunday et al.,2005; Huang et al, 2010; Paul et al., 2017). Another type of facility location modelling aims to locate emergency shelter facilities, which often considers two related trips (i.e., demand – shelter; shelter – hospital) (e.g., Almeida et al., 2009; Coutinho-Rodrigues et al; 2012; Kilci et al; 2015). These studies aim to minimize total distance/travel time from demand locations to shelters and then to hospitals.

Multiple types of facilities have also been a concern of healthcare facility location modelling. For example, Moore and ReVelle (1982) developed a hierarchical model to site successively inclusive facilities such as clinics and hospitals. This problem was further extended by adding different variables or factors, such as the distance decay rule, healthcare capacity, socioeconomic demand groups, risk of disruption, or the referral trip (Hodgson, 1988; Butler et al., 1992; Taborga, 2001; Galvão et al.,2006; Zarrinpoor et al., 2018). A special case was proposed by Church and Eateon (1987) that involved the trip between different types of facilities, such as referral trips in healthcare systems.

With respect to EMS, studies have seldom considered service coverages for different trips involving all of stations, scenes, and hospitals. In general, ReVelle et al. (1976) were the first to suggest that facility location modellings should involve two related one-way trips (i.e., Trip 1 and Trip 2). They introduced the concept of EMS overall coverage from the EMS station to the scene and then to the hospital. Branas et al. (2000) developed the TRAMAH model. The model aims to maximize the number of demands covered at least by hospital coverage (demand – trauma center) using ambulances or covered by overall coverage (Air Depot – demand – trauma center) using helicopters. However, both of them have not considered the importance of ambulance coverage.

As can be seen from the above discussion, multiple coverages, different trips or facility types have been addressed in location optimization of healthcare facilities in various ways. However, the research limitation is that few studies have attempted to coordinately locate EMS stations and hospitals, accounting for the two-related trips. At present, coverage models are still the primary option for EMS location optimization, as EMS systems in many countries and regions have specific service standards of ambulance coverage, hospital coverage, or overall coverage.

4.3. Model Specification

Two spatial optimization models are proposed to seek locations of EMS stations and hospitals, namely Model 1 and Model 2. Model 1 maximizes the amount of demand covered by both Trip 1 (i.e., ambulance coverage) and Trip 2 (i.e., hospital coverage). Model 2 aims to find the maximal number of people that can be served by both Trip 1 and overall trip (i.e., overall coverage).

Both models ensure that as many patients as possible can be quickly served by ambulances. This is because Trip 1 is highly associated with EMS response time, and the standard of ambulance coverage is a common component of EMS systems. The major difference between the two models is the representation of Trip 2, which is explicitly represented by hospital coverage in Model 1, and implicitly represented by the overall coverage in Model 2. In general, Model 1 is an extension of the MCLP, and it explicitly considers two one-way trips. As an extension of ReVelle et al. (1976), Model 2 considers the overall trip as well as the one-way trip to the scene. In order to compare the performance of the proposed models, a general formulation derived from ReVelle et al. (1976) is presented first, namely overall coverage MCLP (i.e., MCLP-OC), which only considers the overall coverage.

4.3.1. The MCLP-OC: considering overall coverage

Generalized from the work by ReVelle et al. (1976), the MCLP-OC seeks the best locations for EMS stations and hospitals in order to maximize the number of EMS demands covered by overall service coverage. Specifically, if the demand is encompassed by the overall overage, the overall travel time for Trip 1 and Trip 2 would be no more than the standard of the overall coverage ($S_{overall}$) (see Figure 4-1). Using the following notation,

i, j, k = index of potential demands, EMS stations, and emergency hospitals, respectively;
I, J, K = set of potential demands, EMS stations, and emergency departments, respectively;
a_i = amount of demand at location i;
$S_{overall}$ = travel standard from the nearest EMS station to a patient location and then to the neatest hospital;
p^{EMS} = number of EMS stations to be sited;
p^{EH} = number of emergency hospitals to be sited;
q^{EMS} = number of existing EMS stations to remain in the system;
q^{EH} = number of existing emergency hospitals to remain in the system;
Φ_{EMS} = set of existing EMS stations;

Φ_{EH} = set of existing EMS hospitals;

t_{ji} = travel time between j and i;
t_{jk} = travel time between j and k;
$M_i = \{(j,k) | (t_{ji} + t_{ik}) \leq S_{overall}\}$ (EMS station - demand - hospital) pairs within

the time standard $S_{overall}$

and the decision variables:

$$X_j^{EMS} = \begin{cases} 1 & \text{if an EMS station is sited at location } j \\ 0 & \text{otherwise} \end{cases}$$

$$X_k^{EH} = \begin{cases} 1 & \text{if an emergency hospital is sited at location } k \\ 0 & \text{otherwise} \end{cases}$$

$$Y_i = \begin{cases} 1 & \text{if demand } i \text{ is covered by the overall service coverage} \\ 0 & \text{otherwise} \end{cases}$$

$$Z_{jk} = \begin{cases} 1 & \text{if a EMS station is located at } j \text{ and a hospital is located at } k \\ 0 & \text{otherwise} \end{cases}$$

the MCLP-OC can be expressed as follows:

Maximize: $\sum_{i \in I} a_i Y_i$ (4.1)

Subject to:

$$\sum_{j \in J} X_j^{EMS} = p^{EMS} \tag{4.2}$$

$$\sum_{k \in K} X_k^{EH} = p^{EH} \tag{4.3}$$

$$\sum_{j \in \Phi_{EMS}} X_j^{EMS} = q^{EMS} \tag{4.4}$$

$$\sum_{k \in \Phi_{EH}} X_k^{EH} = q^{EH} \tag{4.5}$$

$$Y_i - \sum_{(j,k) \in M_i} Z_{jk} \leq 0 \qquad \forall i \in I \tag{4.6}$$

$$Z_{jk} \leq X_j^{EMS} \qquad \forall j \in J,\ k \in K \tag{4.7}$$

$$Z_{jk} \leq X_k^{EH} \qquad \forall j \in J,\ k \in K \tag{4.8}$$

$$X_j^{EMS}, X_k^{EH} \in \{0,1\} \qquad \forall j \in J,\ k \in K \tag{4.9}$$

$$Y_i \in \{0,1\} \qquad \forall i \in I \tag{4.10}$$

Objective (4.1) is to maximize the amount of demand covered within a specific overall distance or travel time ($S_{overall}$) to complete Trips 1 and 2. Constraints (4.2) and (4.3) enforce the total number of EMS stations and emergency hospitals equal to p^{EMS} and p^{ED}, respectively. Constraints (4.4) and (4.5) specify the number of existing EMS stations and emergency departments that will remain open in the system equal to q^{EMS} and q^{EH}, respectively. Constraint (4.6) ensures that the decision variable Y_i must be 0 if no EMS station or emergency department can cover demand i within the overall coverage, that is,

($\sum_{(j,k)\in M_i} Z_{jk} = 0$). Due to the preference of maximizing objective (4.1), Y_i can equal 1 only if demand i is covered by the overall coverage (i.e., $\sum_{(j,k)\in M_i} Z_{jk} \geq 1$). Constraints (4.7) and (4.8) ensure that the decision variables Z_{jk} must be 0 if an EMS station is not opened at location j, or an emergency department is not opened at location k. Constraints (4.9) and (4.10) define the decision variables.

4.3.2. Model 1: considering ambulance and hospital coverages

Model 1 attempts to site EMS stations and emergency hospitals in order to maximize the number of demands covered by both ambulance and hospital coverages (see Figure 4-2). This model ensures that as many people as possible can reach ambulances and emergency departments within their specific time standards, thus ensuring good overall EMS provision. Model 1 addresses a limitation of the MCLP that only considers the coverage for a one-way trip. Using the following added/refined notation:

S_{trip1} = Standard of ambulance service coverage between the EMS station and the scene;
S_{trip2} = Standard of hospital service coverage between the scene and the emergency hospital.
$\mathrm{N}_i^{EMS} = \{j \mid t_{ji} \leq S_{trip1}\}$; the set of EMS stations capable of providing service to demand *i*;
$\mathrm{N}_i^{EH} = \{k \mid t_{ik} \leq S_{trip2}\}$; the set of emergency departments capable of providing service to demand *i*;

$$Y_i^{M1} = \begin{cases} 1 & \text{if demand } i \text{ is covered by both ambulance and hosptial coverages} \\ 0 & \text{Otherwise} \end{cases}$$

Model 1 can be formulated as follows:

$$\text{Maximize:} \sum_{i\in I} a_i Y_i^{M1} \quad (4.11)$$

Subject to:

$$\sum_{j\in J} X_j^{EMS} = p^{EMS} \quad (4.12)$$

$$\sum_{k\in K} X_k^{EH} = p^{EH} \quad (4.13)$$

$$\sum_{j\in\Phi_{EMS}} X_j^{EMS} = q^{EMS} \quad (4.14)$$

$$\sum_{k\in\Phi_{EH}} X_k^{EH} = q^{EH} \quad (4.15)$$

$$\sum_{j\in \mathrm{N}_i^{EMS}} X_j^{EMS} \geq Y_i^{M1} \qquad \forall i \in I \quad (4.16)$$

$$\sum_{j\in N_i^{EH}} X_k^{EH} \geq Y_i^{M1} \qquad \forall i \in I \qquad (4.17)$$

$$X_j^{EMS}, X_k^{EH} \in \{0,1\} \qquad \forall j \in J,\ k \in K \qquad (4.18)$$

$$Y_i^{M1} \in \{0,1\} \qquad \forall i \in I \qquad (4.19)$$

Objective (4.11) aims to maximize the demands that are encompassed by both ambulance and hospital coverages. Constraints (4.12) and (4.13) enforce that the total number of EMS stations and emergency departments should equal p^{EMS} and p^{EH}, respectively. Constraints (4.14) and (4.15) specify that the number of existing EMS stations and emergency departments. Constraints (4.16) (4.17) ensure that the decision variable Y_i^{M1} must be 0 if no EMS station or hospital can cover demand i. Due to the preference of maximizing objective (4.11), Y_i^{M1} can equal 1 only if demand i is located within both ambulance and hospital coverages (i.e., $\sum_{j\in N_i^{EMS}} X_j^{EMS} \geq 1\ and\ \sum_{k\in N_i^{EH}} X_k^{EH} \geq 1$). Constraints (4.18) and (4.19) define the decision variables.

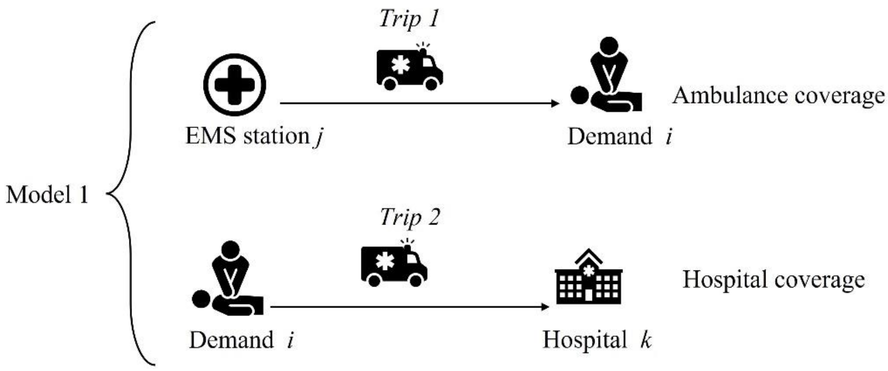


Figure 4-2. Model 1; Considering ambulance and hospital coverages.

4.3.3. Model 2: considering ambulance and overall coverages

Model 2 seeks the best locations for EMS stations and hospitals in order to maximize the number of people covered by both ambulance coverage and overall coverage (see Figure 4-3). Unlike Model 1, the hospital coverage is implicitly included in the overall coverage. Model 2 can be considered as an extension of the works by ReVelle et al. (1976) and Branas et al. (2000). However, unlike these works, Model 2 aims to improve overall EMS service so that demands can easily be severed by both ambulance and hospital services. Using the following added/refined notation:

$$Y_i^{M2} = \begin{cases} 1 & \text{if demand } i \text{ is covered by both ambulance and overall coverages} \\ 0 & \text{Otherwise} \end{cases}$$

Model 2 can be defined as follows:

Maximize: $\sum_{i \in I} a_i Y_i^{M2}$ (4.20)

Subject to:

$$\sum_{j \in J} X_j^{EMS} = p^{EMS} \tag{4.21}$$

$$\sum_{k \in K} X_k^{EH} = p^{EH} \tag{4.22}$$

$$\sum_{j \in \Phi_{EMS}} X_j^{EMS} = q^{EMS} \tag{4.23}$$

$$\sum_{k \in \Phi_{EH}} X_k^{EH} = q^{EH} \tag{4.24}$$

$$\sum_{j \in N_i^{EMS}} X_j^{EMS} \geq Y_i^{M2} \qquad \forall i \in I \tag{4.25}$$

$$\sum_{(j,k) \in M_i} Z_{jk} \geq Y_i^{M2} \qquad \forall i \in I \tag{4.26}$$

$$Z_{jk} \leq X_j^{EMS} \qquad \forall j \in J,\ k \in K \tag{4.27}$$

$$Z_{jk} \leq X_k^{EH} \qquad \forall j \in J,\ k \in K \tag{4.28}$$

$$X_j^{EMS}, X_k^{EH} \in \{0,1\} \qquad \forall j \in J,\ k \in K \tag{4.29}$$

$$Y_i^{M2} \in \{0,1\} \qquad \forall i \in I, j \in J,\ k \in K \tag{4.30}$$

Objective (4.20) maximizes the demands that are served by both ambulance and overall coverages. Constraints (4.21) and (4.22) define the total number of EMS stations and emergency departments, respectively. Constraints (4.23) and (4.24) specify the number of existing EMS stations and emergency departments that will remain open in the system. Constraints (4.25) (4.26) ensure that the decision variable Y_i^{M2} can equal 1 only if demand i is covered by both coverages (i.e., $\sum_{j \in N_i^{ems}} X_j \geq 1$ and $\sum_{(j,k) \in M_i} Z_{jk} \geq 1$). Constraints (4.27) and (4.28) ensure that the decision variables Z_{jk} must be 0 if an EMS station is not opened at location j or an emergency department is not opened at location k. In other words, Z_{jk} can equal to 1 only if an EMS station and an emergency department are opened at locations j and k, respectively. Constraints (4.29) and (4.30) specify the decision variables.

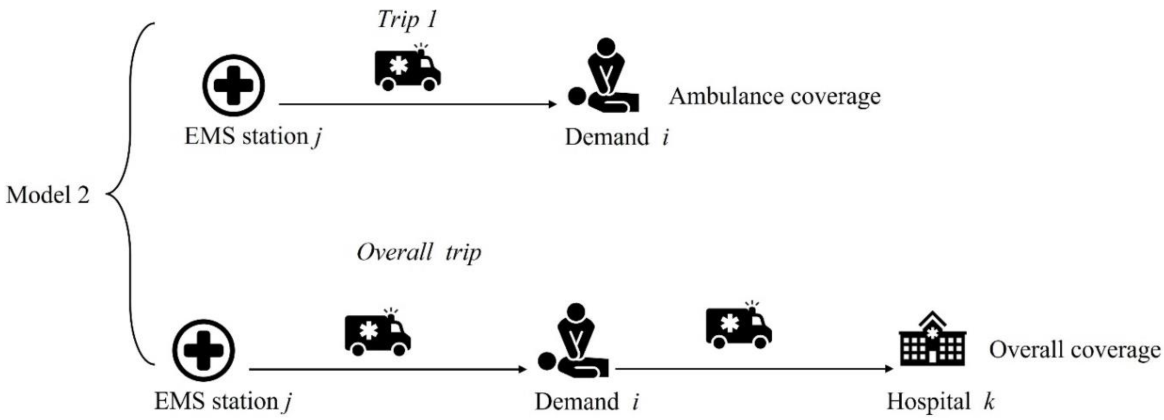


Figure 4-3. Model 2: Considering ambulance and overall coverages.

4.4. Empirical Study

The proposed models are applied in an empirical study in Wuhan, China, to seek EMS stations and stroke centers, ensuring that as many stroke patients as possible can be quickly served by both ambulance and hospital services. To assess the performance of the proposed models, the classic MCLP is also solved and the results from different models are compared.

4.4.1. Planning context of EMS stations and stroke centers in Wuhan

A stroke can occur suddenly anytime and anywhere, affecting the arteries and leading to brain death. Stroke is one of the leading global causes of death and disability, accounting for more than 27% of total fatalities in 2019 (World Health Organization, 2020). It is predicted that 25% of males and 20% of females aged 45 years can expect to suffer a stroke if they reach their 85th year (Wolfe, 2000). The number of strokes in people aged 40 and above has reached 13.18 million in China, with 2.4 million new stroke patients each year and the morbidity trending younger (Wang et al., 2019). China has become one of the countries with the highest lifetime risk of stroke and the heaviest disease burden. Improving the capability of preventing and treating stroke remains a challenge to authorities and healthcare planners.

The development of emergency stroke care systems has been a major concern in many countries or regions. For example, the national Stroke and Cardiovascular Disease Control Act, enacted by the Japanese government, aims to build a speedy ambulance system for transporting and accepting stroke patients (Toyoda et al., 2019). In China, the National Health and Medical Commission (2018) has launched the "60-min treatment circle for stroke" project. It stipulates that the patient should arrive at the affiliated hospital for specialized medical treatment within one hour after a stroke occurs. In addition, the provincial capital cities in China should establish stroke-navigation maps that show the location of stroke care centers. As can be seen from these planning policies, providing speedy ambulance and stroke care systems is a major objective in various countries.

Wuhan Stroke Management (Prevention) Center was launched in 2016, which focuses on controlling high-risk factors for stroke onset, implementing early diagnosis and early treatment, and building a medical and preventive coordination system with the EMS system. The local stroke planning aims to increase the number of general hospitals that have the capacity for stroke treatments and to encourage community-based health centers to establish grassroots prevention projects for preventing stroke and hypertension. Accordingly, the standardization of stroke prevention and treatment should be promoted in an orderly way. The planning also proposes to set up the full coverage of hierarchical diagnosis and fast response emergency care for stroke patients in the following years.

In 2017, Wuhan had only 20 stroke centers deployed in general hospitals; therefore, patients were likely to wait a long time before entering such hospitals. In conjunction with the "golden hour circle for stroke" project that patient can arrive at the affiliated hospital for specialized medical treatment within one hour after a stroke occurs, the Wuhan government plans to increase the numbers of EMS stations or stroke centers. Over its four-year development, the number of stroke centers has increased to 42, and the number is going to increase by 3–5 every year. All new stroke centers will be established based on the Level-II and above hospitals in the urban area and all hospitals in the rural area. The dataset employed includes the census population data based on the finest spatial scale (Shequ), existing EMS stations, hospitals with stroke centers, candidate sites for new stations, and new stroke centers. In this study, the existing hospitals from all levels without EMS stations have been chosen as the candidate locations for new EMS stations. As the task of rescuing stroke patients is also undertaken by general hospitals in Wuhan (medical units at/above Level II), the existing hospitals without stroke centers have been chosen as candidate locations for establishing new stroke centers. The population census data derive from the Geographical Information Monitoring Cloud Platform (http://www.dsac.cn/) that provides population census data at the finest scale currently available, represented by a centroid of shequ. The entire city contains 3,493 shequs. EMS stations, stroke centers, and population are represented as spatial points in the modelling procedure. Existing EMS stations and hospitals and candidate EMS and stroke center locations are extracted from Baidu Maps (https://map.baidu.com/).

The relevant spatial, as well as population, information is presented in Figure 4-4. The data show that some densely populated areas are close to EMS stations but are far from stroke centers, and vice versa. In addition, some shequs are far from both EMS stations and stroke centers. Based on the locations of existing EMS facilities, and population distribution in Wuhan, only 66.1% of the total population can complete the entire ambulance journey (EMS station–demand location–stroke center) within 40 min, and 68.6 % of the population can complete the journey within 50 min.

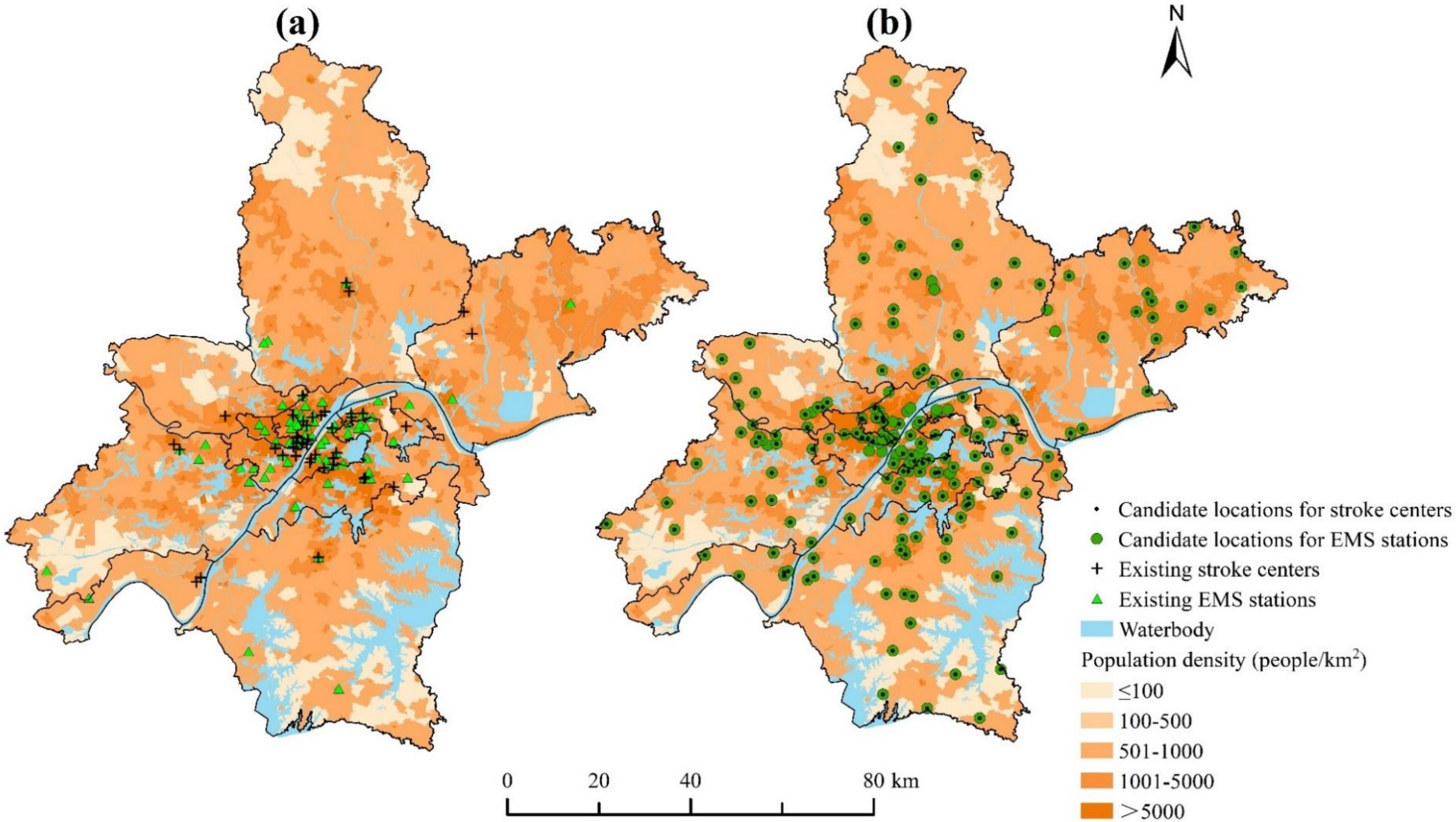


Figure 4-4. (a) Spatial distributions of population, existing EMS stations; (b) stroke care facilitates and candidate locations.

4.4.2. Model settings

Two scenarios, named Scenarios 1 and 2, are employed in the empirical study to demonstrate the performances of the proposed models. They attempt to simulate as to whether existing EMS facilities should remain in the system. Both scenarios are helpful to the planning practice of public services such as EMS systems where the spatial configuration of facilities can be optimized.

Scenario 1 aims to find optimal sites for six new EMS stations and four stroke centers, under the condition that the existing EMS stations and stroke centers remain open (q^{EMS}=79; q^{EH}=42). This scenario is suitable for the short-term EMS planning (i.e., one-year planning) because relocation of existing EMS stations and hospitals usually need long-term discussion and ongoing financial support.

Scenario 2 seeks for optimal locations for two types of facilities under the condition that up to 10% of the existing EMS stations (i.e., maximum eight stations) and 12% of stroke centers (i.e., maximum five centers) can be relocated to other places ($71 \leq \sum_{j\in\Phi_{EMS}} X_j^{EMS} = q^{EMS} \leq 79$; $37 \leq \sum_{j\in\Phi_{EH}} X_j^{EH} = q^{EH} \leq 42$). Therefore, total numbers of EMS stations and stroke centers will increase to 85 and 46, respectively (p^{EMS}=85; p^{EH}=46). This scenario meets the dynamic changing spatial distribution of underlying demand. With the urbanization process in China, especially in large cities such as Wuhan, the increasing number of people are shifting to newly developed towns in the suburbs due to the new working opportunities and more affordable housing prices. Thus, some existing facilities should be changed to other places in order to fit in the demand distribution.

In Wuhan, the "60-min treatment circle for stroke" project stipulates that stroke patients can reach stroke centers within one-hour since the stroke onset. It mainly includes three-time intervals, including ambulance arrival time (Trip 1), on-scene time interval, and transport time (Trip 2). Although there is no on-scene EMS data, the study of Spaite et al. (1993) found that the on-scene time was often between 10 and 20 min. Therefore, this study assumes three different on-scene intervals (10, 15, 20 min), resulting in different standards of service coverages (see Table 4-1). As the standard of rural ambulance coverage is 2 min higher than that in the urban area, this study defines the same difference of the overall coverage standard between urban and rural areas.

Table 4-1. Different time intervals of the service coverages.

Standards	Ambulance coverage (min)	On-scene time (min)	Hospital coverage (min)	Overall coverage (min)
(1)	10 - urban and 12- rural	10	40	50 - urban and 52 - rural
(2)	10 - urban and 12- rural	15	35	45 - urban and 47 - rural
(3)	10 - urban and 12- rural	20	30	40 - urban and 42 - rural

Four facility location models are employed in the empirical study, including the MCLP & Model 1, MCLP-OC and Model 2. The four models can be divided into two groups based on their concerns. One group uses hospital coverage to directly represent Trip 2, which is composed of a classic model (the MCLP) and its extension (i.e., Model 1). Another group employed the overall service coverage to represent Trip 2 implicitly, including the MCLP-OC and its extension (i.e., Model 2). In order to identify whether the proposed models perform better in term of service coverage, the following two sections compare the results within the first group (MCLP *verse* Model 1) and then compare the results within the latter group (MCLP-OC *verse* Model 2). In addition, the MCLP is implemented twice for locating EMS stations and stroke centers, respectively.

The technical implementation for solving optimization problems in this thesis is depicted by Figure 4-5. First, a commercial GIS software (ArcGIS version 10.7) was used for data processing and management. Second, Python scripts were developed to build spatial optimization models and set up relevant parameters, which were based on Python 3.8 with the gurobipy package. Third, the python scripts called Gurobi optimization service (version 9.0.2) to solve the defined spatial optimization problems and to find the optimal solution. Gurobi is a commercial optimization software and one of the fastest and most powerful mathematical programming solvers for linear, mixed-integer linear, quadratic and mixed-integer quadratic programming problems. Finally, the optimal solution found by Gurobi was visualized and presented by ArcGIS 10.7. The codes in this chapter and testing data can be found via the following link (https://github.com/WeicongLuo/PhD_thesis_Chapter_4).

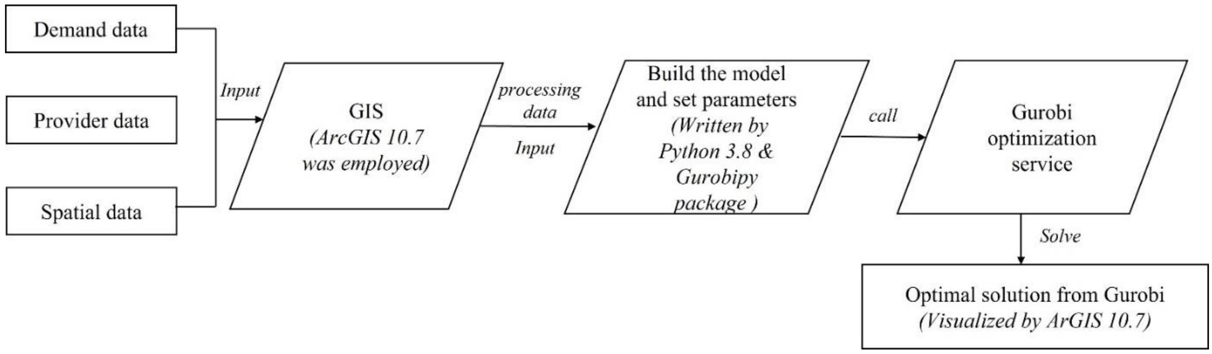


Figure 4-5. The technical implementation for solving the optimization problem.

4.4.3. Results

(1) Scenario 1

Selected sites for MCLP and Model 1

Locations for new EMS stations and stroke centers for the MCLP and Model 1 are depicted in Figures 4-5, with a consideration of three hospital coverage standards (i.e., 30, 35, 40 min) (see Table 4-1). Results from the MCLP model is presented in Figures 4-6 (a)-(c). Figures 4-6 (d)-(f) show the results from the Model 1 that aims to maximize the total population covered by both ambulance and hospital coverages. All results were computed on a desktop with an Intel processor 3.80 GHz and 32GB RAM, and the computational time was 2-3 seconds.

When the 30 min of hospital coverage is applied, the MCLP model suggests that two EMS stations are located in the north of Jiangxia, and the other four EMS stations are located in Hongshan, Hannan, Caidian, and Dongxihu, respectively (see Figure 4-6 (a)). Meanwhile, four-stroke centers are located in Qiaokou, Hongshan, Jiangxia, and Xinzhou. By comparison, Model 1 (Figure 4-6 (d)) suggests that two EMS stations in different locations than Figure 4-6 (a); these are located in Qinshan, and the boundary of Xinzhou and Huangpi, respectively (see Figure 4-6 (d)). The locations for four stroke centers from Model 1 are as same as the MCLP result in Figure 4-6(a).

Considering the 35 min of hospital coverage, the MCLP (Figure 4-6 (b)) suggests that the spatial distribution of EMS stations is the same as in Figure 4-6 (a). Then, four stroke centers are located in Jiangxia, Hongshan, Caidian, and Xinzhou. By comparison, Model 1 suggests that two EMS stations should be located in Hongshan. The other four stations should be located in Hannan, Dongxihu, Jiangxia, and Qinshan (see Figure 4-6 (e)), with four of the six stations different from the MCLP results in Figure 4-6 (b). Then, Model 1 also suggests that four stroke care centers are located in Caidian, Hongshan, Jiangxia, and Xinzhou, with one location different from the MCLP result (the site in Xinzhou).

When hospital coverage is 40 min, the MCLP suggests that two EMS stations should be sited in the north of Jiangxia. The other four EMS stations should be located in the Hongshan, Hannan, Caidian, and Dongxihu. All of them are same to the results of Figures 4-6 (a) and (b). Then, the MCLP suggests two of new stroke centers should be located in the west of Huangpi, and the other two should be sited in Hongshan and Xinzhou (see Figure 4-6 (c)). By comparison, Model 1 suggests that two EMS stations should be located in Hongshan, and the other four stations should be located in Jiangxia, Hanan, Dongxihu, and Qinshan (see Figure 4-6 (f)), with two of the six stations being different from the MCLP result. The Model 1 indicates two of the new stroke centers should be located in the west of Huangpi, and the other two should be located in Xinzhou, and the boundary of Qinshan and Hongshan.

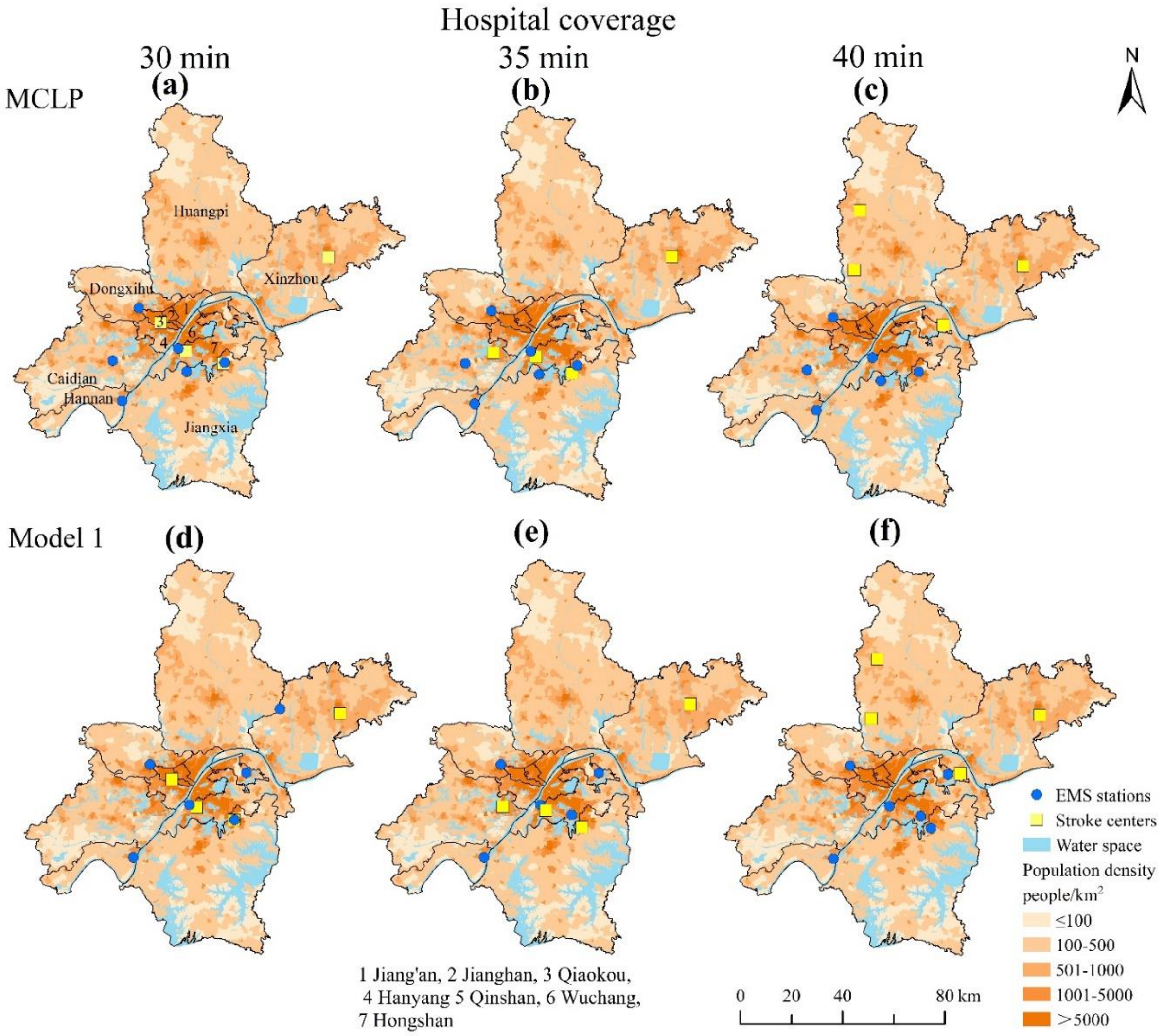


Figure 4-5. Scenario 1 based on 30, 35, 40 min hospital coverages: (a) (b) (c) new sites from MCLP; (d) (e) (f) new sites from Model 1.

The service coverages achieved by the MCLP and Model 1 are summarized in Table 4-2, which shows the different performances of the two models. When considering the 30-min hospital coverage, the MCLP suggests that 7.82 million people is within the ambulance coverage, and 9.09 million people is within the hospital coverage, accounting for 77.7% and 90.3% of the total population, respectively. Meanwhile, the MCLP suggests that 7.59 million people can be covered by both ambulance and hospital coverages, accounting for 75.3% of the total population. By comparison, Model 1 suggests that the number of people covered by either ambulance coverage or hospital coverage is slightly smaller than the same value from the MCLP. However, 7.79 million people can be served by both ambulance and hospital coverages using Model 1, with a 2.2% increase compared to the MCLP result.

When hospital coverage is 35 min, the MCLP results (Table 4-2) show that 7.82 million people is within ambulance coverage, and 9.41 million residents is within hospital coverage, accounting for 77.7% and 94.5% of the total population, respectively. Meanwhile, the MCLP indicates that 7.60 million people can be covered by both coverages, accounting for 75.5% of the total population. In comparison, Model 1 suggests that 77.6% and 91.8% of the total population can be covered by either ambulance or hospital coverage, slightly smaller than the same result for the MCLP model. However, 7.81 million people can be served by both coverages using Model 1, with a 2.1% increase compared to the MCLP result.

As hospital coverage extends to 40 min, the MCLP (Table 4-2) suggests that people covered by ambulance and hospital coverages are 7.82 and 9.59 million respectively, accounting for 77.7% and 93.9% of the total population. In addition, 7.63 million people can be covered by both coverages, accounting for 75.8% of the total population. By contrast, Model 1 shows that the number of people covered by either ambulance or hospital coverage is less than the result from the MCLP. However, 77.7% of the total population can be served by both coverages using Model 1, with a 1.9% of rise compared to the MCLP result.

In summary, regardless of the degrees of hospital coverages (i.e., 10, 15, 30 min), the results from Model 1 and the MCLP show different spatial configurations of new sites and achieve different levels of service coverage when considering two single-trip separately. Although the results from the MCLP enable most patients to be covered by a single-trip coverage (e.g., ambulance coverage or hospital coverage), there is no guarantee that a patient can receive both ambulance and hospital coverages simultaneously. In contrast, Model 1 ensures as many people as possible to have both good ambulance and hospital accessibility by considering both ambulance and hospital coverages.

Table 4-2. Service coverage from Model 1 and MCLP in scenario 1 (Higher value is bold).

	Covered population (million people)					
Hospital coverage	30 min		35 min		40 min	
Covered population (million people)	**Model 1**	**MCLP**	**Model 1**	**MCLP**	**Model 1**	**MCLP**
ambulance coverage	7.79	**7.82**	7.81	**7.82**	7.82	**7.82**
hospital coverage	9.01	**9.09**	9,24	**9.41**	9.45	**9.59**
both coverages	**7.79**	7.59	**7.81**	7.60	**7.83**	7.63
Covered population (%)						
ambulance coverage	77.4%	**77.7%**	77.6%	**77.7%**	77.7%	**77.7%**
hospital coverage	89.6%	**90.3%**	91.8%	**94.5%**	93.9%	**95.4%**
both coverages	**77.5%**	75.3%	**77.6%**	75.5%	**77.7%**	75.8%

Selected sites for MCLP -OC and Model 2

Figures 4-7 show the selected locations for new EMS stations and stroke centers based on both models. Different overall coverages are employed. Figures 4-7 (a)-(c) show spatial outcomes of the MCLP-OC that aim to maximize the total people covered by the overall coverage. Figures 4-7 (d)- (f) show the spatial locations for Model 2 that propose to maximize the total population covered by both ambulance coverage and the overall coverage.

When the overall coverage equals 40/42 min, the MCLP-OC (see Figure 4-7 (a)) suggests that two EMS stations should be located in Huangpi. The other four EMS stations should be located in Hongshan, Hannan, Caidian, and Dongxihu. Meanwhile, the MCLP-OC suggests that two stroke centers should be located in Huangpi. The other two should be sited in Caidian and Xinzhou, respectively. By comparison, Model 2 (see Figure 4-7 (d)) suggests that two EMS stations should be located in the north of Jiangxia. The other four stations should be located in Hongshan, Hannan, Dongxihu, and Caidian, with only one station at the same place as the MCLP-OC result. Then, four stroke stations should be located in Caidian, Xinzhou, Huangpi, and the boundary between Qinshan and Hongshan.

As the overall coverage extends to 45/47 min, the MCLP-OC (see Figure 4-7 (b)) indicates that two EMS stations should be located in Xinzhou, and the other four stations should be located in Caidian, Hannan and Jiangxia and Huangpi. Meanwhile, the MCLP-OC shows that two stroke centers should be located in Xinzhou, and the other two should be sited in Huangpi, respectively. By comparison, Model 2 (i.e., Figure 4-7 (e)) suggests that two EMS stations should be located in the north of Jiangxia, and the other four stations should be located in Hongshan, Hannan, Caidian, and Dongxihu, all of which are different from the locations for the MCLP-OC. Then, four stroke stations should be located in Huangpi, Hannan, Jiangxia and Xinzhou, all of which are different from the locations for the MCLP-OC.

When the overall coverage is 50/52 min, the MCLP-OC (Figure 4-7 (c)) advises that three EMS stations should be located in Huangpi, and the other three stations should be sited in Dongxihu, Caidian, and Xinzhou. Meanwhile, the MCLP-OC also shows that two stroke centers should be located in Xinzhou, while the other two should be sited in the center and the east of Huangpi, respectively. By contrast, Model 2 (Figure 4-7 (f)) suggests that two EMS stations should be located in Jiangxia, with the other four stations located in Hongshan, Hannan, Caidian, and Dongxihu, all of which are different from the locations for the MCLP-OC. Model 2 suggests that four stroke stations should be located in Hannan, Huangpi, Xinzhou, and Jiangxia, all of which are different from the locations for the MCLP-OC. Compared with Figures 4-7 (c) and (f), only one EMS station is at the same location, while other EMS stations and stroke centers are scattered throughout the locations.

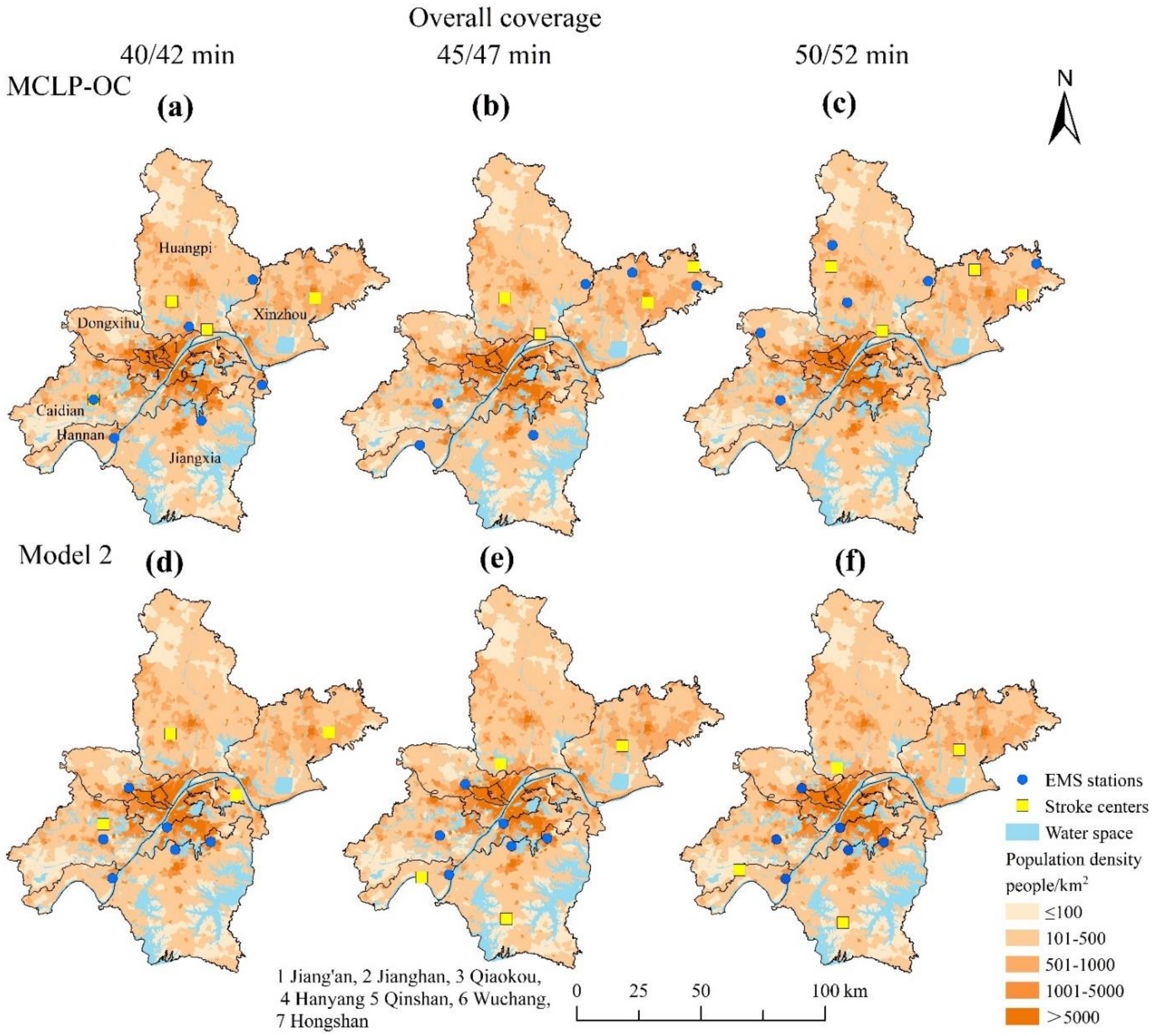


Figure 4-6. Scenario 1 based on 40/42.45/47,50/52 min overall coverages; (a) (b) (c) new sites from MCLP-OC; (d) (e) (f) new sites from Model 2.

According to Table 4-3, the MCLP-OC and Model 2 achieve different levels of service coverage. When considering the 40/42 min overall coverage, the MCLP-OC suggests that 8.61 million people are within the overall coverage, accounting for 85.6% of the total population. At the same time, 7.50 million people can be covered by both ambulance and overall coverages, accounting for 74.5% of the total population in Wuhan. By comparison, 8.35 million people can be served within the overall coverage using Model 2, accounting for 83.0% of the total population, 2.6% smaller than the result for the MCLP-OC. However, 7.80 million people can be served by ambulance and overall coverages using Model 2, accounting for 77.5% of the total population, with a 3.0% increase compared to the MCLP-OC.

When the overall coverage shifts to 45/47 min, 8.81 million people are covered by the overall coverage using the MCLP-OC, accounting for 87.6% of the total population (see Table 4-3). In addition, 7.54 million people can be covered by both ambulance and overall coverages, accounting for 75.0% of the total population. By contrast, residents covered by the overall coverage are 8.57 million using Model 2; this is smaller than the same value for the MCLP-OC. Meanwhile, 7.81 million people can be served by ambulance and overall coverages based on Model 2, accounting for 77.6% of the total population, with a 2.1% increase compared to the MCLP-OC.

When the overall coverage increases to 50/52 min, the MCLP-OC suggests that 9.02 million residents are covered by the overall coverage, accounting for 89.7% of the total population (see Table 4-3). Moreover, 7.72 million residents are covered by both ambulance and overall coverages, accounting for 76.7% of the total population. By comparison, 8.78 million residents can be served within the overall coverage using Model 2, accounting for 87.0% of the total population, with a 2.7% decrease compared to the result of MCLP-OC. Furthermore, Model 2 also indicates that 7.82 million people can be served by ambulance and overall coverages, accounting for 77.7% of the total population, with a 1.0% increase compared to the MCLP-OC.

In summary, regardless of different standards of overall coverages, the results from the MCLP-OC and Model 2 show different spatial layouts of new sites and achieved different levels of service coverages when considering two single trips. Although the MCLP -OC can enable most patients to be covered by the overall coverage, there is no way to guarantee that a patient can receive fast ambulance service. However, the Model 2 ensures that as many people as possible to have both ambulance and hospital accessibility by considering both ambulance and overall service coverages.

Table 4-3. Service coverage from the MCLP-OC and Model 2 in scenario 1 (Higher value is bold).

	Covered population (million people)					
Overall coverage	**40/42 min**		**45/47 min**		**50/52 min**	
	MCLP-OC	**Model 2**	**MCLP-OC**	**Model 2**	**MCLP-OC**	**Model 2**
Overall coverage	**8.61**	8.35	**8.81**	8.57	**9.02**	8.78
Ambulance and overall coverages	7.50	**7.80**	7.54	**7.81**	7.72	**7.82**
Proportion covered by (%)						
Overall coverage	**85.6%**	83.0%	**87.6%**	85.2%	**89.7%**	87.0%
Ambulance and overall coverages	74.5%	**77.5%**	75.0%	**77.6%**	76.7%	**77.7%**

(2) Scenario 2

Selected sites for MCLP and Model 1

Scenario 2 assumes that up to eight EMS stations and five stroke centers in the system can be closed or relocated. Accordingly, the total numbers of EMS stations and stroke centers reach to 85 and 46, respectively.

As the hospital coverage is defined as 30 min, the MCLP (i.e., Figure 4-8 (a)) suggests that eight EMS stations and five stroke centers should be closed, all located in urban districts, including Wuchang, Jiangan, Jianghan, Qiaokou, and Hanyang. Then, 14 new EMS stations and 9 stroke centers should be built or relocated. For new/relocated EMS stations, three selected locations should be located in the south of Huangpi, and Dongxihu, Caidian, Hongshan, and Jiangxia should each contain two locations. The other three new stations should be located in Hannan, Xinzhou, and Qinshan. For planning new stroke centers, three selected locations should be situated in Hongshan, followed by Jiangxia, where two selected locations should be located. The other four stroke centers should be located in Caidian, Dongxihu, Qiaokou, and Xinzhou. By comparison, Model 1 (Figure 4-8 (d)) indicates that eight EMS stations and five stroke centers should be closed, which are sited in the urban area. For new/relocated EMS stations, Model 1 suggests that three selected locations should be located in Xinzhou, while Jiangxia, Dongxihu, and Hongshan should each have two EMS stations. The other EMS stations are sited in Huangpi, Hanyang, and Hannan. For locating stroke centers, three selected locations should be located in Hongshan, and two sites should be situated in Jiangxia. Each of Caidian, Dongxihu, Xinzhou, and Qiaokou should have one stroke center.

When the hospital coverage increases to 35 min, the MCLP model (i.e., Figure 4-8 (b)) suggests that eight EMS stations and five stroke centers should be closed, and they are all located in urban districts. 14 new EMS stations and 9 stroke centers should be built, including relocated facilities. The locations of new EMS stations in Figure 4-8 (b) are the same as the results in Figure 4-8 (a). The locations of stroke centers, however, are different from the previous results. Xinzhou, Jiangxia, Caidian should each have two selected locations for new stroke centers. The other three centers should be located in Dongxihu, Huangpi, Hongshan, respectively. By comparison, Model 1 (Figure 4-8 (e)) indicates that eight EMS stations and five stroke centers should be closed, which are sited in the urban area. Model 1 also suggests that each of Huangpi, Xinzhou, Jiangxia, Hongshan, and

Dongxihu should each have two EMS stations for planning new/relocated EMS stations. The other four stations should be located in Hannan, Caidian, the northwest of Hanyang, and Qinshan. For locating stroke centers, Jiangxia, Caidian, and Huangpi should each have two selected locations, and the other three locations should be distributed in Dongxihu, Xinzhou, and Hongshan, respectively.

If the hospital coverage increases to 40 min, the MCLP model (i.e., Figure 4-8 (c)) suggests eight EMS stations and five stroke centers should be closed, and they are all located in urban districts. All locations of new EMS stations are the same as the previous MCLP results (see Figure 4-8 (a) or (b)). For planning new stroke centers, four selected locations should be located in Huangpi, followed by Xinzhou in which two should be located. Other stroke centers should be sited in Jiangxia, Caidian, and Hongshan, respectively. By contrast, Model 1 indicates that eight EMS stations and five stroke centers should be closed, which are sited in the urban area. For new/relocated EMS stations, Model 1 suggests that three locations should be located in Huangpi, while Caidian, Jiangxia, Hongshan, and Dongxihu should each have two EMS stations; the other three stations should be located in Hannan, Xinzhou, and Qinshan. For locating stroke centers, two locations should be located in Jiangxia, and Huangpi, respectively (Figure 4-8 (f)). The rest of the new stroke centers should be sited in Hannan, Caidian, Caidian, Hongshan, and Xinzhou. In addition, two stroke centers based on Model 1 are the same to the MCLP results.

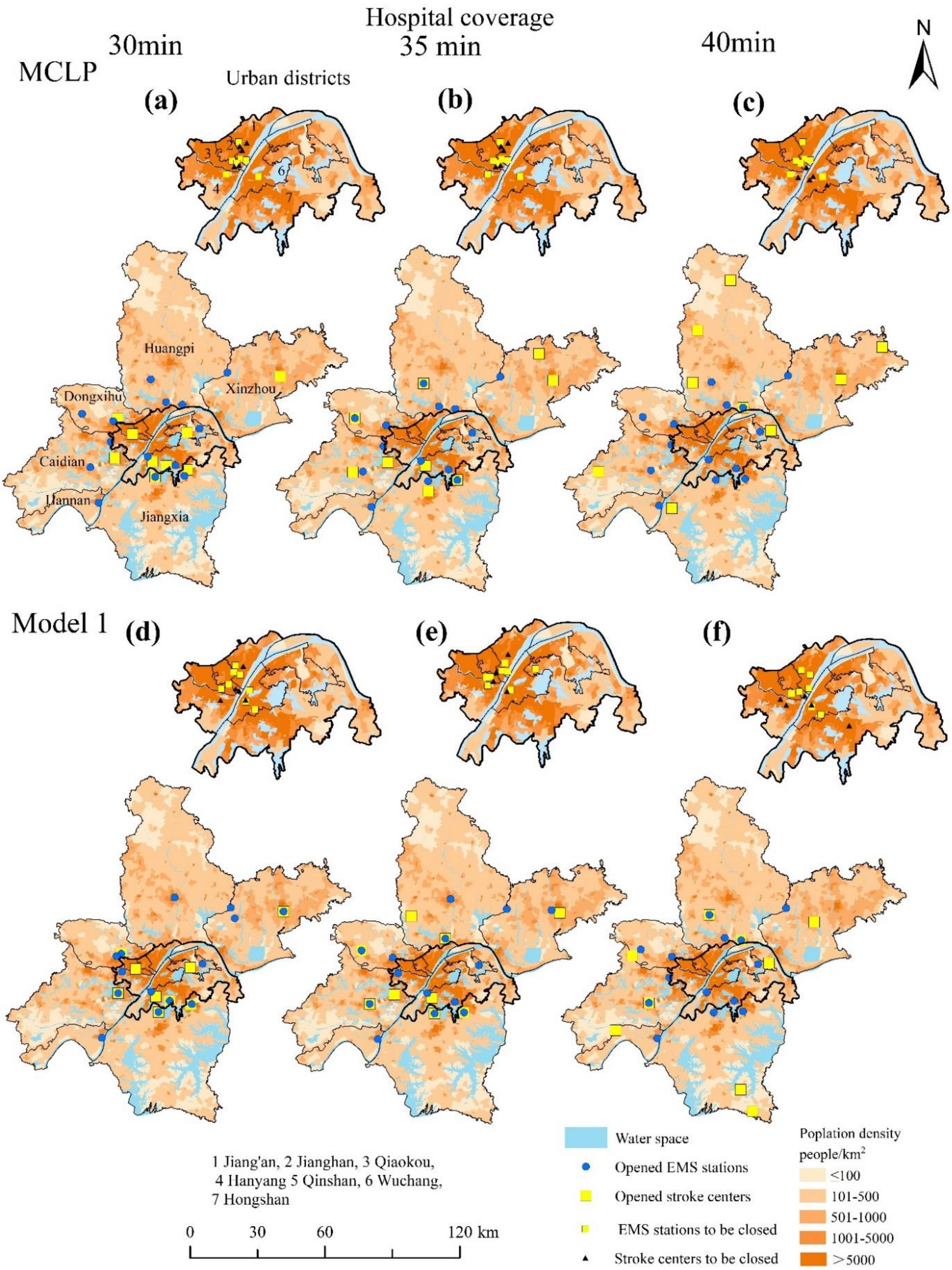


Figure 4-7. Scenario 2 based on 30, 35, 40 min hospital coverage (a) (b) (c) results from MCLP; (d) (e) (f) results from Model 1.

The service coverages achieved by the MCLP and Model 1 are summarized in Table 4-4, and they achieve different performances. Specifically, when considering the 30-min hospital coverage, the MCLP model suggests that 8.10 million people are within ambulance coverage and 9.40 million residents are within hospital coverage, accounting for 80.5% and 93.5% of the total population, respectively. Meanwhile, 7.97 million residents can be served by both ambulance and hospital coverages, accounting for 79.2% of the total population. By contrast, Model 1 suggests that 8.10 million residents are within ambulance coverage and 9.28 million people can be served within the hospital coverage; they are slightly smaller than the same values for the MCLP model. However, 80.4% of the total population can be covered by both ambulance and hospital coverages using Model 1, with a 1.2% increase compared to the MCLP result.

When the hospital coverage is increased to 35 min, 8.10 million people are within either ambulance or hospital coverage using the MCLP, accounting for 80.5% and 94.6% of the total population, respectively. Meanwhile, 8.0 million people can be covered by both ambulance and hospital coverages, accounting for 79.5% of the total population. By comparison, Model 1 indicates that 80.5% and 93.1% of the total population can be covered by either ambulance coverage or hospital coverage; this is slightly smaller than the same results for MCLP. However, 80.4% of the total population can be covered by both coverages, with a 0.9% increase compared to the MCLP result.

When the hospital coverage expands to 40 min, the MCLP model suggests that 80.5% and 97.7% of the total population can be covered by either ambulance or hospital coverages, respectively. Meanwhile, 79.9% of the total population can be covered by both ambulance and hospital coverages. By comparison, Model 1 shows that 80.5% and 95.3% of the total population can be covered by ambulance coverage and hospital coverage, respectively; they are slightly less than the same values for the MCLP model. However, 80.5% of the total population can be served by both coverages based on Model 1, with a 0.6% increase compared to the MCLP result.

In summary, regardless of the degrees of hospital coverages (i.e., 10, 15, 30 min), the results from Model 1 and the MCLP show various spatial layouts of new and relocated sites and achieve different levels of service coverage when considering two single - trip separately. Although the MCLP' results enable most demands to be covered by ambulance coverage or hospital coverage, there is no guarantee that a patient can receive both coverages simultaneously. In contrast, Model 1 ensures as many people as possible to have both good ambulance and hospital accessibility by considering both ambulance and hospital coverages.

Table 4-4. Service coverage from Model 1 and MCLP in scenario 2 (Higher value is in bold).

	People covered by (million people)					
Hospital coverage	30 min		35 min		40 min	
	Model 1	**MCLP**	**Model 1**	**MCLP**	**Model 1**	**MCLP**
ambulance coverage	8.10	8.10	8.10	8.10	8.10	8.10
hospital coverage	9.28	**9.40**	9.37	**9.51**	9.59	**9.83**
both coverages	**8.09**	7.97	**8.09**	8.0	**8.10**	8.04
Proportion covered by (%)						
ambulance coverage	80.5%	80.5%	80.5%	80.5%	80.5%	80.5%
hospital coverage	92.2%	**93.5%**	93.1%	**94.6%**	95.3%	**97.7%**
both coverages	**80.4%**	79.2%	**80.4%**	79.5%	**80.5%**	79.9%

Selected sites for MCLP-OC and Model 2

Figures 4-9 depict the spatial results for the MCLP-OC and Model 1, including the selected locations for new EMS stations, new stroke centers, and the existing facilities to be closed. As the overall coverage is 40/42 min, the MCLP-OC (Figure 4-9 (a)) suggests that eight EMS stations and five stroke centers should be closed, and all closed locations are sited in urban districts. Meanwhile,14 new EMS stations should be established (including relocated facilities), with four in Xinzhou, five in Huangpi, and the other five stations in Dongxihu, Caidian, Hannan, Jiangxia, and Hongshan. There are 9 new stroke centers should be located. Xinzhou and Huangpi should each have three locations, and the other three locations should be located in Caidian, Dongxihu and Hongshan. By comparison, Model 2 (Figure 4-9 (d)) indicates that eight EMS stations and five stroke centers should be closed, which are all sited in the urban area. Then, 14 new EMS stations and 9 stroke centers should be built, including relocated facilities. For new EMS stations, Huangpi should have three EMS stations. Jiangxia, Caidian, Dongxihu, and Hongshan should have two new EMS stations, respectively. The other EMS stations should be located in Qinshan, Hannan, and Xinzhou. For new stroke centers, Huangpi should have three selected locations. The other stroke centers should be distributed in Jiangxia, Hannan, Caidian, Dongxihu, Xinzhou, and Hongshan.

When the overall coverage expands to 45/47 min, the MCLP-OC (Figure 4-9 (b)) shows that eight EMS stations and five stroke centers should be closed, all located in the urban districts. Then, there are 14 new EMS stations and 9 stroke centers, including relocated facilities. For new EMS stations, Huangpi, Xinzhou, and Jiangxia should each have three locations, and Caidian should have two new stations. The rest of stations should be situated in Hannan and Dongxihu. As for stroke centers, four should be distributed in Xinzhou, followed by Huangpi, which should have two new stroke centers. The other stroke centers should be distributed in Jiangxia Hannan, and Caidian, respectively. By contrast, Model 2 (Figure 4-9 (e)) suggests that eight EMS stations and five stroke centers should be closed, all located in the urban area. For planning new EMS stations, one location is located in urban district (Hongshan). The rest of locations should be situated in the six rural areas. As for stroke centers, three locations are located in urban districts (two in Hongshan, one in Qinshan). Other new stroke centers are sited in the six rural districts.

As the overall coverage is increased to 50/52 min, the MCLP-OC (Figure 4-9 (c)) shows that eight EMS stations and five stroke centers should be closed, while all closed facilities should all be located in the urban district. Then, there are 14 new EMS stations and 9 stroke centers, including relocated facilities. New EMS stations are located in all rural districts, and Xinzhou has the highest number of new EMS stations (i.e., 4). As for new stroke centers, new locations are distributed in Xinzhou, Huangpi, Caidian, Hannan, Jiangxia and Qinshan. By comparison, Model 2 (Figure 4-9 (f)) suggests that eight EMS stations and five stroke centers should be closed, all distributed in the urban area. For planning new EMS stations, three stations should be located in Huangpi, while Jiangxia, Caidian, Dongxihu, and Hongshan should each have two selected EMS stations, respectively. The rest of the three selected locations should be situated in Hannan, Xinzhou, and Qinshan, respectively. As for new stroke centers, Jiangxia and Caidian should each have two locations. The rest of the stations are distributed in Hannan, Dongxihu Huangpi, and Xinzhou.

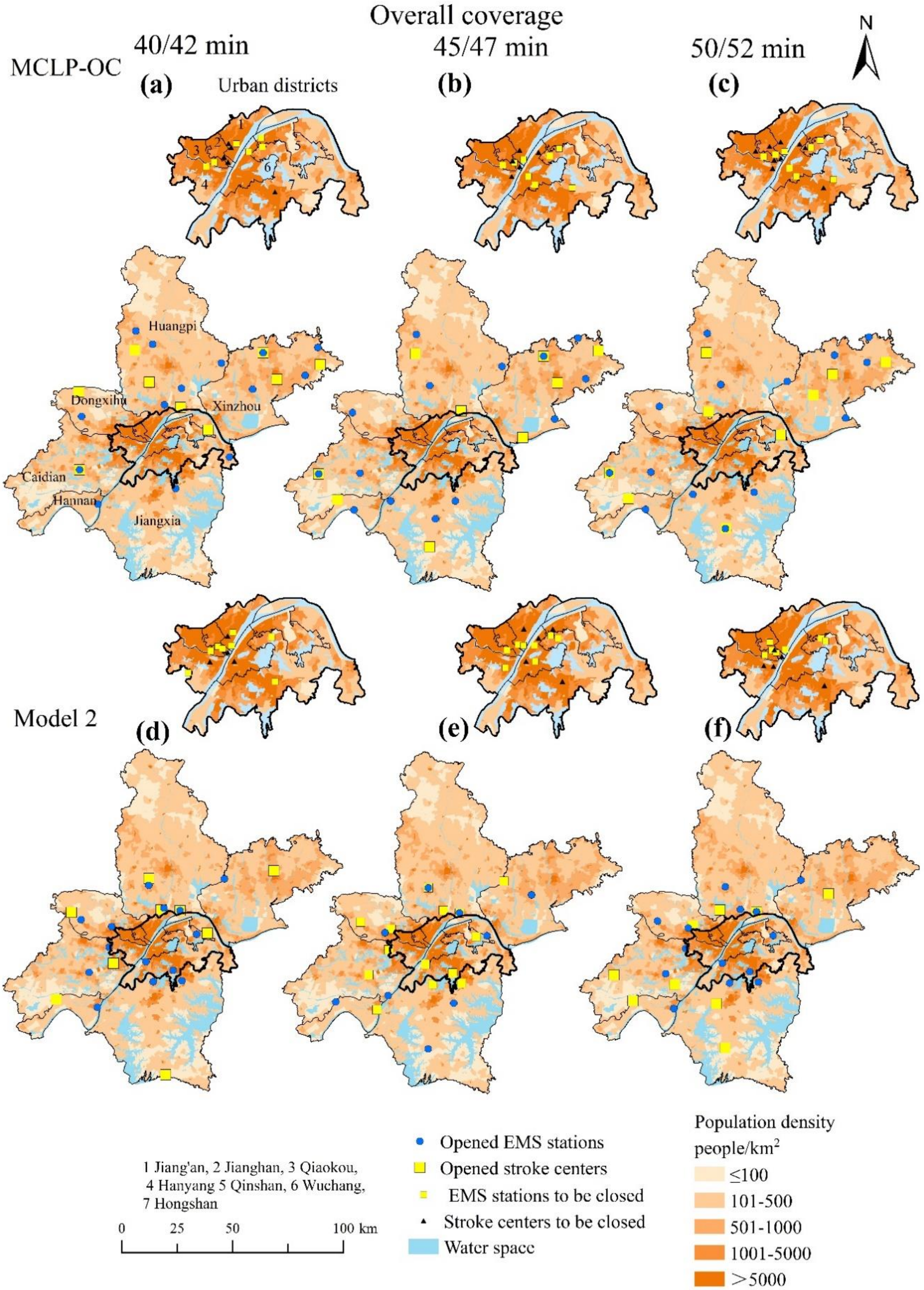


Figure 4-8. Scenario 2 based on 40/42, 45/47, 50/52 min the overall coverage; (a) (b) (c) the results from MCLP-OC; (d) (e) (f) the results from Model 2.

According to Table 4-5, the MCLP-OC and Model 2 achieve different performances in locating EMS stations and stroke centers. When the 40/42 min overall coverage is employed, the MCLP-OC suggests that 88.9% of the total population are covered by the overall coverage. Meanwhile, 78.8% of the total population can be served by ambulance and overall coverages. By contrast, Model 2 suggests 87.6% of the total population can be served within the overall coverage; that is slightly smaller than the same value for the MCLP-OC. However, Model 2 suggests 80.40% of the total population can be covered by ambulance and overall coverages, with a 1.6% increase compared to the MCLP-OC result.

If the overall coverage is defined as 45/47 min, the MCLP-OC model suggests that 93.0% of the total population can be covered by the overall coverage (see Table 4-5). Meanwhile, 79.1% of the total population can be covered by both ambulance and overall coverages. By comparison, Model 2 shows that 91.3% of the total population can be covered by ambulance and overall coverages; that is slightly less than the same value for the MCLP-OC. However, Model 2 shows that 80.44% of the total population can be served by ambulance and overall coverages, with a 1.34% increase compared to the result of the MCLP-OC.

When the overall coverage is increased to 50/52 min, the MCLP-OC suggests that 94.9% of the total population can be served by overall coverage. Meanwhile, 79.4% of the total population can be covered by ambulance and overall coverages. By comparison, Model 2 suggests that 92.7% of the total population can be covered by the ambulance and overall coverages. This result is slightly smaller than the value of MCLP-OC. However, Model 2 shows that 80.5% of the total population can be covered by ambulance and overall coverages using Model 2, with a 1.1% increase compared to the MCLP-OC result.

In summary, regardless of different standards of overall coverages, the results from the MCLP-OC and Model 2 show different spatial layouts of new/relocated sites and achieved different levels of service coverages when considering two trips. Although the MCLP-OC can enable as many people as possible to be covered by the standard of overall coverage, there is no way to guarantee that a patient can receive fast ambulance service. However, the Model 2 guarantees that as many people as possible to have both quickly ambulance and hospital services by considering both ambulance and overall service coverages.

Table 4-5. Service coverages for the MCLP-OC and Model 2 in scenario 2 (Higher value is in bold).

	People covered by (million people)					
Overall coverage	40/42 min		45/47 min		50/52 min	
	MCLP-OC	**Model 2**	**MCLP-OC**	**Model 2**	**MCLP-OC**	**Model 2**
overall coverage	**8.95**	8.81	**9.35**	9.19	**9.54**	9.33
Ambulance and overall coverages	7.93	**8.09**	7.96	**8.09**	7.99	**8.10**
Proportion covered by (%)						
overall coverage	**88.9%**	87.6%	**93.0%**	91.3%	**94.9%**	92.7%
Ambulance and overall coverages	78.8%	**80.4%**	79.1%	**80.4%**	79.4%	**80.5%**

4.5. Discussion

This study proposes two spatial optimization models (i.e., Model 1 and Model 2) for locating EMS stations and hospitals, accounting for service coverages of different trips. Both models are to maximize the amount of demand covered by Trip 1 and Trip 2. The major difference is that Model 1 uses the hospital coverage to represent Trip 2 directly, but the Model 2 employs the overall service coverage to represent Trip 2 implicitly. According to the empirical study, Model 1 performs better than the MCLP when different trips are involved. It is because the former can enable more demands to be covered by both ambulance and hospital coverages than the latter model. The MCLP-OC and Model 2 implicitly involve Trip 2 using the overall coverage. From the results, Model 2 can guarantee that more patients to be covered by ambulance and overall coverages than the MCLP-OC. Therefore, Model 2 has a better performance in considering coverages for different trips as the MCLP-OC cannot guarantee that as many people as possible can be covered by the ambulance coverage.

The proposed models in this chapter are valuable in practice. The empirical results from Chapter 3 have indicated that an accessible Trip 1 cannot guarantee an accessible Trip 2 or the overall trip, and vice versa. This is often caused by different spatial layouts of EMS stations and emergency hospitals, and they lack cooperation in space. Some areas are near EMS stations but far away from their nearest hospitals, such as the east of Caidian (see Figures 3-6 (a) in Chapter 3). By contrast, some places are near hospitals but far away from their nearest EMS stations, such as the west of Xinzhou (see Figures 3-6 (b) in Chapter 3). Therefore, the work in this chapter can add in the collaborative planning of EMS systems that often consist of two trips and different types of facilities, while ensuring that as many people as possible can easily access to different facilities.

Although there are some similarities between Models 1 and 2, the difference is that the former employs hospital coverage to represent Trip 2, and the latter uses overall coverage to represent the trip indirectly. By comparison, Model 1 has a stricter requirement for the service provisions than Model 2. For example, we assume that ambulance, hospital, and overall coverages are 10, 30 and 40 min, and the travel times for Trip 1 and Trip 2 are 1 and 31 min, respectively. It has met the requirement of Model 2 because travel times for Trip 1 and the overall trip are less than 10 and 40 min. However, this area still does not meet the requirement for Model 1 because the travel time for Trip 2 exceeds the standard of hospital coverage (i.e., 30 min). Thus, good ambulance and hospital coverage often ensure good overall coverage. However, good ambulance coverage and overall coverage might not guarantee good hospital coverage. The selection of Model 1 and Model 2 should depend upon local EMS planning criteria. Model 1 is applicable in EMS systems where the standards of one-way trip coverages have been stipulated. Model 2 is suitable for the EMS systems that primarily concern the overall coverage.

Some policy implications emerge from Chapter 4. First, the two scenarios can provide healthcare planners and local authorities with different suggestions. Scenario 1 provides the short-term advice for decision-makers, that is, how to locate new facilities on the existing basis. Scenario 2 provides an additional view regarding which existing stations are suitable to close and move to other places to achieve the long-term planning goals in order to meet the dynamic movement of demands. Second, Wuhan stroke planning criteria have the clarified standards for ambulance coverage and overall coverage, but the hospital coverage has not clearly defined. Hence, Model 2 is more applicable to employ here. Third, according to the existing spatial layouts of EMS stations and stroke centers, about 40% of the population in Wuhan might not be covered by both ambulance and overall coverages. In other words, a large number of residents still cannot be served by fast ambulance and hospital services. Thus, it is necessary to provide additional EMS stations and stroke care facilities to meet those underserved areas. Furthermore, the two proposed models provide decision supports for healthcare planners and policymakers. For example, the application of Model 2 suggests that the next EMS station should be located in Hongshan, and the next stroke center should be sited in Huangpi when existing facilities remain open. Meanwhile, one EMS station in Hanyang and one stroke center in Jiangan should closed and relocated to other places if the scenario 2 is considered.

This chapter has some limitations, including the specification of candidate locations for new EMS facilities and underlying demands. New EMS stations and emergency hospitals can be sited at locations other than existing candidate locations. Moreover, the site suitability analysis can be implemented to identify candidate locations, which often needs the knowledge of land-use restrictions and local development plans in the case study area. Second, this chapter uses residential locations to represent demand locations, which cannot accurately reflect the spatial distribution of stroke patients across the study area. Furthermore, the variation in on-scene accessibility and on-scene building height data have not been considered. For example, the patient's floor (high-rising building vs low-rising building) or the environment of the neighborhood community can affect the on-scene time (e.g., Balamurugan et al., 2016), resulting in a variation in overall travel times across neighborhood communities and different population groups.

There are several potential extensions. First, the proposed models have not considered EMS accessibility in uncovered areas. However, it does not mean that people living further away from EMS stations or hospitals than the standards of service covera ge will not use such services. According to the results in both scenarios, more than 20% of the population remains outside at least one service coverage. Therefore, it is worth considering accessibility to EMS for those uncovered areas. Examples of research on this subject include Church et al. (1991) and Chanta et al. (2014). Furthermore, it is worth determining the minimal number of facilities needed to cover the entire study area, such as using the LSCP-based model. Additionally, factors like facility availability and maximal service capacity can be extended in both studies, which must cooperate with real EMS-running data and specific disease records.

4.6. Chapter Summary

Trip 1, Trip 2 and the overall trip are essential to EMS provisions, often determined by ambulance coverage, hospital coverage, and the overall coverage, respectively. However, fast ambulance service does not necessarily guarantee timely hospital or overall EMS service, and vice versa. This chapter proposes two spatial optimization models to improve the overall EMS provision, ensuring that as many people as possible can be quickly served by both ambulance and hospital services. Specifically, two facility location models are developed to seek the best locations for the given numbers of EMS stations and emergency hospitals, considering coverages for different EMS trips. As an extension of the MCLP, Model 1 seeks the maximal number of people covered by both ambulance and hospital coverages. As an extension of the MCLP-OC, Model 2 intends to maximize the number of patients covered by the ambulance coverage and the overall coverage. According to the empirical study, the two proposed models perform better than the previous models when different EMS coverages and trips are considered. The work presented in this paper can aid the planning practice of public services like EMS systems, where the collaborative work between EMS stations and hospitals is an essential concern.

Chapter 5 Reducing Urban-Rural Inequalities in EMS Through Spatial Optimization

This chapter aims to reduce regional inequalities in EMS through spatial optimization approaches. Two bi-objective optimization models are developed. They have a same primary objective related to service coverage, and two alternative inequality objectives focusing on service accessibility and coverage, respectively. The proposed models are applied in an empirical study in Wuhan, China, to seek optimal locations for EMS stations to improve local EMS capacity in the pandemic period, accounting for urban-rural equalities in EMS. The empirical results indicate that a reduction in urban-rural inequalities in both accessibility and service coverage leads to a decrease in the total covered population, especially in urban areas. The work demonstrated in this chapter can help the planning practice of healthcare services, such as EMS, where improving equalities between urban and rural areas is an essential concern.

5.1. Introduction

Equity in receiving healthcare facilities such as EMS is crucial to social fairness, which is one of the objectives of sustainable development (i.e., Goal 10: Reduce inequality within and among countries) (United Nations, 2015). Inequalities in receiving EMS within/across regions and among population groups widely exist, often attributed to insufficient healthcare resources including financial support (e.g., fundings), traffic infrastructure or geographic barriers (i.e., travel distance/time) (Jennings et al., 2006; Luo et al., 2020; do Nascimento Silva and Padeiro, 2020). Improving spatial equality in the delivery of EMS remains a challenge to national and local governments and authorities.

This chapter focuses on improving equalities in service coverage and accessibility, both of which are common measures for evaluating EMS system performance (ReVelle et al., 1977; Bélanger et al., 2019). Service coverage refers to the amount of demand that can be served with pre-defined service standards. In comparison, accessibility is considered as the ease and speed of action, where shorter responses often lead to more favorable health outcomes. Both dimensions of accessibility and service coverage have been studies in the field of spatial optimization. For example, a classic coverage model (MCLP) was extended to maximize

EMS survival rate (Erkut et al.,2008). P-center problem was used to improve EMS accessibility in rural areas (Chanta et al., 2014).

In general, coverage-based models remain the dominant type of EMS facility location approach because response time standards (or service radius) and EMS provision (e.g., cover 90% population or respond to 90% of calls within a certain time frame) are the most important components of EMS systems (Başar et al., 2012; Church and Murray, 2018). The integration of accessibility and service coverage is a common practice in EMS location optimization (e.g., Church et al., 1991; Pirkul and Schilling, 1991).

Numerous inequality measures have been developed and incorporated into facility location modelling (Mulligan, 1991; Erkut, 1993; Marsh and Schilling, 1994; Barbati and Bruno, 2018). Those models are often based upon the influence or potential outcomes of facility layout on communities or individuals, often represented by distance, travel time or other indexes (e.g., accessibility scores). Common approaches consist of variance (e.g., Wang and Tang, 2013), range (e.g., McLay and Mayorga, 2013), mean deviation (e.g., Ogryczak, 2009), among other indexes. Moreover, some indexes from economic or demographic perspective for evaluating inequities related to socioeconomic status (e.g., income, education level, housing). For example, the Gini coefficient have become a popular measure of evaluating inequalities in EMS (e.g., Drezner et al., 2009; Burkey et al., 2012; Enayati et al., 2019).

The majority of extant studies on facility optimization have concerned EMS equalities between communities, different demographic/socioeconomic groups, or individual users. However, the improvement of regional equality in EMS has received relatively less concern, especially between urban and rural areas. Three exceptions can be discussed. McLay and Mayorga (2013) and Chanta et al. (2014) attempted to improve EMS equality between urban and rural areas by increasing the service coverage of rural population or areas. Amaral and Murray (2016) used the *p*-median model to assess the equity between different states in Brazil in access to a health service.

At present, there is no widely acceptable measure on spatial optimization. Many inequality approaches can be employed relying upon the specific inequality perspective concerned by the researcher. Moreover, service coverage can be varied in different areas even if they are within the same EMS system. For instance, American EMS systems intend to serve 90% of EMS demands within 15 min for rural areas, but within 9 min for urban regions (Fitch, 2005). In Wuhan, China, the standard of ambulance coverage is 10 min in the urban districts, but 12 min in the rural districts (Wuhan Municipal Health Commission, 2020 b). However, the urban-rural difference in standards of service coverages has been widely ignored in extant work.

This chapter intends to improve equalities in EMS accessibility and service coverage between urban and rural areas using spatial optimization approaches that incorporate different EMS planning standards for urban and rural settings. Two bi-objective models are proposed to optimize EMS stations to reduce such urban-rural inequalities in access to EMS. The major contributions are the two proposed models of reducing urban-rural inequalities in the delivery of EMS – one for accessibility and the other for the urban-rural service coverage, as well as the consideration of different service standards for the urban and rural areas. The proposed models are implemented in an empirical study in Wuhan, China, where the planning of EMS system development and promotion (which is in progress) has been highlighted by the COVID-19 pandemic.

This chapter is organized as follows. Next section reviews the urban-rural inequalities in EMS and various facility location models for EMS in general and those accounting for inequality in particular. The proposed two bi-objective spatial optimization models are then presented in section 5.3. The empirical results are described and interpreted in section 5.4. This chapter ends with a discussion of major contributions and policy implications of the empirical study.

5.2. Background

Three topics are reviewed in this section: one is inequality measures adopted in assessing EMS systems, the second is common inequality measures of EMS systems. This section ends with the discussion of various measures of spatial inequalities in EMS.

5.2.1. Urban-rural inequality in EMS

The terms "urban" and "rural" settings are often widely adopted in planning criteria, and their definitions have been widely concerned by geographers, epidemiologists, economists, demographers, or political scholars for many years (e.g., Isserman 2005; Susan et al., 2006; Gianotti et al., 2016; Chen, 2016). The following paragraphs review common measures for classifying urban and rural areas.

First, the population density is the most common indicator for classifying urban and rural areas. Recently, the population density measure has been widely employed to classify urban and rural areas. For example, England is divided into 171,372 Output Areas (OAs), and those

OAs with more than 10,000 people are classified as urban areas (Government Statistical Service, 2011). However, these measures might not be suitable for large-scale countries such as in China or America due to the large range of population density across those countries. For example, in the United States, the population density is 11,535 people per square mile in the District of Columbia versus 1.1 people per square mile in Alaska. The large differences in population density make it impossible to have a nationwide standard for classifying urban and rural areas.

Second, the standardized definition can be used to classify urban and rural areas. For instance, The US Census created a dichotomous standardized definition for urban and rural areas by a complicated algorithm, including many factors, such as income, insurance and so on. The designation of urban and rural areas is often implicated in the finest level like census units, districts, or Metropolitan areas. The US Census 2000 Bureau developed the ZIP Code Tabulation Areas (ZCTAs) to classify urban and rural areas. The most recent US Census 2020 defines the urban area as densely developed territory, which takes into account several factors like commercial indexes, residential factors, and other non-residential urban land-uses (United States Census Bureau, 2020).

Third, classification of urban and rural areas can depend on empiricism, such as traffic networks, cultural, or administrative areas. Some metropolises define their urban area/inner city by traffic networks. For example, urban areas in Beijing, China, can be classified by the communities within the 5th Ring Road. Similarly, the inner city in Shanghai is defined by the area bordered by the Inner Ring Road (Hu et al., 2020). Some cities defined their urban areas by administrative districts. For example, Wuhan, China, describes urban areas as seven districts with intensive socio-economic activities. In summary, the definition of urban and rural areas varies across countries or within a country. At present, there are plenty of measures to delineate urban/rural regions, and we need to classify urban and rural areas. However, compared with rural areas, urban areas in general have denser population and more intensive socio-economic activities.

Various studies have found urban-rural inequalities in delivering EMS service, which relates to Trip 1, Trip 2, on-scene time interval, transfer rates, or survival rates (Grossman et al., 1997; Nordberg et al., 2004; Gonzalez et al., 2009; Masterson et al., 2015). As the urgent EMS response to the scene, this paragraph focuses on urban-rural inequalities in Trip 1. In general, the urban-rural disparities in ambulance arrival time (i.e., Trip 1) have been widely documented in numerous studies, which might cause inequalities in healthcare outcomes between urban and rural residents (e.g., Vukmir et al., 2004; Moore et al., 2008; Aftyka et al., 2014; Masterson et al., 2015).

This study concerns the inequalities in Trip 1 as prehospital medical care is always the most crucial factor in saving lives in emergency. Urban and rural inequalities in Trip 1 can be represented by accessibility as well as service coverage. On the one hand, such inequalities in EMS accessibility have been widely reported (Layon et al., 2003; Gonzalez et al., 2006; Sørensen et al., 2011; Masterson et al., 2015). For example, Gonzalez et al. (2006) reported an average ambulance arrival time of 11.2 min (urban settings) and 13.9 min (rural settings) ($p<0.0002$), which was linked to higher mortality rates in rural areas. Masterson et al. (2015) reported that rural patients received emergency medical care eight min slower than urban patients on average. On the other hand, urban-rural inequalities can be represented by service coverage. For example, Aftyka et al. (2014) indicated more than 80% of urban patients could reach ambulances within 10 km travel distance, but only 7.2% of rural patients could find the same service within the same distance. Overall, urban-rural inequalities in both accessibility and service coverage are still challenges to governments and localities.

5.2.2. Inequality measures of EMS systems

Common measures of inequalities in EMS response/travel time mainly include the variance, standard deviation, average absolute deviation, range, Gini coefficient and among others.

First, the variance of the relative variables (e.g., distance, travel time or survival rate) is a common approach for evaluating EMS inequality (Felder and Brinkmann, 2002; Mapuwei et al., 2013). It often focuses on the difference in spread between EMS values in a dataset, while the high variance value is associated with severe inequality. For example, Felder and Brinkmann (2002) used the variance of average EMS response time to evaluate EMS equality and then used the spatial optimization method to balance the efficiency and equality of the EMS system.

Second, the standard deviation of the relative variables is also frequently employed in measuring EMS equality (e.g., Tomioka et al., 2019; Omidi, 2021). The limitation is that the standard for each cost should be established during the variance analysis, which might cause deficiencies and affect the results. Standard deviation is a statistic value which evaluates the dispersion of a dataset relative to its average value and it is computed as the square root of the variance. A lower standard deviation value often represents smaller inequality. For instance, one recent study used the standard deviation of waiting times to measure spatial inequality in access to fracture treatment facilities in Japan (Tomioka et al., 2019). The limitation of standard deviation is that it has not clearly measured how far a value is from the average point.

The average absolute deviation is also a measure of inequalities in EMS (Li et al., 2022; Newon et al., 2022). It concerns the average difference between each value in the data set and the average value of the data set. Similarly, a higher average absolute deviation value represents higher inequality. For example, Newon et al. (2022) used the absolute deviation of travel time to assess EMS equality before reducing such inequalities. However, this index might bring a larger probable error than the standard deviation (Fisher, 1920).

The range is computed as the difference between the maximum and minimum values of the variables, which is also a common measure of EMS inequalities. For example, Dahllöf et al. (2018) optimized the locations of mobile stroke units and used one of the inequality indexes represented by the range of ambulance response time. The limitation of the range is that this method only concerns the highest data difference.

In addition, the Gini coefficient aims to show the inequality of socioeconomic or the wealth within a social group or a spatial area, which has been widely implemented in assessing inequalities in EMS systems (e.g., Khdaparasti et al., 2016; Yan et al., 2017; Erdenee et al., 2017). For example, Erdenee et al. (2017) used the Gini coefficient to evaluate the spatial distribution of healthcare resources in both urban and rural areas of Mongolia. Further, other measures of inequalities, such as the sum of the absolute deviations and semi deviations, have also been mentioned (Marsh and Schilling,1994). The limitation of the Gini coefficient is that the accuracy is highly dependent on the size of the dataset and sample. Overall, although there are numerous inequality measures of EMS systems, we should select the suitable method based on the research aim, objectives and dataset.

5.2.3. Measures of spatial inequalities in EMS

Classic spatial optimization always concerns efficiency, but another conflicting aspect – equality, is often overlooked. For example, given the fact that the MCLP tends to locate facilities in densely populated areas while leaving sparsely populated areas underserved. The early works on inequality measures were based on the work of Mumphreys et al. (1971), McAllister (1976) and Savas (1978). They started to build an underlying channel between spatial optimization research and equality. Although many facility location measures have been employed in inequalities issues, there is no widely acceptable agreement on equality measures. EMS response/travel time is the common index of evaluating the quality of an EMS system

Many inequality measures have been employed in spatial optimization studies (e.g., Mulligan, 1991; Erkut, 1993; Marsh and Schilling, 1994; Barbati and Bruno, 2018). Table 5-1 summarized some common equality measures in healthcare services include range (e.g., McLay and Mayorga, 2013), variance (e.g., Wang and Tang, 2013) and mean deviation (e.g., Ogryczak, 2009), among many others. In addition, some indices from demographics and economics for assessing inequity of socioeconomic welfare – such as the Gini coefficient – were often considered equivalently as measures of inequality (Burkey et al., 2012) and have been employed by many studies (e.g., Drezner et al., 2009; Chanta et al., 2011; Enayati et al., 2019). Center and median models also involve in addressing inequality problems (Chanta et al., 2014; Amaral and Murray,2016).

Church and Murray (2018) indicated that coverage-based models play a better role in the meaning of equality by using certain service standards to the overall demands. For example, the total number of uncovered geographical units was minimized to reduce the inequality between different demand areas (Chanta et al., 2014; Khodaparasti et al., 2016). More frequently, inequality issues can be represented by an index incorporated into facility location models as a constraint or an objective function. For example, Chanta et al. (2011) proposed an index of “envy” and then developed a facility location problem to minimize the associated index - “*p*-envy” that is associated with the perception of inequity in the delivery of EMS. Based on extra inequalities constraints, McLay and Mayorga (2013) define the index for both the priority level and survival rates by the closest EMS station and developed a facility location model that aimed to minimize this index. Three indices were used by Enayati et al. (2019) to quantify the disparities in individual reaction times: variance, squared coefficient of variation, and Gini coefficient. Each of these indices served as an alternate objective function to be minimized. In addition to the inequalities between users, some scholars also attempted to balance the workload between servers (e.g.Toro-Diaz et al., 2015; Enayati et al., 2019). However, most spatial optimization approaches have only concerned EMS-related inequalities at community/individual level, in a single type of spatial context (i.e., either urban or rural) (e.g., Chanta et al., 2011; Toro-Diaz et al., 2015) or easing off regional disparities in EMS access from a nationwide planning perspective (e.g., Amaral and Murray, 2016). Comparatively, urban-rural disparities in EMS have received less attention even if such inequalities have been widely reported. To the best of our knowledge, the work by Chanta et al. (2014) is one of the few studies that considered the inequalities between urban and rural settings in seeking optimal sites for EMS facilities. This chapter attempts to address urban-rural inequalities in EMS through spatial optimization, with two alternative inequality measures to improve equalities in EMS between urban and rural areas with respect to accessibility and service coverage.

Table 5-1. Common extension of the objectives in classic model with respect to EMS inequality.

Objective functions (this should be the 1st column)	**Inequality measure**	**Dimension of inequality**	**Relevant studies**
Minimize the variance in distance/travel time between an influence on each group and the system.	Variance	accessibility	Maimon, 1983,1986
Minimize the mean absolute deviation of distance/travel time between an effect on each group and the system-wide average effect	Mean absolute deviation	accessibility	Newton et al., 2022
Minimize the sum of the absolute deviations of distance/travel time between groups	Sum of the absolute deviations	accessibility	Lindner-Dutton et al. 1991
Minimize the difference between the highest-lowest values of travel distance/time	Range of travel cost	accessibility	McLay and Mayorga, 2013
Minimize the average absolute values of the variations in travel distance/time between all demand -supplier pairs	Gini coefficient	accessibility	Barbati et al., 2016
Minimize the sum of travel distance/time for the uncovered zones	sum of weighted travel cost	accessibility	Church et al., 1991
Minimize the uncovered zones/people for a disadvantaged group	The number of uncovered areas	Coverage	Chanta et al., 2014

5.3. Model Specification

5.3.1. Mathematical formulation

Two bi-objective optimization models are developed to reduce urban-rural inequalities in service accessibility and coverage of EMS, respectably. As service coverage remain the primary concerns of the EMS planning, the primary objective of the two bi-objective models is from the MCLP, which is to maximize the total covered demand.

As is well-known that, the MCLP is likely to site service facilities in areas with more demands (or more densely populated areas), this might cause rural areas to be underserved (McLay and Mayorga, 2010; Chanta et al., 2014). Hence, two alternative secondary objectives are proposed to consider urban-rural inequalities. The first alternative objective intends to minimize the total weighted travel time (TWT) of the rural uncovered population from their nearest EMS stations. The second alternative objective consider the difference in covered population ratios between urban and rural regions.

With the following parameters:

i, j = index of demands and potential EMS stations, respectively;

I, J = set of demands and potential EMS stations, respectively;

a_i = amount of demand at location i;

S_u = EMS service standard for urban area;

S_r = EMS service standard for rural area;

p = total number of EMS stations to be located;

q = number of existing EMS stations to remain in the system;

d_{ij} = shortest travel time between i and j;

$r_i = \begin{cases} 1 & \text{if demand } i \text{ is in rural area} \\ 0 & \text{Otherwise} \end{cases}$

Ω_i = set of EMS stations capable of providing service to demand i;

$\{j | d_{ij} \leq S_u(1 - r_i) + S_r r_i\}$, that is, $\{j | d_{ij} \leq S_u\}$ for i in urban area and $\{j | d_{ij} \leq S_r\}$ for i in rural area;

Φ = set of existing EMS stations;

W_u, W_r = proportion of covered demand in urban and rural areas, respectively;

and the decision variables:

$X_j = \begin{cases} 1 & \text{if an EMS station is sited at } j \\ 0 & \text{Otherwise} \end{cases}$

$$Y_{ij} = \begin{cases} 1 & \text{if demand } i \text{ is not within the standard of its nearest EMS station } j \\ 0 & \text{Otherwise} \end{cases}$$

Primary objective: maximize the total covered demand

$$\text{Maximize } Z_1 = \sum_{i \in I} a_i (1 - \sum_{j \notin \Omega_i} Y_{ij}) \tag{5.1}$$

First alternative objectives: minimize the TWT of the rural uncovered population from their nearest EMS stations.

$$\text{Minimize } Z_2 = \sum_{i \in I} \sum_{j \notin \Omega_i} a_i d_{ij} Y_{ij} r_i \tag{5.2}$$

Second alternative objectives: minimize the difference in the proportions of the covered demand to the total population between urban and rural regions

$$\text{Minimize } Z_3 = |W_u - W_r| \tag{5.3}$$

In order to investigate how the inclusion of inequality objectives will affect the service coverage, four models are solved in this chapter: two single-objective models – Model 1 (M1) only includes Objective (5.1), Model 2 (M2) only includes Objective (5.2), and two bi-objeictve models – Model 3 (M3) includes Objectives (5.1) and (5.2), and Model 4 (M4) includes Objectives (5.1) and (5.3). The mathematical formulations of the four models are as follows.

Model 1

$$\text{Maximize } Z_1 = \sum_{i \in I} a_i (1 - \sum_{j \notin \Omega_i} Y_{ij})$$

Subject to

$$\sum_{j \in \Omega_i} X_j + \sum_{j \notin \Omega_i} Y_{ij} \geq 1 \qquad \forall i \in I \tag{5.4}$$

$$\sum_{j \in J} X_j = p \tag{5.5}$$

$$\sum_{j \in \Phi} X_j = q \tag{5.6}$$

$$X_j \geq Y_{ij} \qquad \forall i \in I, j \in J \text{ and } j \notin \Omega_i \tag{5.7}$$

$$X_j = \{0, 1\} \qquad \forall j \in J \tag{5.8}$$

$$Y_{ij} \geq 0 \qquad \forall i \in I, j \in J \text{ and } j \notin \Omega_i \qquad (5.9)$$

M1 is equivalent to MCLP, which aims to maximize the demand coverage in the whole study area, which is based on the MCLP model. Constraints (5.4) define that demand location *i* is either covered by an EMS station j ($j \in \Omega_i$) within the coverage or assigned to an open station j ($j \notin \Omega_i$) outside the coverage. If $\sum_{j\in\Omega_i} X_j \geq 1$, demand *i* would be served by at least one station within the coverage, therefore the associated Y_{ij} ($j \notin \Omega_i$) would be equal to zero because of the preference of $\sum_{j\notin\Omega_i} Y_{ij} = 0$ in objective (5.1). If $\sum_{j\in\Omega_i} X_j = 0$, the demand *i* would not be served by the coverage and the value of $\sum_{j\notin\Omega_i} Y_{ij}$ would be equal to one given the nature of objective (5.1); that is, demand *i* would be assigned to only one open station *j* in this case. Constraint (5.5) enforces that the total number of stations to be sited is equal to a constant *p*. Constraint (5.6) specifies the number of existing EMS stations that would remain to open in the system. Constraints (5.7) ensure that demand *i* can be assigned to an EMS station *j* only if this station is opened at *j*. Constraints (5.8) define the binary variable of X_j, and Constraints (5.9) restrict that the decision variables Y_{ij} are non-negativity.

Model 2

Minimization: $Z_2 = \sum_{i\in I} \sum_{j\notin\Omega_i} a_i d_{ij} Y_{ij} r_i$

Subject to

$$\sum_{j\in\Omega_i} X_j + \sum_{j\notin\Omega_i} Y_{ij} \geq 1 \qquad \forall i \in I \qquad (5.10)$$

$$\sum_{j\in J} X_j = p \qquad (5.11)$$

$$\sum_{j\in\Phi} X_j = q \qquad (5.12)$$

$$X_j \geq Y_{ij} \qquad \forall i \in I, j \in J \text{ and } j \notin \Omega_i \qquad (5.13)$$

$$X_j = \{0, 1\} \qquad \forall j \in J \qquad (5.14)$$

$$Y_{ij} \geq 0 \qquad \forall i \in I, j \in J \text{ and } j \notin \Omega_i \qquad (5.15)$$

M2 aims to minimize the TWT of the uncovered rural areas, which is based on an extension of the work of Church et al. (1991) that concerns the overall service coverage as well as service accessibility of uncovered population. Constraints (5.10) refer to that demand location *i* is either assigned to an open station j ($j \notin \Omega_i$) or covered by an EMS station j ($j \in \Omega_i$). When $\sum_{j\in\Omega_i} X_j = 0$, demand *i* would not be served by the coverage and the value of

$\sum_{j\notin\Omega_i} Y_{ij}$ would be equal to one; that is, demand *i* would be assigned to only one open station *j* in this case. When $\sum_{j\in\Omega_i} X_j \geq 1$, demand *i* would be served by at least one station within the coverage, therefore the associated Y_{ij} $(j \notin \Omega_i)$ would be equal to zero because of the preference of $\sum_{j\notin\Omega_i} Y_{ij} = 0$ in the minimization nature of the function in objective (5.2). Constraint (5.11) limits the total number of stations and Constraint (5.12) defines the number of existing EMS stations that would remain to open. Constraints (5.13) ensure that demand *i* can be assigned to an EMS station *j* only if this station is opened. Constraints (5.14) define the binary variable of X_j, and Constraints (5.15) limit the non-negativity decision variables Y_{ij}.

Model 3

Maximize $Z_1 = \sum_{i\in I} a_i(1 - \sum_{j\notin\Omega_i} Y_{ij})$

Minimize $Z_2 = \sum_{i\in I} \sum_{j\notin\Omega_i} a_i d_{ij} Y_{ij} r_i$

Subject to

$$\sum_{j\in\Omega_i} X_j + \sum_{j\notin\Omega_i} Y_{ij} \geq 1 \qquad \forall i \in I \tag{5.16}$$

$$\sum_{j\in J} X_j = p \tag{5.17}$$

$$\sum_{j\in\Phi} X_j = q \tag{5.18}$$

$$X_j \geq Y_{ij} \qquad \forall i \in I, j \in J \text{ and } j \notin \Omega_i \tag{5.19}$$

$$X_j = \{0, 1\} \qquad \forall j \in J \tag{5.20}$$

$$Y_{ij} \geq 0 \qquad \forall i \in I, j \in J \text{ and } j \notin \Omega_i \tag{5.21}$$

M3 is a bi-objective model that contains Objectives (5.1) and (5.2). This model aims to maximize the number of covered demands in the whole study area, while minimizing the TWT of the uncovered rural population. Constraints (5.16) define that demand location *i* is either covered by an EMS station *j* $(j \in \Omega_i)$ or assigned to an open station *j* $(j \notin \Omega_i)$. Constraints (5.16) and (5.17) enforce that the total number of stations to be sited and the existing EMS stations that would remain to open in the system, respectively. Constraints (5.19) ensure that demand *i* can be assigned to an EMS station *j* only if this station is sited at *j*. Constraints (5.20) and (5.21) define the binary variable of X_j and the non-negativity decision variables Y_{ij}.

Model 4

Maximize $Z_1 = \sum_{i \in I} a_i (1 - \sum_{j \notin \Omega_i} Y_{ij})$

Minimize $Z_3 = |W_u - W_r|$

Subject to

$$\sum_{j \in \Omega_i} X_j + \sum_{j \notin \Omega_i} Y_{ij} \geq 1 \qquad \forall i \in I \tag{5.22}$$

$$\sum_{j \in J} X_j = p \tag{5.23}$$

$$\sum_{j \in \Phi} X_j = q \tag{5.24}$$

$$X_j \geq Y_{ij} \qquad \forall i \in I, j \in J \text{ and } j \notin \Omega_i \tag{5.25}$$

$$W_u = \frac{\sum_{i \in I} a_i (1 - r_i)(1 - \sum_{j \notin \Omega_i} Y_{ij})}{\sum_{i \in I} a_i (1 - r_i)} \tag{5.26}$$

$$W_r = \frac{\sum_{i \in I} a_i r_i (1 - \sum_{j \notin \Omega_i} Y_{ij})}{\sum_{i \in I} a_i r_i} \tag{5.27}$$

$$X_j = \{0, 1\} \qquad \forall j \in J \tag{5.28}$$

$$Y_{ij} \geq 0 \qquad \forall i \in I, j \in J \text{ and } j \notin \Omega_i \tag{5.29}$$

M4 is a bi-objective model that contains objectives (5.1) and (5.3). This model intends to maximize the number of the overall covered people in the whole city, while minimizing the difference in service coverage between urban and rural areas. Constraints (5.22) are same as constraints (5.4) or (5.10). Constraints (5.23) and (5.24) defines the total number of stations to be sited and the existing EMS stations that should remain open. Constraints (5.25) defines that demand *i* cannot be assigned to an EMS station *j* only if there is no station at *j*. Constraints (5.26) and (5.27) are the equations to compute W_u and W_u. The binary variable of X_j and the non-negativity decision variables Y_{ij} are defined by Constraints (5.28) and (5.29).

5.3.2. Solution approach

Common approaches for solving multi-objective problems include the ε-constraint, weighted sum and weighted-norm approaches. In this chapter, the ε-constraint method is employed, developed by Haimes et al. (1971), and a wide discussion can refer to Chankong and Haimes (1983). The main idea of the ε-constraints method is to transform the original multi-objective model into a single-objective formulation by only maintaining one objective whilst incorporating the other objectives into the constraints of the transformed model, where their values are bounded at acceptable levels.

As M1 and M2 only include one objective and can be solved by commercial optimization, this section focuses on the solution approaches of the bi-objective problems (M3 and M4). As two conflicting objectives are affiliated to Objectives (5.1), (5.2) & (5.3), the Pareto-optimal solutions (also called as non-dominated solutions) involve the trade-offs between various objectives. The Pareto-optimal solution is a non-inferior solution in the objective space that specifies a limit beyond which none of the objectives can be improved without compromising at least one of the other objectives

Step 1. Find the initial solutions for M3 and M4

Solve M1 and get the outcome as the initial solution of M4. Use the calculated Y_{ij} values to compute the values of objectives (5.1) and (5.3), represented as Z_1^0, Z_3^0, W_u^0 and $W_r{}^0$, respectively. Based the nature of the MCLP, it is not difficult to find that $W_u^0 \geq W_r{}^0$, while Z_1^0 and Z_3^0 are the upper bounds of Z_1 and Z_3, respectively.
Similarly, solve M2 and get the outcome as the initial solution of M3. Use the calculated Y_{ij} to compute objective (5.1) and (5.2), denote as Z_1', Z_2^0. It is not tough to find that Z_2^0 is the lower bound of Z_2.

Step 2. Initialize iteration parameters and reformulate M3 and M4.

Considering following additional notation:

k: iteration indicator, set $k = 1$;

K: maximum number of iterations;

ε_1: a constant representing the percent of total covered demand to be increased in each iteration;

ε_r: a constant representing the percent of covered rural demand to be increased in each iteration;

ε_{Z_1}, ε_{Z_3}: threshold of the objective value difference in two consecutive iterations for (1) and (3), respectively.

Additional constraints can be defined as in (5.30) and (5.31).

$$Z_1^k \geq Z_1' + \sum_{i \in I} a_i * k * \varepsilon_1 \tag{5.30}$$

$$W_r{}^k \geq W_r{}^{k-1} + \varepsilon_r \tag{5.31}$$

Constraint (5.30) defines the minimum number of total covered demands, which should be not less than a constant number $Z_1' + \sum_{i \in I} a_i * k * \varepsilon_1$. Constraint (5.31) stipulates the minimum proportion of covered rural population in each iteration, which should be equal or higher than a constant $W_r^{k-1} + \varepsilon_r$. Accordingly, the transformed M3 consists of objective (5.2), subject to constraints (5.16) - (5.21) and (5.30), and the redefined M4 is composed of objective (5.1), subject to constraints (5.22) - (5.29) and (5.31).

Step 3. Update the solutions of M3 and M4.

Solve M3 and M4 based on the new formulation in Step 2. Calculate the values of (5.1) and (5.3), Z_1^k and Z_3^k, respectively.

Step 4. Decide whether to continue or stop the iteration.

For M3, if $Z_1^0 - Z_1^k > \varepsilon_{Z_1} \sum_{i \in I} a_i$ and $k < K$, set $k = k + 1$ and go to **Step 3**; otherwise, go to **Step 5**.
For M4, if $Z_3^{k-1} - Z_3^k > \varepsilon_{Z_3}$ and $k < K$, set $k = k + 1$ and go to **Step 3**; otherwise, go to **Step 5**.

Step 5. End the solving procedure.

All models and the solving process are written in Python scripts, and the models are solved using the commercial optimization software Gurobi (version 9.0.2). The most widely used commercial GIS software, ArcGIS (version 10.7), is used for all spatial data processing, management, and result visualization.

5.4. Empirical Study

5.4.1. Study area and data

Based on the locations of current 79 EMS stations and population distribution in Wuhan, currently, only 71.4% of residents are within the standards of service coverages – 10 min for urban areas and 12 min for rural districts. Meanwhile, urban-rural inequalities are evident. For example, 94.9% of urban residents are within the urban service coverage standard, while only 32.2% of rural people are within the rural coverage standard. Considering the dramatic climbed demands for public health services, the frequency of the pandemic and uncertainty in the duration, the Wuhan Municipal Health Commission planned to start constructing six new EMS stations at the end of 2022. In addition to increasing the overall covered population within the service standards, one of the primary objectives is to reduce urban-rural disparity (Wuhan Government, 2021).

The dataset employed consists of current EMS stations, potential candidate locations for new stations, and the spatial distribution of population in Wuhan (see Figure 5-1). Based on the strong collaborations between EMS system and hospitals in Wuhan, the candidate sites for new EMS stations includes the levels II and III hospitals in the urban area and all levels of hospitals in the rural area. Same to chapter 3, the population data are obtained from the Geographical Information Monitoring Could Platform (http://www.dsac.cn/), which offers the population census dataset at the finest scale (*Shequs*) currently available. This chapter uses centroids of shequs to represent the demand locations. In total 3,493 shequs within the study area are adopted as the demand.

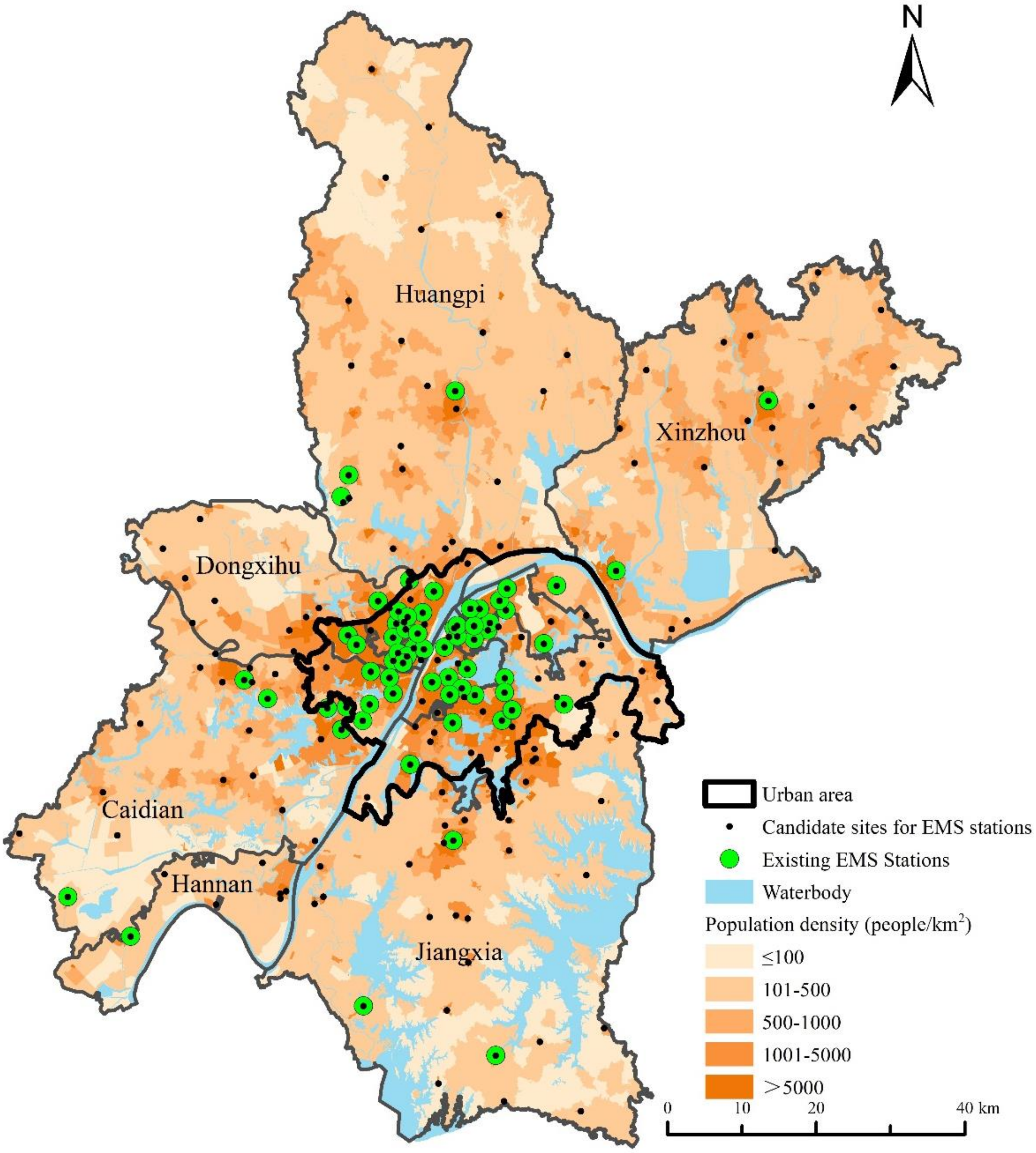


Figure 5-1. Spatial distributions of population and EMS stations.

5.4.2. Model settings

Two scenarios are considered here: Scenario 1 assumes keeping all existing EMS stations in the system and Scenario 2 allows relocating some of the existing stations. Both scenarios are helpful to the planning practice of public services such as EMS systems where the spatial configuration of facilities can be optimized.

Scenario 1 aims to select optimal sites for six new EMS stations to be built, assuming that the existing 79 EMS stations remain open. This is a common approach for planning new EMS stations particularly during the short-term EMS planning due to financial and governance constraints.

Scenario 2 considers the relocation problem of EMS stations, under the assumption that at least 90% of existing stations remain open at existing places. In other words, up to eight existing EMS stations can be relocated to other places (that is, $71 \leq \sum_{j \in \Phi} X_j = p \leq 79$). This scenario is to meet the dynamic changing spatial distribution of underlying demand. With the urbanization process in China, especially in large cities such as Wuhan, the increasing number of people are shifting to new towns in the suburbs due to the new working opportunities and more affordable housing prices. This scenario provides a general blueprint for long-term EMS planning.

In terms of the parameters for solution procedure, the maximum number of iterations (K) is defined as 100; the percent of total covered demand to be increased in each iteration (ε_1) is defined as 0.2%; the percent of covered rural demand to be increased in each iteration (ε_r) enforces to 0.01%; threshold of the objective value difference in two consecutive iterations for (5.1) –(ε_{Z_1})and (5.3) – (ε_{Z_3}) are defined as 0.2% and 0.01%, respectively. For the empirical study, the four models are solved using Gurobi (version 9.1.1) on a desktop with an Intel processor 3.80 GHz and 32GB RAM. The technique procedure is the same as Figure 4-5. Codes for all models in this chapter with testing data can be found via the following link (https://github.com/WeicongLuo/PhD_thesis_Chapter_5).

Table 5-2. Parameter values for the empirical study.

Parameter	Value	Parameter	Value
p	85	ε_1	0.2%
q	79 (Scenario 1) 71-79 (Scenario 2)	ε_r	0.01%
S_u	10 min	ε_{Z_1}	0.2%
S_r	12 min	ε_{Z_3}	0.01%
K	100		

5.4.3. Results

For Scenario 1, the computational time is 2-3 seconds for both single-objective models and about 1-5 mins for the Pareto-solutions of the two bi-objective models. For Scenario 2, the computational time is 10 - 60 seconds for both single-objective models and about 3-10 min for the Pareto-solutions of both multi-objective models. The total computational time is about 1 hour for the model parameter values in Table 5-2.

(1) Scenario 1

Results from single-objective models

The selected locations for new EMS stations for the optimal solutions for two single-objective models (M1 and M2) are depicted by Figure 5-2. M1 intends to maximize the total number of covered demands with locating six new EMS stations. M1 suggests that only one EMS station is located in the urban district (the southwest of Hongshan), and other five new EMS stations are distributed in rural districts. Among those rural districts, two EMS stations are located in the north of Jiangxia. One new EMS station is located in each of the east of Hannan, and the central of Caidian, and the southeast of Dongxihu. As a result, the total number of 7,820,914 people can be covered by the urban/rural service coverage, with an increase of 635,692 population compared with the current service provision. When considering the covered population ratio, 77.63% of the total population can be covered by the urban/rural service coverage, with an increase of 6.2% compared with the current service provision. In particular, 96.6% of urban residents could be found by the ambulance within 10 min, and the ambulance could reach 46.1% of rural people within 12 min, with an increase of 1.7% and 13.9% compared with the existing EMS provision respectively.

M2 is to improve EMS accessibility for the uncovered population in rural areas. It is not surprising that all six new EMS stations are located in rural districts (see Figure 5-2). Specifically, three selected locations are located in the north, the west and the east of Huangpi. One EMS station is located in the southeast of Dongxihu. The rest of two EMS stations are located in the east of Hannan and the middle of Caidian, respectively, which are coincide with the selected sites of M1. Compared with the existing provision, the Z_2 value decreases from 8.2E+7 to 5.9E+7 min, with a reduction rate of 28.2%. If considering the average travel time (ATT) – computed as the Z_2 value divided by the total uncovered rural population (i.e., $Z_2 / \sum_{i \in I} \sum_{j \notin \Omega_i} a_i Y_{ij} r_i$), the value decreases from 34.3 min (current service deployment) to 28.5 min, which is still 16.5 min longer than the service standard in the rural region.

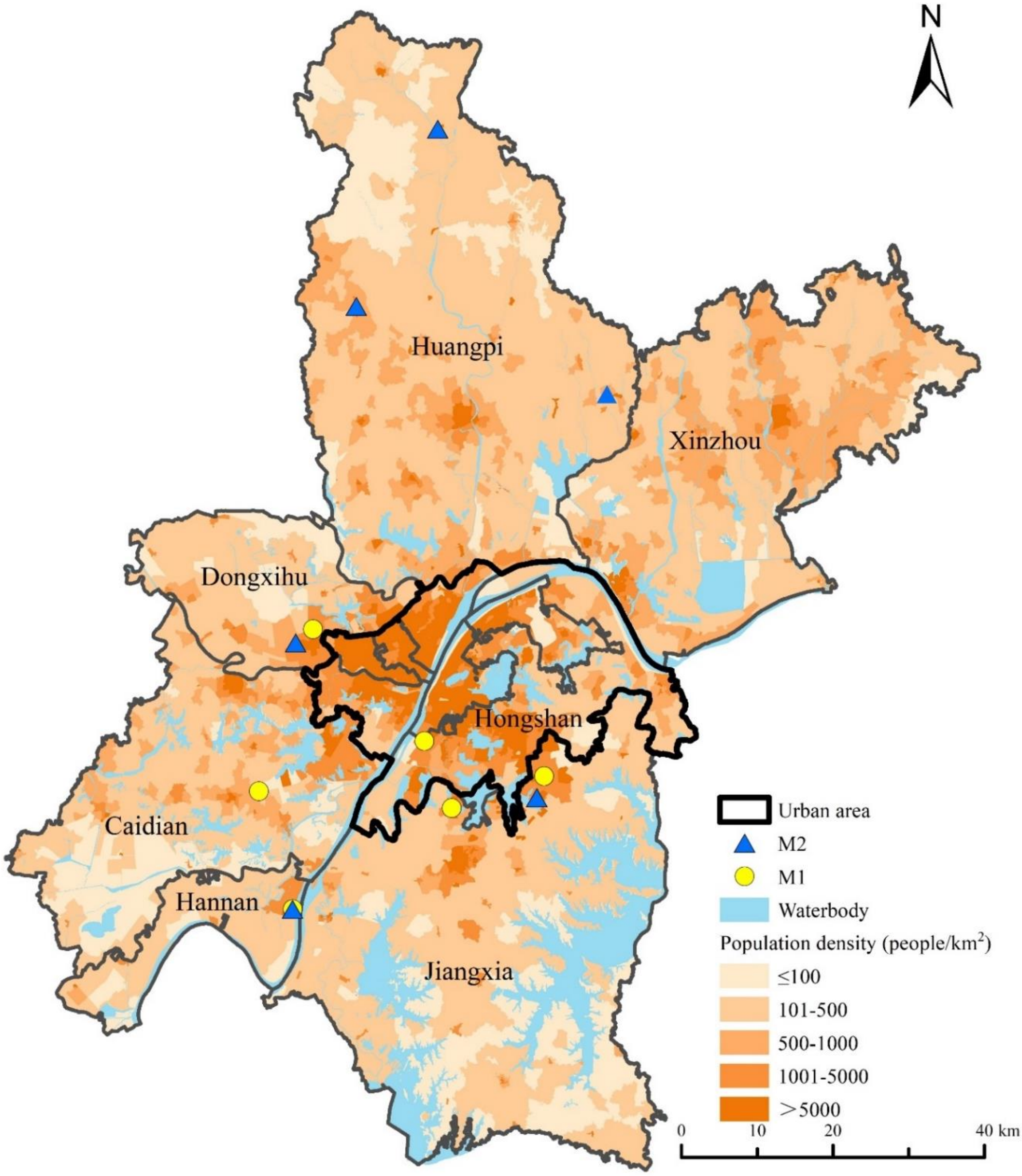


Figure 5-2. Selected sites for new EMS stations.

Results from bi-objective models

Figure 5-3 depicts the Pareto-optimal solutions of M3, with data labels representing the order of the computed solutions. In total, nine solutions are computed, where the initial obtained solution (labelled by "1") is the same as that of M2 and the last solution (labelled by "9") is the same as that of M1. It serves to show that the range of the Z_2 value is between 5.91E+07 and 6.95E+07, and the range of the ATT in the uncovered rural areas is between 28.5 and 34.5 min. The difference between the highest and lowest values are 1.04E+07 min for the Z_2 value, and 6.0 min for the ATT in the uncovered rural areas, showing a largely difference from the two optimal solutions. Meanwhile, the difference between the highest and lowest Z_1 values is 1.56%, and therefore the reduction in the Z_2 value significantly impacts EMS overall coverage. In detail, the rise in total covered population ratio (Z_1) follows the increase in the Z_2 value and the ATT in uncovered rural areas. In other words, the improvement of EMS efficiency is at the cost of equality between urban and rural settings, especially in sparsely populated areas. Specifically, the initial solution from M2 results in the smallest Z_2 value (5.91E+07 min) and the smallest AAT value (28.5 min), but it reaches the smallest proportion of the covered population, 76.18%. On the contrary, the 9th solution ensures the largest Z_2 value (6.95E+07 min) and the highest ATT value (34.5 min), resulting in the highest proportion of the total covered population, 77.74%. Z_2 and ATT values increase slightly between the 1st and 4th solutions. Since the four iterations (i.e., from the 5th solution), the values of Z_2 and ATT values sharper increase than previous results. To the 8th solution, the Z_2 value increases by 1.42E+07 min and ATT raise by 5.9 min compared to their minimum levels. From the 8th -9th solution, Z_2 and ATT values increase stable again at the last iteration, increasing by 0.015E+07 min for the Z_2 value and 0.1 min for the ATT. Meanwhile, the rise of the total covered population rate is relatively stable, at 0.2% - 0.4% for each iteration.

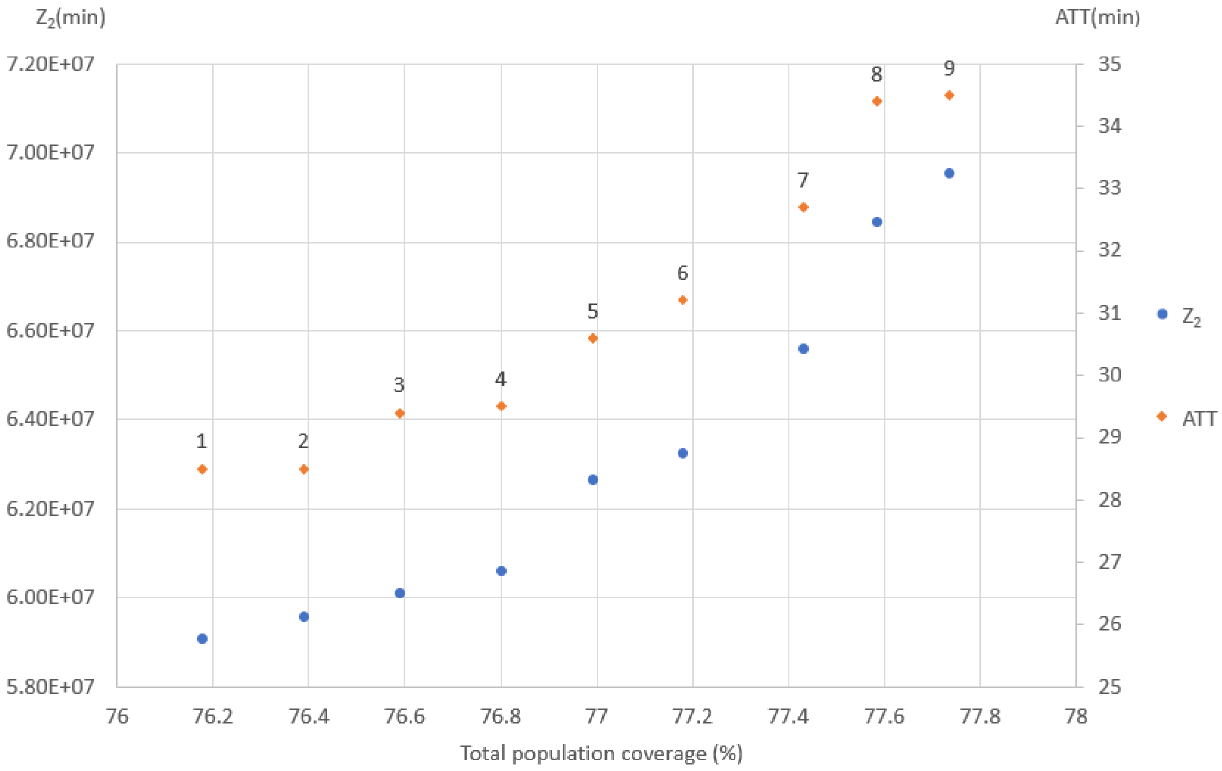


Figure 5-3. Variations of total covered population (Z_1) and service accessibility for uncovered rural population (Z_2).

Figure 5-4 shows the spatial locations of all Pareto-optimal solutions of M3. Although nine solutions are obtained, only 14 unique locations for new EMS stations are contained in the solution set as some locations are included in multiple solutions. Again, the labels near to the selected locations represent the number of solutions. For instance, one EMS station located in the east of Hannan district is included all solutions from one to nine. In detail, most selected locations are distributed in rural districts; only one selected site (belonging to Solution 9, i.e., the solution of M1) is in the urban area. Six selected locations are near the urban-rural boundary (three in the north of Jiangxia, two in the east of Dongxihu, and one in the south of Huangpi). Among rural districts, the most selected EMS locations (i.e., four) are distributed in Huangpi. Besides, three selected locations are located in the north of Jiangxia. Two selected locations are located in the middle of Caidian, and two selected locations are distributed in the east of Dongxihu. One selected location is located in the east of Hannan, and the last selected location is sited in the west boundary of Xinzhou. Notably, only one site is included in all Pareto-optimal solutions, which is located in the east boundary of Hannan. One selected location in the north of Jiangxia is included in six Pareto-optimal solutions (2nd, 4th-9th Solutions), ranked the second highest. The selected location is located in the east of Dongxihu, which is also included in six Pareto-optimal solutions (1st-4th, 6th-

7^{th} Solutions). Five selected locations are only included in one solution, and three of them are near to other selected locations. For example, one selected location in the Caidian is only included in the 6^{th} Pareto-optimal solution. However, it is very close to another selected location on the eastern side.

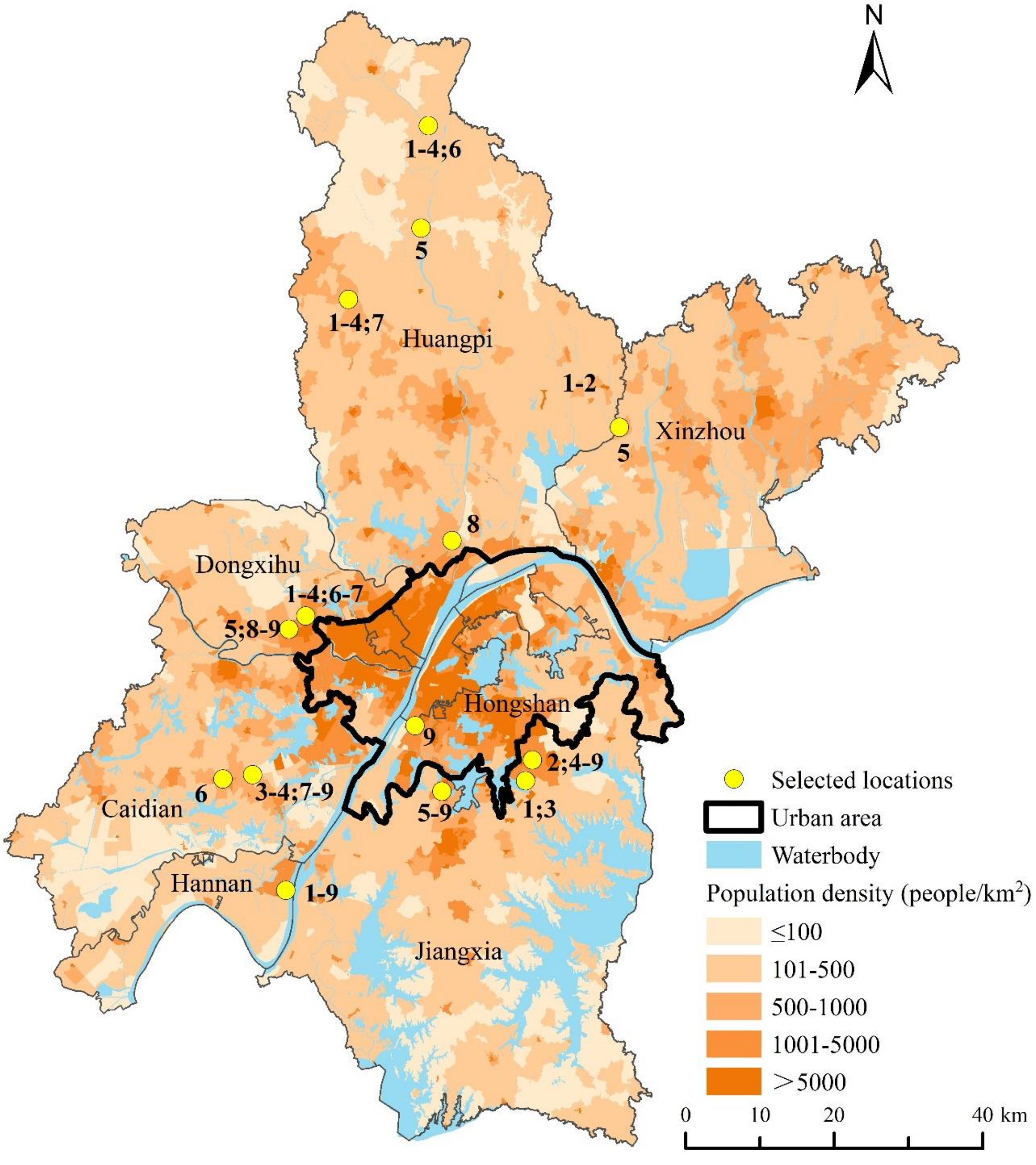


Figure 5-4. Selected sites for new EMS stations for M3.

According to Figure 5-5, four Pareto-optimal solutions are computed by M4, which aims to reduce urban-rural inequality in EMS coverage. In addition to solutions of two objectives – the total covered population in Wuhan (Z_1, converted to percentages) and the difference in covered population ratios between urban and rural areas (Z_3), two additional types of solutions are presented: the trade-off between urban covered population (W_u) and rural covered population (W_r), respectively. It serves to show that the range of the covered population ratio (Z_1) is between 77.37% and 77.74%, with a 0.37% difference. the range of the Z_3 value is between 47.49% and 50.50%, with a 3.01% difference (Z_1). Therefore, a reduction in the Z_3 value significantly impacts on EMS overall coverage. According to the 1st solution for M4, the urban covered ratio is 96.63% and the rural covered population ratio is 46.13%, resulting in the highest urban-rural disparity in ratio of covered population (Z_3), 50.5% and the largest Z_1 value (77.74%). The final solution (4th solution) finds the smallest urban-rural difference in the covered population ratio (47.65%), and also the smallest service coverage ratio (77.37%). At the first iteration (1st -2nd Solutions), the values of Z_1 and Z_3 decreased by 0.05% and 0.93%. For the second iteration (2nd Solution -3rd Solution), the values of Z_1 and Z_3 reduced by 0.16% and 1.82% compared to the initial values. For the third iteration (3rd Solution - 4th Solution), the values of Z_1 and Z_3 dropped by 0.37% and 3.01% compared to values from the initial values. When considering the trend of the results, the decrease in the Z_3 value follows the reduction in the overall service coverage in the entire city, which is similar to the previous findings. In other words, reducing urban-rural inequality in urban-rural covered demand ratios is also at the cost of the decline of EMS efficiency.

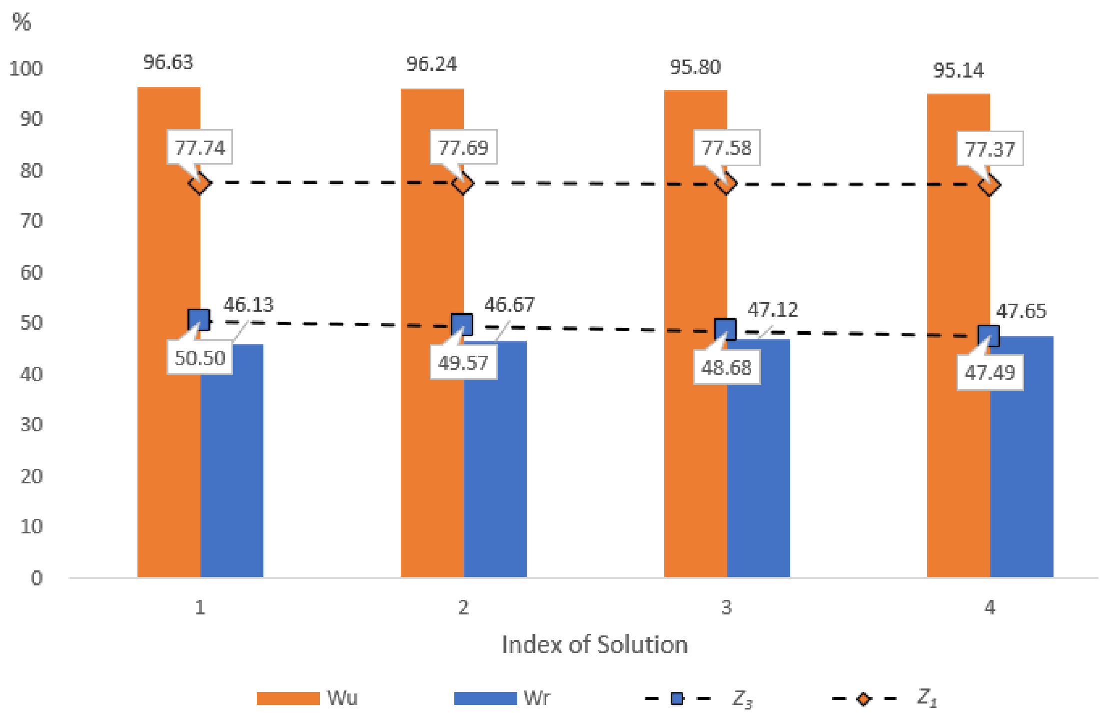


Figure 5-5. Variations of total covered population (Z_1) and urban-rural inequality in service coverage (Z_3).

The spatial locations of four Pareto-solutions for M4 are described in Figure 5-6. It is clear to observe that ten unique selected sites are included in the four solutions, with the labels next to the selected sites depicting the solutions. In detail, it is clear to see that most selected locations are distributed in rural districts; only two selected sites are located in the urban area, which are all located in the south of Hongshan district (i.e., 1st and 2nd Solutions). Seven selected locations are near the urban-rural boundary (four in the north of Jiangxia, one in the east of Dongxihu, one in the south of Huangpi, one in the south of Hongshan), which can share the coverages for urban and rural populations. Among the districts, four selected sites are located in the north of Jiangxia. Two selected locations are sited in the south and the southwest of Hongshan. One EMS station is sited in the east of Hannan. The central of Caidian has one selected EMS station. A selected site is located in the east of Dongxihu, and a selected site is located in the south of Huangpi. In detail, four selected sites are included in all Pareto optimal solutions, which are distributed in the east of Hannan, the middle of Caidian, the east of Dongxihu, and the north of Jiangxia, respectively. Two selected sites are involved in two solutions, which are located in the south of Huangpi and the north of Jiangxia, respectively. Four sites are only included in one solution, and all of them are close to other potential selected EMS sites. In fact, eight of ten selected locations for M4 are depicted in the selected locations for M3 as well. For example, the selected locations in the middle of Caidian and the east of Hannan are included in all solutions of M3 and M4.

Meanwhile, the 4th solution is the result of the minimal Z_3 value. According to Figure 5-6, it is not surprising that all the six selected sites are located in rural districts. Specifically, two EMS stations are located in the north of Jiangxia. One EMS station is located in the east of Hannan, and the middle of Caidian has one EMS station. the other two EMS stations are located in the east of Dongxihu, and the south of Huangpi, respectively. Meanwhile, the 4th Solution has the minimal Z_3 value. It is not surprising that all the six selected sites are located in rural districts (see Figure 5-6). Specifically, two EMS stations are located in the north of Jiangxia. One EMS station is located in each of the east of Hannan, and the middle of Caidian. the other two EMS stations are located in the east of Dongxihu, and the south of Huangpi, respectively.

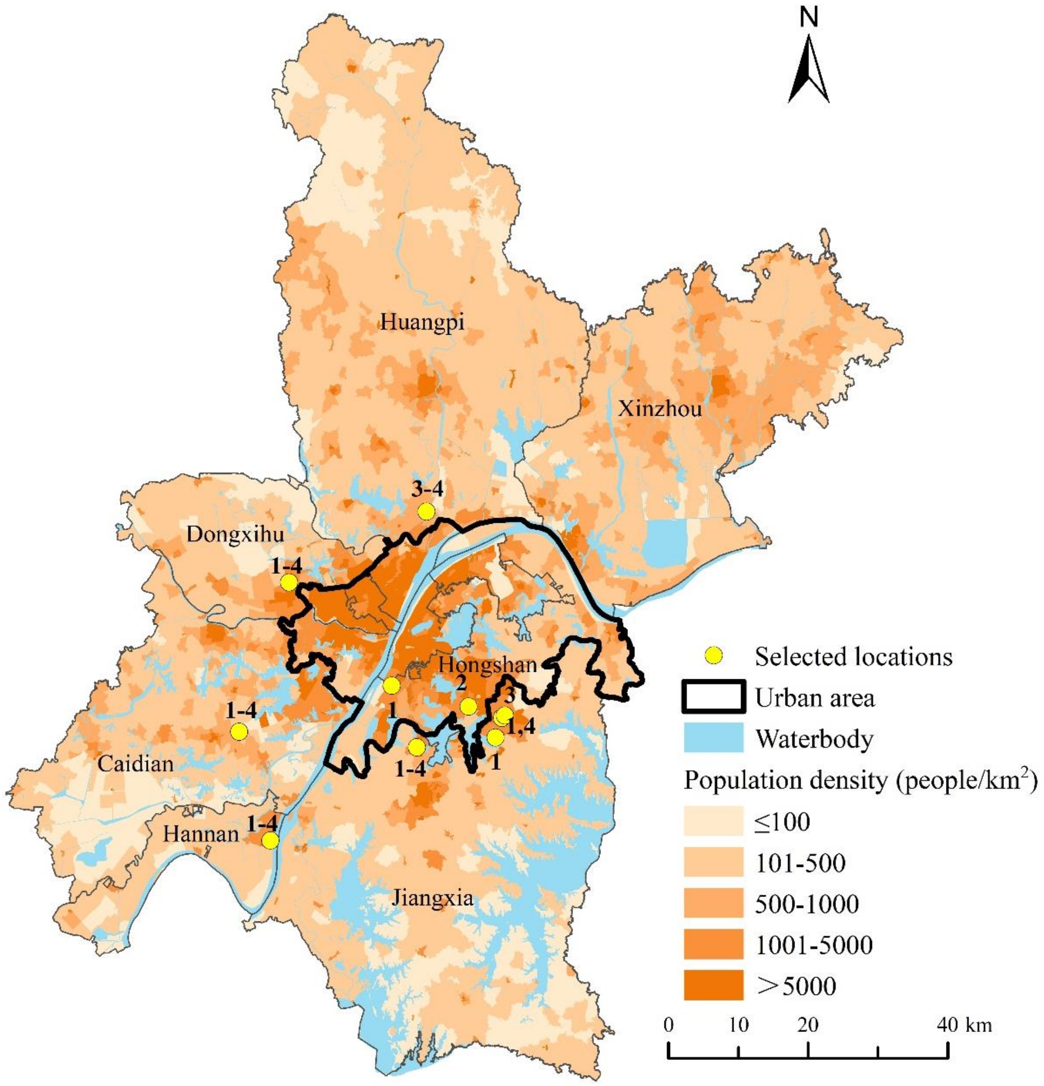


Figure 5-6. Selected sites for new EMS stations for M4.

(2) Scenario 2

Results from single-objective models

The selected locations for closed and new EMS stations for M1, and M2 have been depicted in Figure 5-7. To the total number of covered people (Z_1), M1 suggests that 71 existing EMS stations should remain open (that is, q=71) because the model finds 8 existing EMS stations to be closed and relocated to other places. Specifically, one EMS station located in the middle of Wuchang should be closed. Three EMS stations in Jiangan should be moved to other places. Then, two stations in the south of Jianghan and one station in the north of Hanyang should be moved to other places (see Figure 5-7 (a)). On the contrary, the optimized locations are depicted in Figure 5-7 (b), which includes six new EMS stations and eight relocated stations. In detail, three optimized locations are located in urban areas, including one in the middle of Qinshan and two locations in the south and west of Hongshan. Among rural areas, two optimized stations are located in the north of Jiangxia. One optimized site is distributed in the east of Hannan, and two optimized EMS station is located in the middle and northeast of Caidian. Dongxihu has two selected locations that are located on the southwestern side and the eastern side, respectively. Three EMS stations are distributed in the south of Huangpi, and one EMS station is located in the west of Xinzhou. As a result, the total number of 8,223,025 population can be covered by the urban/rural service coverage, with the 1,037,803 more-population compared with the current service provision. When considering the covered population ratio, 80.5% of the total population can be covered by the urban/rural service coverage, increasing 9.1% compared with the current service provision. After the optimization, 98.1% of urban residents could be served by ambulances within 10 min, and 51.2% of rural people could reach ambulances within 12 min, with an increase of 3.2% and 19.0% compared with the existing EMS provision respectively.

To minimize the TWT in uncovered rural areas (Z_2), M2 suggests that eight existing EMS stations should be closed and moved to other places, that is p = 71, and there are 14 optimized locations for new and relocated stations. All relocated locations are distributed in urban districts (see Figure 5-7 (a)). In general, one EMS station to be closed is located in the middle of Jiangxia, and the two stations to be closed in the north of Jiangxia. Then, two stations to be closed are located in the middle of Wuchang, and two locations to be closed are distributed in the middle of Jianghan. One EMS station to be closed is located in the southeast of Qiaokou. In contrast, the optimized locations of 14 stations (i.e., new and relocated EMS stations) are depicted in Figure 5-7 (b). In detail, none of the optimized locations is located in urban districts, and all locations are distributed in rural districts. Two optimized locations are located in the north and the west of Jiangxia, respectively. One EMS station is located in the east of Hannan. Two optimized sites are distributed in the middle, and the west of Caidian, and two sites are located in the east and the southwest of Dongxihu, respectively. Four optimized locations are distributed in the Huangpi, where three are on the eastern side, and one is located on the western side. Three EMS stations are distributed in the north, the northeast and the south of Xinzhou, respectively. As a result, the Z_2 value decreases from 82,345,572 min (existing EMS provision) to 45,358,098 min, with a reduction rate of 44.9 %. When considering the ATT in the uncovered rural areas, the value decreases from 34.3 min (existing EMS provision) to 19 min. However, it is still 6.0 min longer than the service standard in the rural region.

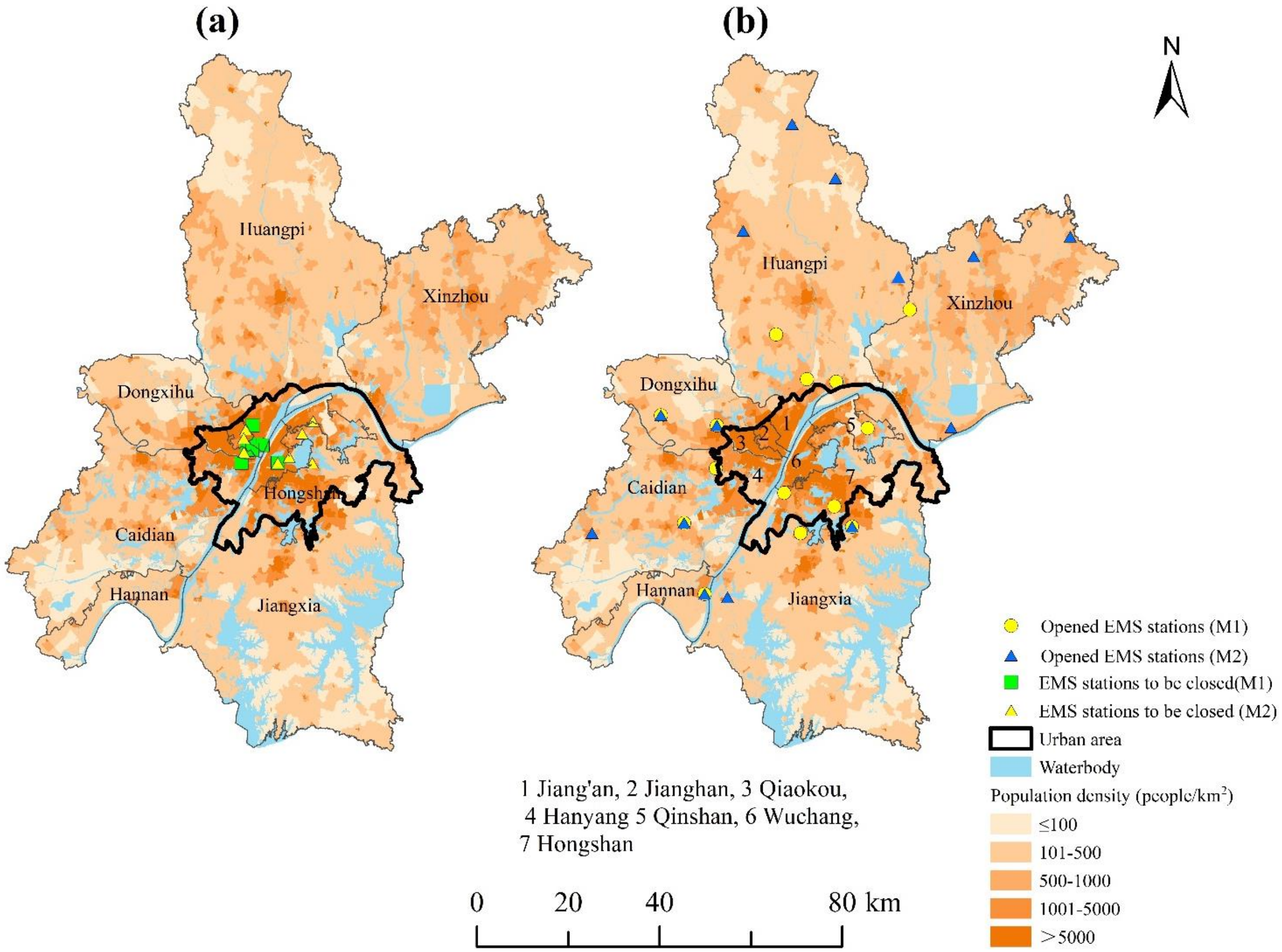


Figure 5-7. Selected EMS locations for M1 and M2 (a) stations to be closed; (b) new/relocated stations.

Results from bi-objective models

Twelve Pareto-optimal solutions of M3 are found for M3 (see Figure 5-8) with labels representing the order of the computed solutions. The first solution (labelled by 1) is the same as that of M2 and the final solution (labelled by 12) is the same as that of M1. All Pareto-optimal solutions from M3 have 71 existing EMS stations that remain open (that is, q=71) because every solution finds 8 existing EMS stations to be closed and relocated to other places. As same as the results in Scenario 1, the number of covered population (Z_1) is derived to the ratio of total covered population in the entire city. It serves to show that the range of Z_2 values is between 4.53E+07 and 6.13E+07, and the range of the ATT in the uncovered rural areas is between 24.18 and 33.3 min. The difference between the highest - lowest values of Z_2 and the ATT are 1.60E+07 min and 9.12 min, respectively, showing a significant disparity between accessibility outcomes from the two Pareto-optimal solutions. Meanwhile, the range of the total covered population ratio is between 78.1% and 80.5%, with the 2.4% difference. Obviously, the first solution from M3 reaches the lowest Z_2 value (4.51E+7 min) and the smallest ATT of the uncovered rural population (24.18 min). Meanwhile, it computes the lowest ratio of the total covered population (Z_1), only 78.1%. In contrast, the 12th Solution ensures the highest Z_2 value (6.13E+07 min) as well as the highest ATT of the uncovered rural population (33.3 min). It also results in the highest proportion of the total covered population (80.5%). Hence, the rise in the covered population ratio (Z_1) follows the increase in the Z_2 value as well as the ATT of the uncovered rural population. In other words, the improvement of EMS efficiency is at the cost of equality between urban and rural settings, especially in sparsely populated areas. Between the initial and 7th solutions, the Z_2 and ATT values are steady growth, which increased by 0.19E+07 min and 1.75 min, respectively. Since the seven iterations (i.e., from the 8th Solution), Z_2 and the ATT raise sharply than before. Up to the 11th Solution, values are decreased by 0.98E+07 min for Z_2 and 5.91 min for the ATT compared to the smallest values, respectively. At the last iteration, the values increase by 0.6E+07 min and 3.21 min for the Z_2 and ATT, respectively. Meanwhile, the rise of the total covered population rate is relatively stable, at 0.2% - 0.5% for each iteration.

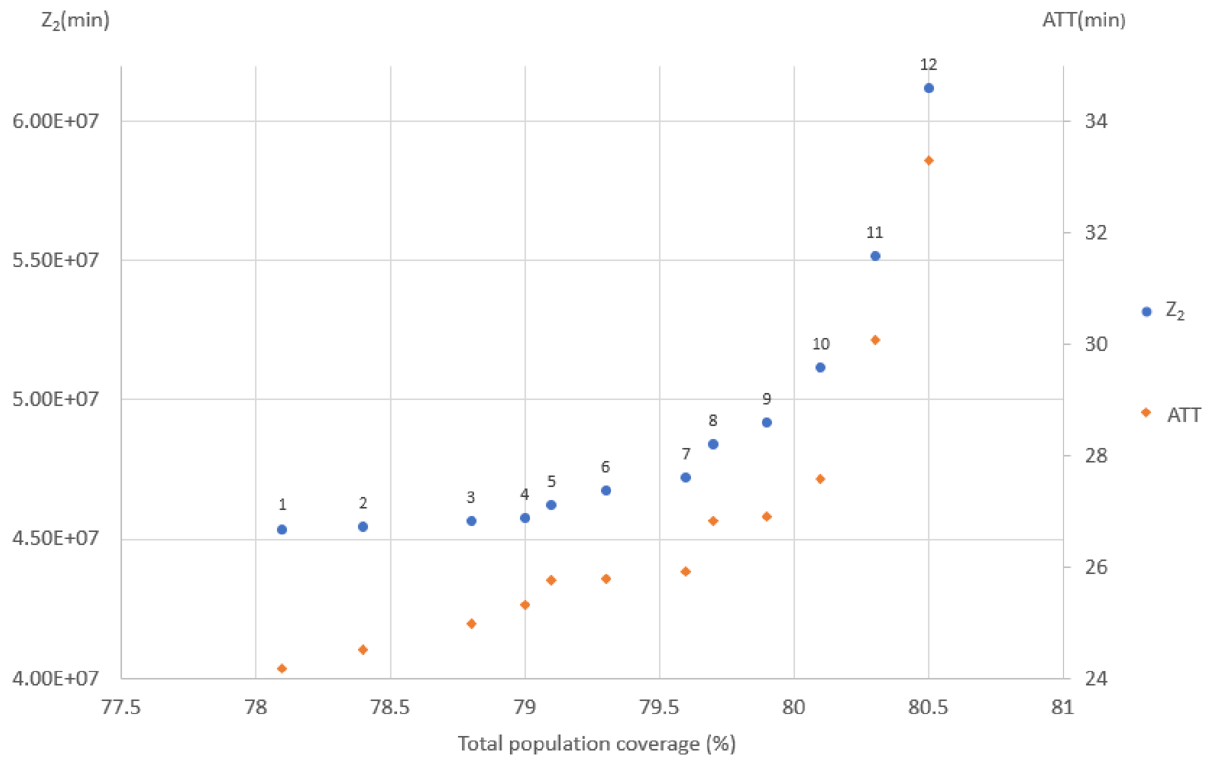


Figure 5-8. Variations of total covered population (Z_1) and accessibility for uncovered rural population (Z_2).

Figure 5-9 shows spatial locations of all Pareto-optimal solutions of M3. Although the M3 contains twelve solutions, there are 27 unique locations for closed/relocated EMS stations and 25 unique locations for new EMS stations. All solutions have eight existing stations should be closed/relocated. On the one hand, all stations to be closed are distributed in urban districts. In detail, Hongshan has the most EMS locations to be closed (i.e., nine), followed by Wuchang, which has five locations to be closed. Four selected sites to be closed are located in Jiangan. Jianghan has three selected sites to be closed. Each of Hanyang, Qiaokou have two selected sites to be closed. The highlighted locations represent the selected sites included in more than six solutions. In other words, those highlighted sites are highly suggested to close and relocate to other places. The three highlighted locations are sited in the middle of Qiaokou, the north of Hongshan, and the west of Jiangan (see Figure 5-9 (a)). In general, those highlighted stations to be closed are extremely near to many EMS stations nearby, and they responsibility can be undertaken by many stations nearby.

On the other hand, Figure 5-9 (b) shows the locations of new/relocated EMS stations. The labels next to the selected locations represent the number of solutions that belongs to each location. For instance, the selected location located in the east of Hannan district is included all solutions from one to twelve. In detail, it is clear to see (Figure 5-8 (b)) that most selected locations are distributed in rural districts; only three selected sites are located in urban districts (i.e., two in the south, the southwest of Hongshan, and one in the middle of Qinshan). Eight selected locations are near the urban-rural boundary (three in the north of Jiangxia; one in the south of Hongshan, one in the east of Caidian, one in the west of Dongxihu, and two in the south of Huangpi). Among those rural districts, the most selected EMS locations (i.e., seven) are distributed in Huangpi, with four sites in the north, and three in the south. Besides, five selected locations are located in Xinzhou, mainly distributed near to boundary. Then, four selected locations are located in Jiangxia, distributed on the north and west sides. Three selected locations are located in the west, the middle and the east of Caidian, and two stations are located in the south and east of Dongxihu. Further, one selected location is located in the east of Hannan. Particularly, four selected sites are included in all Pareto-optimal solutions, which are located in the east of Hannan, the middle of Caidian, the southwest and the east of Dongxihu, respectively. One selected site in the north of Jiangxia is included in eleven solutions (Solutions 1-5; 7-12), ranked the second highest. Three selected locations are included in ten solutions located in the north of Jiangxia (Solutions 3-12), the west and the east of Huangpi (Solutions 1-10), respectively. In contrast, four selected locations are included in one solution, located in the north and south of Huangpi, and the north of Jiangxia. It is worth noting that three selected locations from the 1st solution (M2) are only included in one solution.

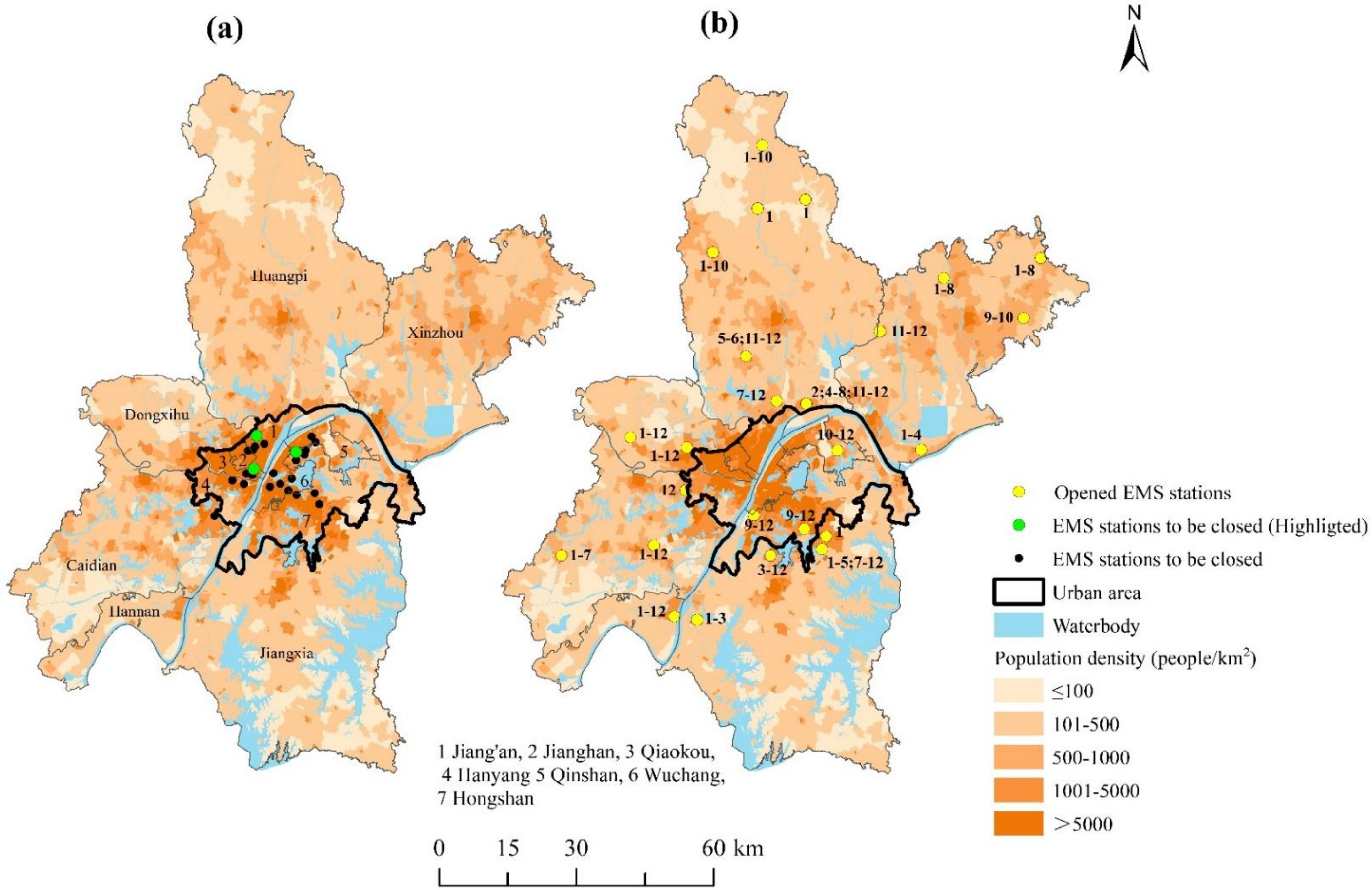


Figure 5-9. Selected EMS locations for M3 (a) stations to be closed (b) new/relocated stations.

Nine Pareto-optimal solutions are found for M4 (see Figure 5-10) with labels representing the order of the computed solutions. All Pareto-optimal solutions from M4 have 71 existing EMS stations that remain open (that is, q=71) because every solution finds 8 existing EMS stations to be closed and relocated to other places. The first solution (labelled by 1) is the same as that of M1, and the final solution (labelled by 9) is the result for minimizing Z_3. Like the results in the Scenario 1, the covered population ratio (Z_1) is derived from the total covered population in the entire city. It shows that the range of urban population ratio is between 82.98% and 98.06%. The highest - lowest value of the rural population ratio is between 51.18% and 53.44%, with a 2.26% of difference. The range of the Z_1 value is from 71.91% to 80.05%. The range of the Z_3 value is between 29.50% and 46.90%. The set of solutions show a notable difference in the EMS overall coverage. The 1st Solution from M4 reaches the largest Z_3 value (46.90%), the smallest rural covered ratio (W_r – 51.18%) and the highest urban covered ratio (W_u – 98.06%). However, it computes the highest ratio of the total covered population (Z_1), 80.5%. In contrast, the 9th Solution results in the lowest Z_3 value (29.51%), the highest rural covered ratio (Wr – 53.44%) and the lowest urban covered ratio (W_u – 82.95%). Meanwhile, the solution obtains the lowest ratio of the total covered population (Z_1), 71.91%. It is obvious that the reduction of the Z_3 value follows the decrease in the Z_1 value. In other words, the improvement of EMS efficiency is at the cost of equality between urban and rural settings. The Z_1 value decreases from 80.5% (1st Solution) to 79.6% (8th Solution), with the 0.9% of difference. The Z_3 value reduces from 46.9% (1st Solution) to 42.4% (8th Solution), with the 4.5% difference. Meanwhile, the value of W_u decreases from 98.06% to 95.51%, and the value of W_r increases from 51.18% to 53.44%. During the last iteration, the values of Z_1 and Z_3 drop down dramatically. The Z_1 value decreases from 79.6% (8th Solution) to 71.9% (9th Solution), with the 7.7% difference. The Z_3 value reduces from 42.4% (8th Solution) to 29.5% (9th Solution), with a 12.9% difference.

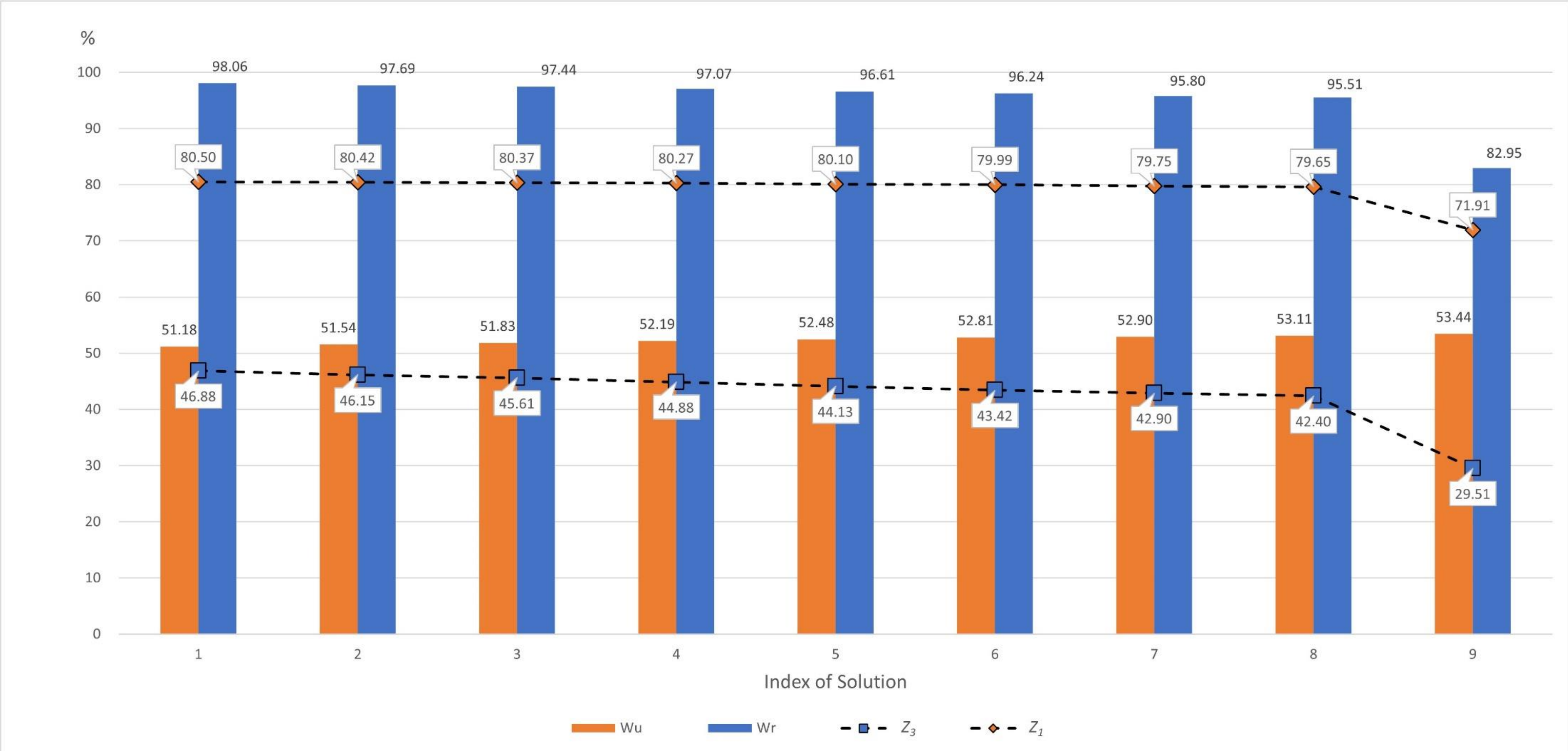


Figure 5-10. Variations of total covered population (Z_1) and urban-rural inequality in service coverage (Z_3).

Figure 5-11 shows the spatial locations of nine Pareto-optimal solutions for M4. Although the M4 computes various solutions, there are 25 common locations for EMS stations that should be closed or moved, and 19 unique locations for new EMS stations. Each of solution has eight existing EMS stations should be closed/relocated. On the one hand, most stations to be closed/relocated are distributed in urban districts (see Figure 5-11 (a)). Only two EMS stations to be closed are located in rural districts, in the middle of Huangpi and the west of Caidian, respectively. In detail, each of Wuchang and Hongshan has six EMS stations to be closed, which are the most among all districts. Besides, four EMS stations to be closed are located in Jianghan, ranked the second highest. Jiangan has three EMS stations to be closed, followed by Qinshan and Qiaokou, which each have two EMS stations to be closed. In addition, we find seven highlighted EMS stations to be closed, which are distributed in the middle and the north of Hongshan, the middle of Wuchang, the west of Qinshan, the east of Jianghan, and the south of Qiaokou, the north of Hanyang and the east of Caidian, respectively. The highlighted locations mean that those sites are included in more than six solutions. In other words, we highly suggest closing those highlighted EMS stations in the future.

On the other hand, Figure 5-11 (b) shows the locations of new EMS stations, including the optimized locations of relocated EMS stations. The labels next to the selected locations represent the number of solutions that belongs to each location. For instance, the EMS station located in the east of Hannan district is included all solutions from one to nine. In detail, it is clear to see (Figure 5-11 (b)) that most new EMS stations are distributed in rural districts; only three selected sites are located in urban districts (i.e., two in the south of Hongshan, and one in the middle of Qinshan). Eight selected locations are near the urban-rural boundary (three in the north of Jiangxia; one in the south of Hongshan, one in the east of Caidian, one in the west of Dongxihu, and two in the south of Huangpi). Among those rural districts, the most selected EMS locations (i.e., five) are distributed in Huangpi, with one site in the eastern area, two in the southern part, and two in the western area. Besides, three selected EMS stations are located in the north, east and middle of Xinzhou. Then, three selected locations are located in the north of Jiangxia. Two selected EMS stations are located in the middle and the east of Caidian. One EMS station is located in the east of Hannan. Two stations are located in the south and the east of Dongxihu. Mainly, nine selected sites are included in all Pareto-optimal solutions, which are distributed in the north of Jiangxia, the east of Hannan, the middle of Caidian, the south and east of Dongxihu, the south of Huangpi and the west of Xinzhou, respectively. One selected site is included in eight solutions, located in the north of Jiangxia.

The last solution (9th Solution) is in relation to the minimal value of Z_3. In detail, one EMS station in each of Wuchang, Jiangan and Jianghan should be relocated to other places. Three EMS stations are located in Qiaokou should be closed. Two existing EMS stations in Hanyang should be closed. In contrast, the locations of 14 new/relocated stations are all located in rural districts. Specifically, two new EMS stations are located in the north of Jiangxia, and one station is located in the west of Hannan. The central of Caidian has one EMS station. Two new EMS locations are distributed in the east and south of Dongxihu, respectively. Huangpi has four selected locations, which are located in the south, the middle and the west sides. Then, four selected locations are located in the west, the middle, the east and the north of Xinzhou, respectively.

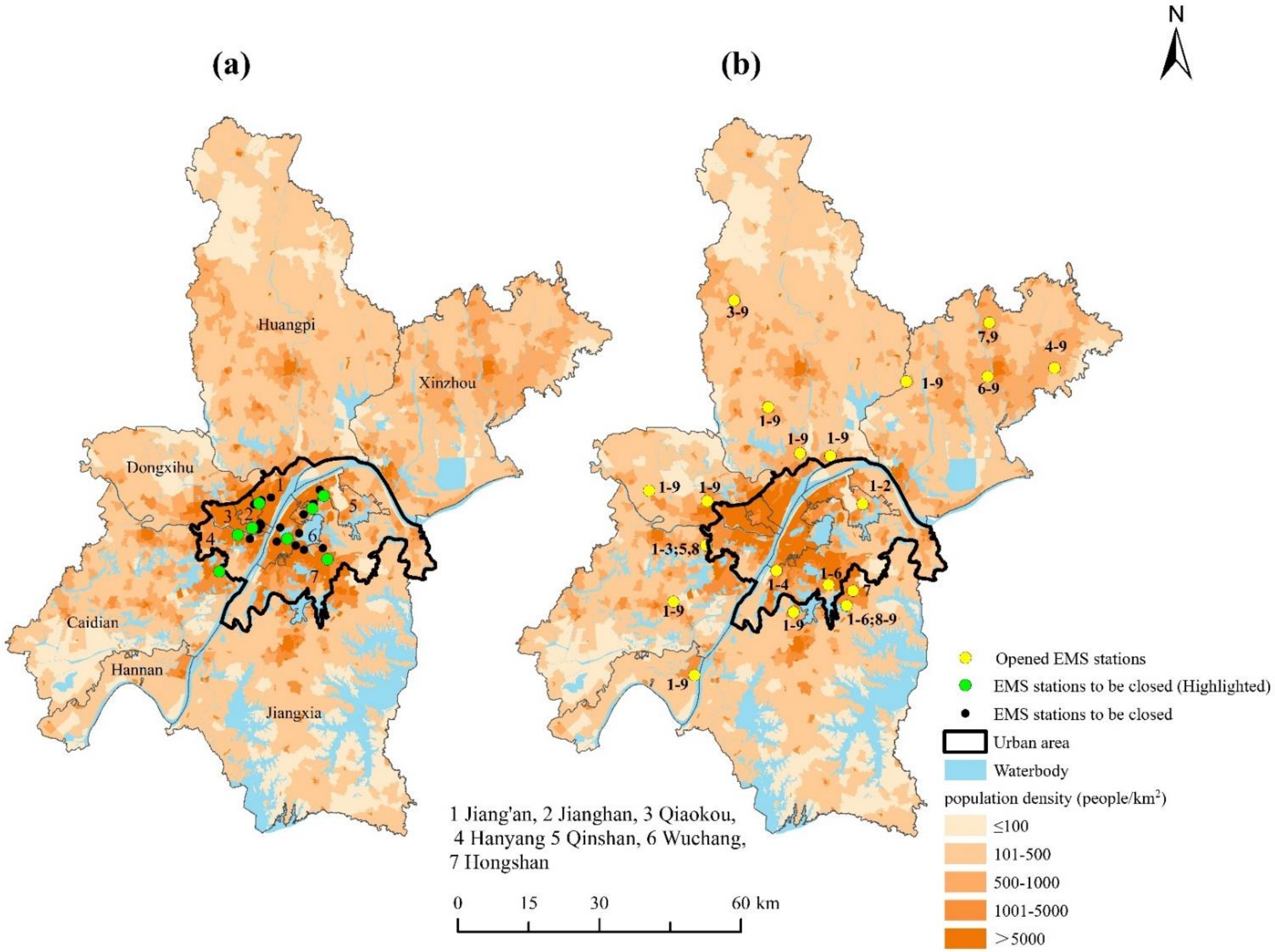


Figure 5-11. Selected EMS locations for M4 (a) stations to be closed (b) new/relocated stations.

5.5. Discussion

This chapter proposes two bi-objective optimization models for locating EMS stations, aiming to improve equalities in EMS accessibility and service coverage between urban and rural areas. Instead of seeking the most equitable solution, bi-objective formulations are usually necessary for finding the trade-off between service provision and equality. In general, service efficiency and inequality objectives are usually conflicting with each other. For instance, in this study, optimizing objective (5.1) tends to locate EMS stations in densely populated areas (e.g., urban areas), leaving sparsely populated sites (e.g., rural areas) with worse accessibility or service coverage. On the other hand, optimizing the inequality measures alone, objective (5.2) or (5.3), often contradicts the objective of improving the service quality. An extreme example is that EMS stations are sited infinitely further away from the city, so all demands in urban and rural areas have the same spatial accessibility. The trade-offs between two or multi conflicting objectives are often explored by the Pareto-optimal solutions.

Because of the time-sensitive nature of EMS and other emergency services, the standard of service coverage can be defined as travel distance or travel time. At present, service coverages are commonly adopted in facility location modelling of EMS stations and often the maximal service coverage is perused. However, residents living further away from the nearest stations than the coverage standard will also need to use EMS or other emergency services. A common approach to improving EMS accessibility in relation to those uncovered population is to reduce the total weighted distance/travel time as much as possible with the available facilities (e.g., Church et al., 1991). This is applied in objective (5.2) in this research. Unlike Church et al. (1991), which focuses on accessibility for the uncovered people in a whole study area, only uncovered rural people are considered in this study to migrate inequality in EMS accessibility between urban and rural areas. The developed models are also different from the model proposed by Chanta et al. (2014) that used the objective of p-center problem (i.e., minimizing the longest travel time between any uncovered demand location and its closest facility). Objective (5.2) in this study considers all uncovered rural people rather than only the worst-off individual users/communities involved (i.e., the shequ/patient with the poorest accessibility to EMS), which can better represent the nature of equality.

Different from objective (5.2) that only considers EMS accessibility for the uncovered rural population, objective (5.3) involves EMS inequality in urban-rural service coverages explicitly. It is represented by the disparity of achieved levels of the ratios of the covered population in urban/ rural area (i.e., service provisions). As the EMS mortality rate in rural areas is usually higher than that in urban areas (do Nascimento Silva and Padeiro, 2020), a frequently used approach in optimizing EMS facilities when concerns urban-rural inequality is to improve the service coverage for rural areas (e.g., McLay and Mayorga, 2013; Chanta et al., 2014). Objective (5.3) gives a novel inequality objective to consider urban-rural service coverages, which can be employed in spatial optimization in EMS facilities. Meanwhile, an acceptable level of urban-rural inequality in service coverage (i.e., Z_3) can be reached based on the solution procedure with a pre-defined parameter ε_{Z_3}. Given the opposite changing directions of W_u and W_r, an equivalent formulation of objective (5.3) can be derived by minimizing the ratio of uncovered population in rural areas. Compared with previous inequalities studies (e.g., Chanta et al.,2014; McLay and Mayorga,2013) that aim to minimize the number of uncovered rural demand zones or population, objective (5.3) arguably concerns the whole demand in the study areas as well as their equality levels.

Different from many studies devoted to finding the most equitable solution (e.g., Lindner-Dutton et al. 1991; Zheng et al. 2013; Kim & Jung, 2017), this chapter intends to seek a trade-off to balance EMS efficiency and equities in EMS accessibility and service coverage between urban and rural areas, while ensuring that there is satisfactory EMS efficiency. According to the results, higher equitable solutions often imply lower service efficiency. For example, in scenario 2, the most equitable solution (9th solution) of urban-rural coverage ratio results in 71.9% of the total covered population, with a 7.7% decrease compared to the 8th Solution's result. The improvement in EMS fairness is at the expense of a decrease in EMS efficiency, and there is a common way to reduce such inequalities by finding a trade-off point to balance efficiency and equality instead of the most equitable solution.

The proposed models in this chapter strongly connect with chapter 3, which found the inequality in EMS accessibility between urban and rural areas. Recently, many new towns have been developed in rural districts of Wuhan, such as the Economic development zone in Hannan. Due to more job opportunities and affordable housing prices, the increasingly number of people are moving to suburban and rural areas, resulting in a dramatic increase the in demand for medical care and bringing much pressure on the local EMS system. In addition, due to the COVID-19 pandemic, in particular the Omicron variant, there is likely to be an exponential increase in the number of potential infections requiring EMS services in the coming years, which puts much potential stress on the local healthcare system, especially in large cities with tens of millions of people. Although EMS has played a crucial role in the pandemic response, it also suffered tremendous pressure due to limited capacity and increasingly amount of potential demand. Under the conditions of limited resources and the increase in EMS demands, the adjustment of existing EMS locations and seeking optimized sites for new EMS stations are common approaches that are necessary, especially in the situation where urban-rural inequalities in EMS accessibility and service coverage have been clearly confirmed. Thus, the models proposed in this study can be a future approach to help balance the relationship between EMS efficiency and equality, especially during the fast urbanization and pandemic periods.

Further, this research has significant policy implications. First, two scenarios employed in this study can provide different advice to healthcare planners and local authorities. Scenario 1 assumes that all existing EMS stations are open, thereby providing the decision support in relation to the optimal locations for new EMS stations. It gives the most realistic suggestions for decision-makers, that is, how to locate new stations on the existing basis. Scenario 2 is to optimize the spatial layout of EMS facilities under the assumption that up to 10% of existing EMS stations (the maximum number of 8 stations) can be relocated to other places. It provides an additional view on which existing stations are suitable to relocate in order to achieve the planning goals. Second, given the existing spatial configuration of EMS stations, service coverage and accessibility to EMS stations in seven urban districts are much better than those in rural areas. To reduce the urban-rural inequalities in EMS accessibility, M3 and M4 in both scenarios suggest that the one new EMS station should be located in the east of Hannan. Then, M3 suggests one EMS station should be located in the middle of Caidian, but M4 advises that the north of Jiangxia needs a new EMS station in both scenarios. Besides, M3 and M4 in Scenario 2 suggest some existing EMS stations in urban districts can be relocated to the rural areas in order to improve such inequalities. For instance, one station in the north of Hongshan should be moved to rural areas. It is worth noting that an EMS station in the middle of Huangpi needs to move to other areas because its coverage overlays another EMS station nearby. Finally, the Pareto-optimal solutions in various scenarios can help decision-makers explore trade-offs between service efficiency and urban-rural equality. In Scenario 1, to reduce urban-rural inequalities in EMS accessibility, Figure 5-3 shows that the Z_1 value of the 7th Solution is 0.94% lower than that of the maximal value, but values of Z_2 and the ATT in the uncovered rural population sharply decrease. It means a small decrease in EMS efficiency can result in a significant improvement of the equality in accessibility in the 7th Solution. Hence, the 7th Solution can be often preferable in practice. To reduce urban-rural inequalities in EMS accessibility, Figure 5-5 shows that the 4th Solution is a reasonable choice for decision-makers, which can reduce the urban-rural disparity in covered ratios, meanwhile it keeps the covered ratio of the entire city at an acceptable level. In Scenario 2, to reduce urban-rural inequalities in EMS accessibility, Figure 5-8 shows that the Z_1 value of the 10th Solution is often preferable in practice because the values of Z_2 and the ATT in the uncovered rural population have a notable reduction than the last solution, but still maintains the good overall coverage (Z_1 >80%). To reduce urban-rural inequalities in the service coverage, the 8th Solution might be a suitable option for decision-makers. It is because this solution has much smaller urban-rural disparity in the service coverage than the 9th Solution, but the covered population ratio of the entire city at an acceptable level (Z_1 >95%).

This work presented in this chapter has several limitations. The first limitation concerns the specification of candidate locations for new EMS stations and demand locations since the new EMS stations may be sited in other places than the existing candidate location. Moreover, additional weight can be assigned to the demand points to represent the proportions of vulnerable people (e.g., with heart disease, ageing population, shequs) who are more possibly EMS calls, better reflecting the spatial variations of EMS in need. Again, the study requires more accurate dataset, such as historical EMS data related to personal health information or specialized disease records because the population census cannot accurately represent their spatial distribution. A further limitation is that fixed or static travel times are used to represent service standards and travel costs for urban and rural areas. In practice, the travel time can vary within the response time threshold (e.g., 10 to 12 min in the case of Wuhan) due to various periods, traffic conditions, road types and weather. Historical ambulance trajectories can improve the distance and travel-time estimations.

Based on the work presented here, two extensions are possible. An obvious extension is to increase the number of new EMS stations to be sited. In both scenarios, the ambulance coverage still does not cover the significant numbers of potential demands. Hence, it is worth exploring how much more population can be served by siting additional stations based on existing candidate locations or other new sites by increasing the number of EMS facilities to be built and then solving the models using the same procedure.

Another extension would be locating some EMS stations in other places rather than existing candidate locations, cooperating with land-use restrictions and development plans in the case study area. Moreover, it is necessary to explore the optimal spatial layout of locations based on other inequality indicators because there is a lack of widely acceptable consensus on measures of inequalities related to EMS systems. Furthermore, factors like facility availability and maximal service capacity can be extended in further studies.

5.6. Chapter Summary

In this chapter, two bi-objective optimization models are developed to reduce urban-rural inequalities in EMS accessibility and service coverage, respectively. This is achieved through two alternative inequality measures that are incorporated into Objectives (5.2) and (5.3). The former intends to minimize the total weighted travel time of uncovered rural population (i.e., accessibility), and the latter reduces the urban-rural disparity in achieved coverage level. Two bi-objective models have a common objective (5.1), which maximizes the total covered population in the entire study area. The Pareto-optimal solutions of the two bi-objective models from the empirical study show various spatial configurations of the new stations and stations to be relocated, which demonstrate the trade-offs between the overall service provision and urban-rural inequalities.

In both scenarios, the value of Z_1 increases with the values of Z_2 and Z_3. In other words, the improvement of EMS equalities in relation to accessibility and service coverage is often at the expense of decreases in overall service coverage. According to the results in Scenario 1, when the value of Z_1 is at the highest level, the values of Z_2 and Z_3 are also located at the highest levels as well. In Scenario 2, if the value of Z_1 is at the highest level, there are the highest values of Z_2 and Z_3. The above finding is consistent with the previous findings that the improvement of EMS equality is usually at the cost of reductions in the overall service coverage.

Again, the major contribution of this study lies in the two ESM inequality measures, which are incorporated into spatial optimization models to reduce urban and rural inequality in EMS. The empirical results suggest that the improvement of service accessibility for uncovered rural people is at the expense of a decrease in the total covered population. Also, reducing the urban-rural gap in achieved service level is at the cost of reduced coverage in the urban area and the entire city. The work presented in this paper can aid the planning practice of public services like EMS systems, where reducing urban-rural inequalities is an essential concern.

Chapter 6 Discussion and Conclusions

EMS is a crucial component of the public healthcare system, which provides emergency medical care and hospital transportation service to patients with severe illnesses or injuries. Currently, many EMS systems face two common challenges: insufficient EMS provision and inequalities in delivering EMS. The main focus of the thesis is to improve service efficiency and equality of EMS systems using GIS-based spatial analysis and spatial optimization. Empirical studies are carried out using the data from Wuhan, China.

Specifically, three objectives are achieved in this research:

- Research objective 1: to measure spatiotemporal accessibility to EMS with GIS-based spatial analyses.
- Research objective 2: to improve EMS service coverage using spatial optimization approaches.
- Research objective 3: to reduce regional inequality in EMS through spatial optimization approaches.

These objectives were designed to expand the scope of knowledge and complement the existing literature by measuring potential spatiotemporal accessibility to EMS and optimizing EMS/healthcare facility location.

According to the literature review, four research gaps are found. First, the majority of studies on EMS accessibility are based on fixed travel speed even if many studies have indicated that real-time traffic conditions can greatly affect EMS accessibility, especially during traffic peak hours. Second, most studies on EMS accessibility have only considered a one-way EMS trip from the facility to demand location, and vice versa. Although this is commonly the case for general healthcare-seeking behavior (e.g., primary care, general hospital), it is not suitable to seek EMS, which includes two related trips. The third limitation is that most spatial optimization research with regards to EMS only considers service coverage for one partial trip (e.g., Trip 1 or Trip 2). The final research gap is that most spatial optimization research consider EMS inequalities between nationwide, communities or individual users. However, rare of relevant studies have considered urban-rural inequalities in EMS even if such inequalities have been widely documented (e.g., Jennings et al., 2006; do Nascimento Silva and Padeiro, 2020).

This chapter summarizes the major findings, highlighting the contributions of this research to the field of health geography as well as spatial optimization. As the empirical study is an important component of this thesis, its policy implications are also discussed. Finally, the limitations of this research and further work are discussed.

6.1. Research summary

The three research objectives of this research are addressed by Chapters 3, 4 and 5, respectively. The remainder of this section summarizes the major findings, emphasizing the contributions to methodology and/or substantive applications.

Chapter 3 aims to measure spatial and spatiotemporal accessibility to EMS, accounting for two related EMS trips and real-time traffic conditions. Specifically, Chapter 3 attempts: (1) to measure spatial accessibility (static) and spatiotemporal accessibility to EMS, (2) to compare spatial layouts of EMS accessibility between Trip 1, Trip 2, and the overall trip; (3) to explore and investigate EMS accessibility considering real-time traffic information. Two spatial methods, geographic proximity and the E-2SFCA approaches, are employed to measure spatiotemporal accessibility to EMS.

Major findings of Chapter 3 include: (1) notable differences in spatial patterns of EMS accessibility between Trips 1 and 2, (2) a significant urban-rural disparity in EMS accessibility for all trips, and (3) traffic peak hours significantly impacting EMS accessibility, especially in urban areas. First, good ambulance accessibility cannot necessarily guarantee good hospital accessibility or overall accessibility, and vice versa. It frequently occurs in EMS systems across many countries and regions, mainly caused by different spatial configurations of EMS stations and hospitals and the uneven distribution of EMS demands. Second, urban areas have better EMS accessibility than suburban and rural areas. This finding is consistent with numerous GIS-based studies on EMS that have indicated regional disparities in accessibility to healthcare services (e.g., Gabrysch et al., 2011; Tansley et al., 2015; Luo et al., 2018). Finally, real-time traffic conditions can significantly impact EMS accessibility, especially in urban areas.

Chapter 3 makes two contributions. First, it demonstrates the impact of two related trips on EMS accessibility, suggesting that it is necessary to consider two related EMS trips when measuring potential spatial accessibility to EMS. Second, it shows the impact of real-time traffic on spatiotemporal accessibility to EMS, indicating that traffic conditions should be considered when measuring spatiotemporal accessibility to EMS.

Chapter 4 focuses on improving EMS accessibility through spatial optimization approaches. We consider service coverages for two related EMS trips. Chapter 4 develops two facility location models (i.e., Model 1 and Model 2) to improve overall accessibility to EMS. Model 1 attempts to improve overall accessibility by considering ambulance and hospital coverage cooperatively so that more people can enjoy fast ambulance and hospital services. Model 2 integrates ambulance coverage and overall coverage, guaranteeing that the rapid ambulance and hospital services can provide more potential demands.

There are several interesting findings in Chapter 4. According to the empirical study in Wuhan, China, the two proposed models can effectively improve EMS overall accessibility while ensuring that more patients are served on time by ambulances. If siting the same number of new EMS stations and stroke centers, the spatial layout given by proposed models can cover more population compared with the traditional MCLP and MCLP-OC models.

The contribution of Chapter 4 lies in two facility location models (Model 1 and Model 2), which seek the best locations for EMS stations and hospitals simultaneously and ensure that as many people as possible can be quickly served by ambulance and hospital services collaboratively. The two proposed models relate to the travel-time standards of ambulance, hospital, and overall coverages. Thus, the work of chapter 4 can aid the planning practice of public services like EMS systems, where the collaborative work between ambulances and hospitals is essential.

Chapter 5 intends to reduce regional inequality in accessibility to EMS using spatial optimization approaches. Two bi-objective models are proposed to reduce urban-rural disparities in EMS accessibility and coverage, respectively. In addition to the primary goal of maximizing the total covered demand, the two models attempt to reduce urban-rural inequality in EMS in different ways: the first model aims to minimize the TWT in uncovered rural areas, and the second model attempts to minimize the disparity in covered population ratios between urban and rural areas.

The major finding of Chapter 5 is, according to the empirical results from Wuhan, China, the improvement of EMS equalities in relation to accessibility and service coverage is often at the expense of decreases in overall service coverage. The trade-offs between two or multi conflicting objectives are often explored by the Pareto-optimal solutions. The two proposed models can effectively reduce urban-rural inequalities in EMS accessibility and service coverage.

The contribution of Chapter 5 lies in the two inequality measures, one for EMS accessibility and the other for EMS coverage, which are incorporated into two bi-objective optimization models for locating EMS stations considering urban and rural inequalities as well as different service standards for different geographic settings. Thus, this work of Chapter 5 can aid the planning practice of public services, such as EMS systems, where reducing inequalities between urban and rural areas is essential.

6.2. Policy Implications

There are several policy implications of the empirical results, particularly with respect to future EMS planning and management in relation to improve overall EMS provision and reduce urban-rural equality in accessibility and service coverage:

(1) This study suggests that the existence of urban-rural inequalities in accessibility to EMS, and the reduction of urban-rural inequalities in EMS is still a challenge. According to the empirical findings, rural districts have poorer accessibility to EMS in relation to all trips. Therefore, more EMS resources are needed in rural districts, particularly in Jiangxia and Hanan districts, with relatively poor EMS accessibility.

(2) The study indicates that the improvement of urban-rural equality in EMS, in terms of either accessibility or service coverage, is at the cost of decreased overall service coverage, particular in urban districts. In other words, improving urban-rural equalities in EMS is often at the expense of the system's efficiency. In order to pursue urban-rural equity, the action that the movement of EMS resources from urban to rural areas might reduce the efficiency of the urban EMS system, causing urban residents to be dissatisfied with the policy implication. Thus, balancing the efficiency and urban-rural inequality in EMS through a set of Pareto-optimal solutions is necessary, ensuring that the system maintains efficiency while reducing such inequalities. A suitable Pareto-optimal solution is necessary for decision-makers to reduce the urban-rural disparity while keeping the overall service coverage of the entire city at an acceptable level. Therefore, urban and rural residents are willing to accept the policy implication.

(3) Government and local authorities should take corresponding measures (e.g., real-time traffic light system) to reduce the impact of traffic condition on EMS accessibility, especially in the urban area. It is because the real-time traffic condition during peak hours can greatly decrease EMS accessibility, especially in urban districts in Wuhan. For example, the temporal traffic variation ratios for Trip1 or Trip 2 are higher than 0.2 in

all urban districts, but the values are extremely smaller than 0.2 in five of six rural districts (see Chapter 3, Figure 3-12). In Wuhan, areas with the largest difference of travel time between off-peak and peak hours are mainly located in the urban area. Some measures can be adopted to reduce the traffic impact, such as the intelligent traffic control system that plays a critical role in clearance for being congested emergency vehicles (Sundar, Hebbar and Golla, 2015). This system is increasingly implementing in the world, such as Liverpool, UK (Woods et al., 2017), or Beijing, China (Zhang and Qi, 2010).

(4) There is a need to coordinate the planning of EMS stations and hospitals or emergency centers receiving patients. Given the essential contribution of both Trip 1 and Trip 2 to the overall EMS trip, the results from Chapter 3 demonstrate that good ambulance accessibility cannot guarantee good hospital accessibility or overall accessibility, and vice versa. Thus, we urge the need to account for both related trips (i.e., Trip 1 and Trip 2) in evaluating EMS accessibility. Therefore, healthcare planers are necessary to build a collaborative system for EMS stations and emergency hospitals. Chapter 4 further shows that the proposed facility location models (i.e., Model 1 and Model 2), which account for both ambulance and hospital accessibility can generate more service coverage than classic MCLP and MCLP-OC models, given the same number of EMS stations to site.

(5) Two different scenarios adopted provide various options for future EMS planning and management. Scenario 1 only considers new planning facilities and the existing EMS facilities remain open. This scenario is suitable for short-term EMS planning (i.e., one-year planning) because closing EMS stations and hospitals or moving existing EMS faculties to other places usually need long-term planning and ongoing financial support. Scenario 2 considers both location and relocation problems that some of existing facilities can be closed and relocated to other areas. This scenario to meet the dynamic changing spatial distribution of underlying demand. With the urbanization process in China, especially in large cities such as Wuhan, the increasing number of people are shifting to newly developed towns in the suburbs due to the new working opportunities and more affordable housing prices.

(6) This research can be implicated in the broad planning context of other public services. First, the idea of involving different trips in accessibility and spatial optimization can be used in the planning of services like warehouses or emergency shelters, which are necessary to consider different trips. Then, the work can also be employed in other

emergency services (such as firefighting or policing) that also require the quick reaction capability in both urban and rural areas. Further, the proposed methods can be revised to meet a specific public policy requirement. For example, the Ministry of Education of the People's Republic of China (2021) plans to provide more educational resources (e.g., schools, and teachers) to improve school accessibility in impoverished areas. The proposed models in this thesis can be modified to meet their planning requirements and provide suitable decision-support to policymakers, such as which areas/groups have poor school accessibility or how to allocate those resources optimally.

6.3. Limitations and Further Research

6.3.1. Limitations

The limitations of the thesis are mainly associated with the representation of service demand and services, measurement of travel distance/time, spatial abstraction, and social engagement. The following context discusses those dimensions in detail. This section ends with a discussion of the most critical limitation.

(1) Online map services were employed in measuring O-D travel time in Chapter 3. It might lack precision because the locations of demands and service facilities cannot be adjusted, and it is also difficult to visualize those selected routes. In online map services, all computations are conducted in a black box from API services, and private researchers are hard to control those processes. Meanwhile, when considering the traffic off-peak and peak hours analyzed above, it may be possible for two EMS trips (Trips 1 and 2), one occurring during off-peak hours and the other during peak hours, or vice versa, which might be impacted by the EMS and on-site rescue time again.

(2) The variation in on-scene accessibility has not been considered in the study. For example, the patient's floor (high-rising building vs low-rising building) or the environment of the neighborhood community can affect the on-scene time (e.g., Balamurugan et al., 2016), resulting in a variation in overall travel times across neighborhood communities and different population groups.

(3) The specification of candidate new locations of service providers may be sited in other places than the existing candidate locations in facility location research (see Chapters 4 and 5). In our research, candidates of new EMS facilities are mainly based on the existing planned service locations, but more appropriate places are not considered, which may lead

to some better solutions being ignored. In addition, the site suitability analysis has not been implemented to identify and evaluate those candidate locations, which often needs the knowledge of land-use restrictions and local development plans in the case study area.

(4) Spatial abstraction is often necessary in facility location model. In this research, both demand and service in EMS systems are represented by spatial points. Further, residential locations are adopted as scenes due to the lack of real-world EMS-run data. However, emergency calls can also occur in other sites, such as workplaces and highways. Similarly, general hospitals are employed here without considering different types of emergency centers. In some countries/regions, patients with specific severe diseases (e.g., stroke and trauma) can only access specialized hospitals.

(5) Our research uses the total population to represent the EMS demands, but some specific vulnerable groups (e.g., with heart disease, ageing population) have not considered here. However, those vulnerable groups are often more possible need healthcare services such as EMS, and they can better reflect the spatial variations of EMS in need.

(6) Some limitations are associated with social and political dimensions. First, it is not necessary to consider two related EMS trips in some EMS systems like Beijing, China, because EMS stations and emergency hospitals are often located in the same locations in those systems (Hung et al., 2009). Second, people might not be willing to live near the EMS station or emergency hospital as they often make disturbing noises (e.g., ambulance alarm). Therefore, residents might disagree that the EMS station or hospital is located in their community. Third, setting stroke centers or emergency centers needs consider more realistic factors, such as finance, staffing and the planning for the selected hospital. For example, some hospitals are not willing to set up stroke centers due to the lack of financial supports even if they are located in suitable places.

The most crucial limitation is that the actual EMS data has not applied, which influences the results and outcomes in this thesis. For example, the potential EMS demand is represented by the residential population in this research due to the lack of actual data. However, the spatial distribution of EMS demands might often be determined by many factors, such as age, income, environmental and sanitary conditions. The residential locations cannot accurately describe the actual distribution of EMS demands, which is likely to cause errors or deviations, thus affecting the results, findings, and study outcomes. In addition, if the actual EMS data is available, many other factors could be considered, such as the EMS busyness fraction, real ambulance travel time, demand uncertainty, survival rate, or a specific type of EMS demand.

6.3.2. Further research

Several further works can be extended in the future, which include the implementation of actual EMS data, more candidate locations needed, the consideration of uncovered residents in Chapter 4, and exploration of other inequality indicators for spatial optimization.

(1) The estimation of travel time can be improved by using the real-world ambulance-run records and historical EMS data. The ambulance-run records can be employed to validate the EMS travel time predicted by ArcGIS's network analyst and online map services to improve the accuracy of estimating EMS accessibility. The spatial variation of the on-scene time if those data will be considered. Historical EMS data can better reflect the spatial distribution of demands in relation to different types of diseases. It will help to be integrated with disease-specific accessibility measures. Moreover, EMS survival rates, health outcomes, and other EMS information can be incorporated into further work.

(2) Alternative candidate locations can be employed for the future EMS and hospital planning. The future work should cooperate with land-use restrictions and development plans in the case study area. Then, demand locations can be represented by the surface rather than the set of points, which might better reflect the locations of EMS demands. Meanwhile, real-time conditions and dynamic relocation models for ambulances are necessary to developed in the future. In addition, other factors like facility availability and maximal service capacity should be extended, which need to cooperate with actual EMS-running data and specific historical EMS records. Meanwhile, both studies need to increase the number of new facilities to be sited in order to explore how much more population can be served by siting additional stations based on existing candidate locations or other new sites.

(3) Dynamic relocation problem (for ambulances) with a consideration of temporal factors needs to be addressed in the future work. Temporal relocation problem can be determined such as how many ambulances should be placed at each EMS station at different times in order to deal with temporal factors such as traffic congestion or peak demand period. Sometimes, an ambulance may be dispatched to a new task before it returns to the corresponding EMS station. Therefore, it is also necessary to plan to build temporary EMS stations to improve EMS response time.

(4) EMS accessibility in areas that are not covered by both service coverages is necessary to consider. In Chapter 4, the two proposed facility location models only consider the service coverage as most of the traditional coverage-based models (e.g., LSCP, MCLP). However, it does not mean that people living further away from EMS stations or hospitals than the standards of service coverage will not use such services. Thus, EMS provision and equality in overall EMS service can be studied in the future.

(5) Alternative inequality measures can be adopted in EMS/hospital location optimization. As there is a lack of widely acceptable consensus on measures of inequalities related to EMS systems, it is necessary to explore the optimal spatial layout of facility locations based on other inequality indicators in facility location research. Moreover, it is worth comparing various indicators of inequality measures in facility location research and discussing their similarities and differences.

(6) The future work is necessary to incorporate recent developments in spatial accessibility and optimization (e.g., Li et al., 2022, Griffith, 2021; Griffith et al., 2022). For example, Li (2022) found that the 2-step optimization model could provide a more effective strategy to balance equality and efficiency in EMS accessibility and availability. Recent studies also indicated that spatial statistics could contribute to spatial optimization by helping to determine the spatial optima (Griffth, 2021), exploiting spatial autocorrelation to deal with missing data problems in any georeferenced dataset, or by examining the colocation of spatial medians and local spatial autocorrelation hotspots (Griffith et al., 2022). Thus, the focus on recent developments is conductive to improving the quality of current work in this thesis.

(7) The impact of demographic heterogeneity (e.g., gender, age, race, socioeconomic status, educational attainment, etc.) should be considered in the future. For example, many studies indicated that the probability of using EMS would increase with rising age, especially for the group aged 70 years and older (e.g., Veser et al.,2015). In addition, some studies also found that poor socioeconomic status (e.g., low-income residents) and socio-cultural barriers (e.g., minorities) tended to experience poor accessibility to healthcare services (e.g., Wang and Luo, 2005; Wang et al., 2008). Therefore, the future work should consider the impact of demographic factors and focus on those groups with a high need for EMS.

6.4. Conclusion

EMS is an essential public service in protecting public health and safety. This research includes three studies with respect to measuring EMS accessibility, improving overall provision/efficiency, and reducing spatial inequalities in EMS, respectively. This research recommends that it is necessary to consider two related trips and traffic conditions when measuring spatiotemporal accessibility to EMS. spatial optimization research can help improving service efficiency and equality in EMS systems. Overall, the work presented in this thesis can aid the planning practice of public services like EMS and provide decision support for policymakers.

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