Locating emergency medical services to reduce urban-rural inequalities

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\textbf{ABSTRACT}

Emergency Medical Service (EMS) systems provide fundamental services in relation to public health and safety. The spatial configuration of EMS stations is crucial to the efficiency and equality of service provision. While urban-rural inequalities in EMS have been widely acknowledged, how to optimize EMS station locations to reduce such inequalities remains challenging. This research proposes a multi-objective optimization model to reduce urban-rural inequalities in EMS accessibility and coverage, in addition to maximizing the total covered population. The proposed model is applied in an empirical study in Wuhan, China, to seek locations for new EMS stations in order to improve local EMS capacity in the pandemic period. The results indicate that the total covered population, particularly in urban area, decreases when urban-rural equality in service accessibility increases, but it has a U-shaped relationship with urban-rural inequality in service coverage. Pareto-optimal solutions suggest that all new stations should be located in rural areas if lower urban-rural inequality in EMS is to be obtained, but one new station is needed in the urban area if higher coverage of total population is more desirable. 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.

1. Introduction

Emergency Medical Services (EMSs) are fundamental to public health and safety, providing prehospital medical care and transportation services to patients with severe illnesses as well as people with serious injuries in accidents or disasters. Fair access to public services like EMS is crucial to overall social equity and is one of the sustainable development goals set by the United Nations (i.e., Goal 10: Reduce inequality within and among countries) [1]. However, inequalities in EMS within/across regions and between population groups are common worldwide and are often attributed to limited resources, including funding or physical barriers such as distance and road infrastructure [2-5]. For example, patients experiencing out-of-hospital cardiac arrest in urban areas had higher survival rates than those in rural districts in Victoria, Australia, where a key influential factor was proximity to the nearest ambulance station [2]. In Lisbon, it was found that deprived areas generally had worse geographic access to EMS than affluent areas [4]. Such inequalities and their implications for care, have been exacerbated by the outbreak of Coronavirus Disease-2019 (COVID-19). EMS have played a key role in the pandemic response but also experienced great pressure due to limited and inelastic capacity in many countries and regions [6]. While reducing inequalities in EMS remains a challenge to many governments and local authorities, the pandemic has highlighted the urgent need to improve EMS provision as well as service equality.

This research focuses on inequalities in geographic accessibility and service coverage, both of which are common measures for evaluating EMS system performance [7-9]. Although accessibility can be defined in many ways (e.g., using floating catchment-based approaches) [10,11], geographic accessibility is considered here as the ease and speed of action, where timelier responses usually imply more favourable health outcomes. Service coverage is the amount of demand that can be encompassed within pre-defined service standards. These two aspects primarily rely upon the spatial layout of EMS. This has been studied extensively in the field of spatial optimization which seeks the best locations of EMS facilities by integrating geographical information systems (GIS) and operations research. Common models for EMS location optimization include median problems, center problems and coverage problems – the first two concern accessibility and the latter relates to
Several inequality measures have been proposed and applied in facility location modeling \cite{19–22}. Such measures are usually defined by the outcome or effect of facility layout on individual users or communities, such as travel distance/time/costs. Common measures include range (e.g. Ref. \cite{23}), variance (e.g. Ref. \cite{24}), and mean deviation (e.g. Ref. \cite{25}), among many others. In addition, indices from demographics and economics for assessing inequity of socioeconomic welfare – such as the Gini coefficient – have been considered as measures of inequality \cite{26} and employed by many studies (e.g., Refs. \cite{27–29}).

However, most of the existing studies on EMS location optimization have focused on the inequality between individual users or communities. ‘Regional’ inequality (e.g., between urban and rural areas) has received comparatively less attention. Some exceptions include work by McLay and Mayorga \cite{23}, Chanta et al. \cite{17} and Amaral and Murray \cite{30}. The former two studies attempted to reduce urban-rural inequality in EMS by improving the service coverage of rural demand zones or population within the service standards (e.g., response time), whilst the latter assessed inequity between states in access to healthcare using median models.

There is no consensus within EMS location modeling over how to measure urban-rural inequality. It can be quantified in many different ways depending on the inequality dimension under concern. Further, service standards can be different for different regions within the same EMS system. For example, in the United States, the EMS systems aim to respond to 90% of calls within 9 min (hereinafter denoted as min) for urban areas, but within 15 min for rural areas \cite{31}. In most Chinese cities and peripheries, the coverage radius of an EMS station is 5 km in urban areas but 10–20 km in rural areas \cite{32}. Such disparity in service standards between urban and rural areas has been largely ignored in previous work.

The aim of this paper is, therefore, to reduce urban-rural inequalities in EMS accessibility and coverage through spatial optimization approaches that incorporate different planning criteria for urban and rural areas. A multi-objective optimization model is proposed for siting EMS stations, and the impact of the inclusion of inequality objectives on the overall service provision is examined. The major contribution of this research lies in the proposed multi-objective model accounting for regional (e.g., urban-rural) inequalities in EMS – one inequality objective for service accessibility and the other for service coverage, as well as the consideration of different service standards for different geographic settings. The proposed approach is applied in an empirical study in Wuhan, China, where the planning of EMS system expansion and upgrades has been prompted by the COVID-19 and is now in progress. The results provide alternative options for siting EMS stations in the metropolitan area of Wuhan and support decision-making in emergency service resource deployment.

The paper is organized as follows. The next section reviews the facility location models for EMS in general and those accounting for inequality in particular. The proposed multi-objective spatial optimization model is presented in section 3. Empirical results are described and interpreted in section 4. The paper ends with a discussion of major contributions and policy implications of the empirical study.

2. Related research

Numerous facility location models have been proposed for siting EMS stations, which can be grouped into three main categories: coverage problems, built upon work by Toregas et al. \cite{22} and Church and ReVelle \cite{34}, and center and median problems based on the work by Hakimi \cite{35}. Coverage problems seek the minimum number of facilities to serve the whole population (i.e., a location set covering problem (LSCP)) or how to locate the given number of facilities in such a way so that the covered service demand is maximized (i.e., the maximal covering location problem (MCLP)). Center problems consider the worst case – the maximum travel distance or time an ambulance might take to arrive at a scene, with the goal of minimizing that value. Median problems aim to minimize the total weighted travel costs (e.g., distance or time) to reach patients with the given number of facilities. Detailed descriptions of these models, including mathematical formulations and common solution approaches, can be found in several review articles such as ReVelle et al. \cite{7}, ReVelle \cite{12}, Goldberg \cite{13}, Başar et al. \cite{8} and Belenger et al. \cite{9}.

In addition to travel costs and service coverage, many other aspects of EMS operation have been incorporated into classic models to better reflect the practice of emergency services. For example, the MCLP has been extended to account for backup/multiple/gradual coverage, service availability, demand uncertainty, cooperation between multiple stations, vehicle types, traffic congestions, the priority of calls and so on \cite{14,36}. While the uncertainty in most coverage models is associated with service provision, it is mainly related to emergency calls in most median models \cite{37,38}. Further, rather than response time or the proportion of responded calls, Erkut et al. \cite{39} argued that survival rates – which better represent medical outcomes – should be employed to assess the performance of EMS and proposed the maximal survival location problem (MSLP). McLay and Mayorga \cite{40} examined the links between response time and patient survival rates using real-world data from Hanover County, Virginia, USA, and found that the maximal survival rates could be obtained using a 7- or 8-min service standard.

Recently, there have been increasing concerns about inequalities in EMS systems. Center problems have long been considered to address inequality by following a Rawlsian principle – that is, minimizing the maximum service distance/time \cite{19–21}. Rather than the worst-case scenario defined by a sole individual or community, Church and Murray \cite{14} argued that coverage models could better reflect the meaning of fairness by applying certain service standards to the overall demand. For example, the total number of uncovered districts could be minimized to reduce disparity between demand zones \cite{17,41}. More commonly, inequality is represented by an index that is incorporated into EMS location models as an objective function or a constraint. Chanta et al. \cite{28} proposed an index of “envy” and an associated minimum p-envy location problem whereby “envy” reflected users’ perceptions of equity in service provision. Enayati et al. \cite{29} employed three indices, each as an alternative objective function to be minimized, to measure the inequalities between individual response time: variance, squared coefficient of variation and the Gini coefficient. Using extra constraints, McLay and Mayorga \cite{23} set minimum values for both survival rates and share of demand at each priority level to be served by the nearest station. In addition to the inequalities between users, some scholars have attempted to balance the workload between service providers. For example, McLay and Mayorga \cite{23} set a value range for the probability of an ambulance being busy, as well as the minimum rate at which ambulances were dispatched to high-priority patients. Toro-Diaz et al. \cite{42} adopted two criteria – squared coefficient of variation and the Gini coefficient – to equalize the workload of each EMS station, a method also applied by Enayati et al. \cite{29}.

As can be seen from the discussion above, inequality can be approached in many ways in EMS location optimization depending on the aspect of EMS of interest. This research proposes a spatial optimization model using alternative inequality measures to reduce urban-rural inequalities in EMS, with a focus on service coverage and accessibility. The proposed model is built upon MCLP in which the total weighted distance is adopted as an indicator of accessibility. Coverage models remain the primary approach for EMS location optimization, since standards of response time (or coverage radius) and service provision (e.g., cover 90% population or respond to 90% of calls within a certain time frame) are common components of EMS systems \cite{8,14,15,36}. The combination of coverage and distance (either total weighted or average) is a common practice in facility location modelling to account for both equality and efficiency (e.g., Refs. \cite{43,44}).
3. Model specification

First, a multi-objective optimization model is proposed. MCLP tends to locate facilities in more densely populated areas with higher demand, and this tends to leave rural districts underserved [17,40]. Therefore, in addition to maximizing the total covered demand, two additional objective functions are proposed in this study to reduce urban-rural inequalities in geographic accessibility and service coverage of EMS, respectively. Then, a solution procedure based on the ε-constraints method is presented.

3.1. Mathematical formulation

With the following parameters.

\(i, j = \text{index of demands and potential EMS stations, respectively};\)
\(I, J = \text{set of demands and potential EMS stations, respectively};\)
\(a_i = \text{demand at location } i;\)
\(S_u = \text{service standard for urban areas};\)
\(S_r = \text{service standard for rural areas};\)
\(p = \text{number of EMS stations to be sited};\)
\(q = \text{number of existing EMS stations to remain in the system};\)
\(d_{ij} = \text{shortest travel distance or time between } i \text{ and } j;\)
\(\Phi = \text{set of existing EMS stations};\)
\(W_u, W_r = \text{proportion of covered demand in urban and rural areas, respectively};\)

and the decision variables:

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

\[Y_q = \begin{cases} 1 & \text{if demand } i \text{ is not within the service standard of its nearest EMS station } j \\ 0 & \text{otherwise} \end{cases}\]

the proposed spatial optimization approach can be expressed as follows:

**Maximize**

\[Z_1 = \sum_{i,j \in \Omega} a_i \left(1 - \sum_{j \in \Omega} Y_q \right) \tag{1}\]

**Minimize**

\[Z_2 = \sum_{i,j \in \Omega} a_i d_{ij} Y_q r_i \tag{2}\]

**Minimize**

\[Z_3 = |W_u - W_r| \tag{3}\]

Subject to

\[\sum_{j \in \Omega} X_j + \sum_{j \in \Omega} Y_q \geq 1 \quad \forall i \in I \tag{4}\]

\[\sum_{j \in \Omega} X_j = p \tag{5}\]

\[\sum_{j \in \Phi} X_j = q \tag{6}\]

\[X_j \geq Y_q \quad \forall i \in I, j \in J \text{ and } j \notin \Omega \tag{7}\]

\[w_u = \frac{\sum_{i \in \Omega} a_i (1 - r_i) \left(1 - \sum_{j \in \Omega} Y_q \right)}{\sum_{i \in \Omega} a_i (1 - r_i)} \tag{8}\]

\[w_r = \frac{\sum_{i \in \Omega} a_i r_i \left(1 - \sum_{j \in \Omega} Y_q \right)}{\sum_{i \in \Omega} a_i r_i} \tag{9}\]

\[X_j = \{0, 1\} \quad \forall j \in J \tag{10}\]

\[Y_q \geq 0 \quad \forall i \in I, j \in J \text{ and } j \notin \Omega \tag{11}\]

This formulation is based on work by Church et al. [43] which primarily concerns service efficiency and uncovered demand. Objective (1) is to maximize the service coverage. Objective (2) is to minimize the total weighted distance (TWD) of the uncovered demand from the nearest open EMS station in a rural area, which virtually maximizes the accessibility of uncovered rural demand. Objective (3) is to minimize urban-rural inequality in service coverage. Constraints (4) indicate that demand \(i\) is either covered by a station \(j (j \in \Omega)\) or assigned to an open station \(j (j \notin \Omega)\). If \(\sum_{j \in \Omega} X_j \geq 1\), demand \(i\) will be covered by at least one station and the associated \(Y_q (j \notin \Omega)\) will be zero due to the preference of \(\sum_{j \in \Omega} Y_q = 0\) in objective (1) and the minimization function in (2). If \(\sum_{j \in \Omega} X_j = 0\), demand \(i\) will not be covered and the value of \(\sum_{j \in \Omega} Y_q\) will equal one, given the nature of objectives (1) and (2); that is, demand \(i\) will be assigned to only one station \(j\) in this case. Constraint (5) requires that \(p\) stations in total are to be sited. Constraint (6) specifies the number of existing stations that will remain in the system. Constraints (7) ensure that demand \(i\) can be assigned to \(j\) only if a station is sited at \(j\). Constraints (8) and (9) are the expressions to calculate \(W_u\) and \(W_r\). Constraints (10) restrict the value of \(X_j\) to be 0 or 1, and Constraints (11) impose non-negativity restrictions on \(Y_q\).

3.2. Solution approach

For multi-objective optimization problems, Pareto-optimal solutions (also known as non-dominated solutions) that represent trade-offs between objectives are often useful. In a Pareto-optimal solution, there are no other better solutions in respect of all the objectives [45]. In this research, the commonly used ε-constraints method is employed to find the Pareto-optimal solutions. The main idea is to transform the original multi-objective formulation to a single-objective problem by keeping only the primary objective while incorporating the other objectives into the constraints, where their values are bounded at acceptable levels.

Specifically, Objective (2) is kept as the primary objective and Objectives (1) and (3) are included as constraints. The bounds of \(Z_1\) and \(Z_3\) are obtained through the following procedure:

- **Solve the above model without Objectives (2) and (3).** Denote the values of \(Z_1, Z_3, W_u\) and \(W_r\) as \(Z_1^0, Z_3^0, W_u^0\) and \(W_r^0\), respectively. Given the nature of the MCLP, it is not difficult to infer that \(W_u^0 \geq W_r^0\), and \(Z_1^0\) and \(Z_3^0\) are the upper bounds of \(Z_1\) and \(Z_3\), respectively.

- **Solve the above model without Objectives (1) and (3).** Denote the value of \(Z_1\) as \(Z_1^\prime\), which will be used as the lower bound of \(Z_1\).

Consider the following additional notation:

\(k, m, n, n_{iter} : \text{iteration indicator; }\)
\(K : \text{maximum number of iterations; }\)
\(\varepsilon_1, \varepsilon_2 : \text{the percent of the total and rural covered demand to be increased in each iteration, respectively; }\)
\(\varepsilon_{Z_1}^1, \varepsilon_{Z_1}^2 : \text{threshold of } (Z_1^0 - Z_1^1) \text{ and } (Z_3^0 - Z_3^1), \text{ respectively. }\)
Additional constraints can be defined as in (12) and (13).

\[ Z^i_t \geq Z^i_t + max_i \sum a^i_{tj} \]  \( (12) \)

\[ W^i_t \geq W^i_t + ne \]  \( (13) \)

Constraint (12) sets the minimum total demands to be covered. Constraint (13) sets the minimum percent of rural demands to be covered. Accordingly, the proposed multi-objective model is reformulated as a single-objective model defined by (2), (4)-(13).

The complete solution procedure can be described by the pseudo-code in Fig. 1.

4. Empirical study

4.1. Study area and context of EMS planning

The study area is Wuhan, the capital city of Hubei province, China, which is located on the middle reach of the Yangtze River. It is the largest city in Central China with an area of 8569.2 km² and one of the nine National Central Cities, leading the development of politics, economics, and culture in the surrounding area. It contains 13 administrative districts: 7 urban and 6 rural/suburban. According to the Seventh National Population Census, the city’s permanent residents reached 12.3 million in 2020, an increase of 25.9% from 2010, largely attributed to the inflow of both rural-urban and inter-urban migrants [46]. Meanwhile, there was also a growth in both the urban and elderly population. In 2020, the share of urban population was 84.3%, about a 7.2% increase over that of 2010; about 17.2% of the population were over sixty and 11.8% over sixty-five, with an increase of 4.5% and 3.7% over that of 2010, respectively [46].

This rapid population growth and aging population have placed great pressure on public health services, including the EMS system. Based on the locations of existing 73 EMS stations and population distribution in Wuhan, currently only 63.3% of the total population are within the EMS service standards, that is, 4 km for urban areas and 6.5 km for rural districts. Meanwhile, associated urban-rural inequality is also evident. For example, 88.9% of urban residents are within 4 km of their closest EMS stations, while only 38.9% of rural people are within 6.5 km of rural EMS stations. Furthermore, between December 2019 and April 2020, COVID-19 caused more than 3800 deaths and there were over 50,000 confirmed cases [47]. Considering the increased demand for public health services, as well as the uncertainty in the duration and frequency of the pandemic, Wuhan Municipal Health Commission planned to start building six new EMS stations in 2021. One of the primary goals, in addition to increasing the covered population within the service standards, is to reduce urban-rural disparity [48].

4.2. Data

The data adopted in this research include existing EMS stations, candidate sites for new stations, and the city’s population as demand. Of the 73 EMS stations in Wuhan, 54 are in the central urban area and 19 in the rural region. The service standard is 10 min (or 4 km) for the former and 12 min (or 6.5 km) for the latter [48]. Fifty of those stations are located next to hospitals. Given the close collaboration between EMS and hospitals, 125 existing hospitals (medical units at/above Level II) in urban areas and community hospitals in rural regions) currently without EMS are selected as the potential sites for new stations. The population data are from the Geographical Information Monitoring Cloud Platform (http://www.dsac.cn/) that provides census information at the finest available scale, represented by a 1 km * 1 km lattice dataset. The entire city contains 7600 grid cells. Both EMS stations and population are represented as spatial points (i.e., centroids of the associated spatial units) in the modeling procedure. Existing, as well as candidate EMS locations, are extracted from Baidu Map (https://map.baidu.com/) – the largest and most popular online map service in China.

Relevant spatial and population information is shown in Fig. 2. It is obvious that the urban area is more densely populated than the rural region. The central seven urban districts cover 10.5% of the city’s overall area but 51.9% of the total population. It is thus not surprising that most of the existing EMS stations are located in the urban area. Among the 13 districts, the highest population density is 19,380 people/km² (Jianghan) while the lowest is 485 people/km² (Jiangxia). In the urban area, only the northeast of Hongshan is relatively sparsely populated. In the rural areas, population concentrates around town centers where local EMS is provided.

The parameter values adopted to solve the sub-models for the empirical study are given by Table 1. As six new EMS stations are to be built from 2021, all existing stations remained in the system (q = 73) and the total number of available stations is 79 (p = 79). Service standards in urban and rural areas are represented by distance, i.e., 4 km and 6.5 km respectively. The rest of the parameters are used to adapt the constraints in the iterations of the solution procedure.

The proposed model and the solution procedure is written in Python and implemented with the commercial optimization software Gurobi (version 9.1.1). All spatial data processing, management and result visualization are carried out in ArcGIS (version 10.7).

4.3. Results

The proposed multi-objective model for the empirical study is solved on a desktop with an Intel processor 3.80 GHz and 32 GB RAM. The computational time is about 10 min for the model parameter values in Table 1.

In this section, the Pareto-optimal solutions of the multi-objective model are presented first and the inclusions of inequality objectives affect the overall service coverage is explored. Then, the solutions with optimal values of Z₁, Z₂ and Z₃ are examined to investigate the maximum service coverage and the minimum urban-rural inequalities in EMS accessibility and service coverage, respectively.

4.3.1. The pareto-optimal solutions

The total eighteen Pareto-optimal solutions are depicted by Fig. 3, where each solution point is labeled by a number in ascending order of Z₁ and denoted as (Sᵢ, t = 1, 2, ..., 18) hereafter. For example, S₁ and S₁₈ have the minimum and the maximum values of Z₁, respectively. For the case of interpretability, the values of Z₁ are converted to the proportions of the total covered population, which varies between 69.9% and 72.6%.

For the rural population who cannot receive the EMS within the service standard, the TWD is between 1.58E7 km and 1.95E7 km. If considering the average travel distance (ATD) – calculated as the TWD divided by the total uncovered rural population (i.e., Z₂/Ω ∑ aᵢⱼ rᵢ j), the distance from the nearest open EMS station is 10.7–13.9 km, about 4.2–7.4 km longer than the service standard (i.e., 6.5 km). The urban-rural difference in received service level ranges from 33.7% to 38.5%.

The selected sites of Pareto-optimal solutions are presented in Fig. 4, and there are thirteen unique locations. The labels next to the selected sites are the values of t, indicating the solutions that each site belongs to. For example, the site in the northernmost part of Huangpi is included in nine solutions, (Sᵢ, t = 1 – 8, 10). Apart from the site in Hongshan, all the other sites selected are located in the rural area, with three near the urban-rural fringe (two in Dongxihu and one in Jiangxia). Among the six rural districts, Huangpi has the most sites selected (i.e., five), with four contained in at least six solutions (except the one that only belongs to S₁₈). Caidian and Dongxihu each have two sites selected. The remaining

\[^1\] In China, hospitals in cities are mainly classified into a 3-tier system: primary (Level I), secondary (Level II) and tertiary (Level III), with higher level representing larger capacity and better service quality.
three rural districts only contain one site in each of the associated solutions. There are two sites included in all the Pareto-optimal solutions—one in Jiangxia but near Hongshan and the other in the east of Hannan, close to the border with Jiangxia.

To understand how the inclusion of inequality objectives affects the overall service coverage, Figs. 5 and 6 plot $Z_2$ and $Z_3$ against $Z_1$, respectively. In Fig. 5, the ATDs derived from $Z_2$ are presented in addition to the TWD. It can be observed that the increase in total covered population is at the cost of an increase in the TWD as well as the ATD of uncovered rural population. $S_1$ guarantees the shortest ATD, 10.7 km, to the nearest open EMS station for uncovered rural population, but it also has the lowest percent of the total covered population, 69.9%. In contrast, $S_{18}$ achieves the maximum population coverage, 72.6%, but has the longest ATD, 13.8 km. The increase of the total covered population from $S_4$ to $S_5$ is the largest (about 0.8%) when compared to changes between other consecutive solutions. For ATD, the biggest
increase is from $S_{13}$ to $S_{14}$, with a value of 0.7 km.

In Fig. 6, in addition to the values of $Z_1$ (converted to percentages) and $Z_3$, two additional types of values are shown: the share of covered population in urban ($W_u$) and rural ($W_r$) areas. Again, $S_{13}$ has the highest coverage of the total population, 72.6%, as well as the largest difference in urban-rural covered population, 38.4%. $S_{14}$ has the minimum level of urban-rural inequality in service coverage, 33.7%, while the coverage of the total population reaches 72.3%. Unlike the trend shown in Fig. 5, where $Z_1$ and $Z_2$ change in the same direction, in Fig. 6 $Z_6$ initially decreases with the increase of $Z_1$ before reaching a minimum value of 33.7%, and then increasing again as $Z_6$ increases. Meanwhile, the value of $W_u$ increases from 88.9% to 92.3%. However, the value of $W_r$, rises from 51.8% ($S_{13}$) to 55.9% ($S_{13}$) and then drops to 53.8% as $Z_6$ increases. It can be observed that from $S_{13}$ to $S_{14}$, the decreases in both $W_u$ and $W_r$ contribute to the growth of the overall covered population, but the latter grows faster than the former, which leads to the reduced urban-rural inequality in service coverage. From $S_{13}$ to $S_{18}$, the increase of total service coverage is attributed to the growth of $W_r$ when $W_u$ decreases or keeps unchanged, resulting in larger gaps in service coverage between urban and rural areas.

### 4.3.2. Examining the maximum service coverage and the minimum urban-rural inequality

Figs. 5 and 6 suggest that $S_{18}, S_1$ and $S_{14}$ give the optimum value of $Z_1$ (72.6%), $Z_2$ (10.7 km – ATD) and $Z_3$ (33.7%), respectively. The geographic locations of new EMS stations for $S_1, S_{14}$ and $S_{18}$ are depicted by Fig. 7. The selected sites for $S_{18}$ are in six different districts, with only one in the urban area (i.e., Hongshan). Two stations are near the urban-rural border: one in Dongxihu and the other in Jiangxia. The other three are in Caidian, Huanan and Xinzhou, respectively. As a result, the overall service coverage reaches 72.6% of the total population, an increase of 9.3% compared with current service provision. In particular, 92.3% of urban population and 53.8% of rural population can be reached by an ambulance within the service standards, an increase of 3.4% and 14.9%, respectively.

As Objectives (2) and (3) are to reduce urban-rural inequality through improving accessibility of uncovered rural population and decreasing urban-rural difference in received service coverage, respectively, it is not surprising that all the selected sites for new stations of $S_1$ and $S_{14}$ are in rural districts. For the six new stations in $S_1$, three are in Huangpi and one is in each of Caidian, Huanan and Jiangxia. Accordingly, the ATD of $S_1$ is reduced to 10.7 km from 15.7 km of current service deployment, though this is still 4.2 km longer than the service standard (i.e., 6.5 km). $S_{14}$ has one new station in each of the six rural districts, and the corresponding urban-rural inequality in service coverage is decreased to 33.7% – a deduction of 16.3% compared with existing service configuration. It is worth noting that the selected sites in Huanan and Jiangxia (one for each) are included in all three solutions.

### 5. Discussion

This research develops a multi-objective optimization model for siting EMS stations, attempting to reduce urban-rural inequalities in service accessibility and coverage. Multi-objective models are often necessary for seeking the balance between service provision and equality. The objectives of service provision are often tackled via coverage or median problems (i.e., maximizing service coverage or accessibility for the entire study area) (e.g., Refs. [17, 41]), and the objectives of equality are usually approached by minimizing inequality measures such as range, variance or mean deviation of the travel costs (e.g., Ref. [23]). Those two types of objectives can conflict with each other. For example, in this research, on the one hand, optimizing Objective (1) alone favors the more densely populated (urban) area, leaving the more sparsely populated (rural) area with worse access to services. On the other hand, minimizing the inequality measures alone, Objective (2) or (3), often contradicts the goal of maximizing service provision. An extreme illustration would be that EMS stations are located infinitely further away from the city, so everyone has the same geographic accessibility. The trade-offs between conflicting objectives are often explored by the Pareto-optimal solutions, as shown in Figs. 3, 5 and 6. For instance, when the uncovered rural people have the smallest ATD (10.7 km), 69.9% of the total population is covered; when the maximum overall service coverage (72.6%) is achieved, the corresponding ATD increases to 13.8 km (see Fig. 5). This is consistent with the previous findings that improvement of EMS equality is often at the expense of decreases in the overall service coverage (e.g., Refs. [17,23]).

Due to the inherent time-sensitivity of emergency services, service standards – defined in either distance or time – are commonly adopted in location modeling of EMS stations and the maximal service coverage is often pursued. This, however, does not mean that people living further away from stations than the service standard will not receive services. One way to improve service accessibility of the uncovered population is to reduce their TWD as much as possible with the available facilities [43]. This is implemented by Objective (2) in this research. Unlike the formulation in Church et al. [43], which concerns the uncovered demand in an entire region, only the uncovered rural population is considered here to reduce urban-rural inequality in EMS accessibility. Further, compared with work by Chanta et al. [17], which adopted the objective of center problems (i.e., minimizing the maximum distance between uncovered demand zones and their closest EMS stations), Objective (2) involves the whole uncovered rural population rather than individual users/communities, therefore better reflecting the meaning of equality.

Unlike Objective (2) which only focuses on rural population, Objective (3) explicitly considers the disparity between urban and rural areas, represented by the difference in achieved service levels (i.e., the proportions of covered population). As patient survival rate in rural areas is often lower than that in urban areas [2,4], a common practice in EMS location optimization when focusing on reducing urban-rural inequality is to increase the service provision to rural areas (e.g., Refs.
Objective (3) provides an alternative inequality objective that can be adopted in EMS location optimization. In addition, an acceptable level of urban-rural inequality (i.e., $Z_3$) can be achieved through the solution procedure with a pre-specified parameter $\varepsilon_{Z_3}$. Objective (3) also can be formulated as minimizing the proportion of uncovered rural population. Compared with the number of uncovered rural demand zones adopted by Chanta et al. [17], the proportion of covered population in McLay and Mayorga [23] and Objective (3) arguably better reflects the actual demand (i.e., population) under concern.

This research has important policy implications. First, in the current spatial layout of EMS stations, the proportion of the urban population within the service standard is more than twice as high as in the rural population. When the overall service coverage is more of concern, Fig. 4 suggests that at most one of the six new stations should be sited in the urban areas (i.e., Hongshan). Second, if higher urban-rural equality in EMS is pursued, each of the two rural districts – Hannan and Jiangxia – needs at least one new station (see Fig. 4). Fig. 4 also suggests that a new station in Dongxiu near the urban-rural fringe is desirable. Finally, the findings from Figs. 5 and 6 can help policy makers explore various trade-offs between service provision and urban-rural equality. For example, if comparing $S_4$ and $S_5$ (see Fig. 5), the ATD of the uncovered rural population of $S_5$ is only 0.2 km (from 11.0 km to 11.2 km) longer than that of $S_4$, but the stations of $S_5$ can cover 0.8% (from 70.3% to 71.1%) more of the total population, which is equivalent to about 98,400 people. Hence, $S_5$ is often preferable in practice.

There are limitations to this research. One is the specification of candidate EMS station locations and underlying demands for services. It is possible that new EMS stations could be sited in locations other than at the 125 existing hospitals. This could be achieved by site suitability analysis which requires knowledge of urban development plans and

![Fig. 4. Selected sites for new EMS station (all solutions).](image-url)
land-use restrictions in Wuhan. In addition to population, additional weights could be assigned to the demand points to represent the proportions of vulnerable people (e.g., with heart disease) who are more likely to use EMS, thereby better reflecting the spatial variations in need. Again, this requires personal health information and historical EMS records. A further limitation is that fixed travel distances were employed to represent the service standards for both urban and rural areas. In practice, the travel distance can vary within the response time threshold (e.g., 10 or 12 min for the case of Wuhan) due, for example, to different traffic conditions [5], road types or weather. Historical ambulance trajectories can help improve the estimation of the travel distance in a specified response time.

There are several potential extensions of this work. One is to increase the number of new EMS stations to be sited. As indicated by $S_{18}$, the maximum coverage that can be achieved with six new stations is 72.6% of the total population, with 27.4% of the population still outside of the service standards. Thus, it would be worth exploring how much more population can be covered by additional siting stations, based on either the existing 125 candidate locations or other new sites. This could be achieved by increasing the value of $p$ in Constraint (4). Another extension would be to relocate existing stations, rather than create new ones, to meet the changing spatial distribution of underlying demand. With the progress of urbanization in China, particularly in big cities like Wuhan, more and more people are moving to new towns in the suburbs drawn by new job opportunities and more affordable housing. Examples of the work along these lines can be found in Schilling et al. [49] and Yao et al. [50]. Further, as there is a lack of consensus on the inequality measures in relation to EMS systems, it would be worth exploring the optimal spatial configuration of EMS stations based on other indicators of inequality. Again, in addition to service accessibility and coverage, the dimensions of inequality can be extended to ambulance availability and health outcomes, as well as the workload of EMS stations or...
ambulances.

6. Conclusions

This research proposes a multi-objective optimization for siting EMS stations with a consideration of urban-rural inequalities. EMS remains a fundamental public service and plays an important role in saving lives, particularly in the context of the current COVID-19 pandemic. This research demonstrates how urban-rural inequalities in EMS could be reduced by using spatial optimization approaches. This is achieved through a multi-objective optimization model which aims to minimize two measures of the disparities in EMS between urban and rural areas: the TWD of the uncovered rural population (i.e., accessibility) and the urban-rural disparity in the covered population (i.e., coverage), in addition to maximizing the total covered population. 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.

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

The datasets used and analysed during the current study are
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Authors’ contributions

WcL and JY designed the research. RM and WqL assisted in the research design. WcL and XZ performed the analysis and programming. JY and RM oversaw the completion of the study. WcL and XZ prepared the manuscript. All authors read and approved the final manuscript.

Declaration of competing interest

The authors declare that they have no competing interests.

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