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Influence of Urban Flooding on the Spatial Equity of Access to Emergency Medical Services Among Nursing Homes in Shanghai

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Abstract: With the rapid aging of the population and increasing demand for elderly care services, ensuring equitable access to emergency medical service (EMS) for nursing homes has become a critical public health challenge. As the first Chinese city to experience an aging society, Shanghai faces compounding pressures from rapid urbanization and recurrent urban flooding, both of which exacerbate disparities in healthcare accessibility. This study investigates the spatial equity of EMS access among nursing homes in Shanghai, with a particular focus on the impacts of urban flooding. Using ordinary least squares and geographically weighted regression models, the study reveals that EMS accessibility is relatively equitable under normal conditions but deteriorates significantly during flood events, particularly in suburban and low-lying areas. The findings show that flood-induced disruptions to road networks disproportionately impact nursing homes in peripheral districts, widening accessibility gaps. Additionally, the study identifies that factors such as road density, emergency center distribution, and flood inundation depth play critical roles in shaping spatial equity. The results underscore the need for strategic interventions to enhance healthcare resilience, including optimized facility allocation and flood-resistant infrastructure. Policymakers should adopt integrated planning approaches to ensure equitable EMS access for vulnerable elderly populations during emergencies.

Keywords: nursing home; flood; spatial equity; accessibility; emergency medical service

Academic Editor: Dianfeng Liu

Received: 24 December 2024
Revised: 26 January 2025
Accepted: 29 January 2025
Published: 2 February 2025

Citation: Zhou, X.; Wang, S.; Yao, S.; Fang, L. Influence of Urban Flooding on the Spatial Equity of Access to Emergency Medical Services Among Nursing Homes in Shanghai. *Land* **2025**, *14*, 309. https://doi.org/10.3390/land14020309

1. Introduction

In recent decades, an aging population has emerged as a profound social challenge faced by nations worldwide [1–3]. According to United Nations projections, the number of individuals aged 65 and above is expected to surpass those aged 15–24 by 2050 [4]. This shift is particularly pronounced in China, where the latest national census reports that 13.50% of the population is aged 65 and above—a figure that continues to rise [5]. As aging progresses, the prevalence of chronic illnesses and age-related disabilities increases, necessitating the professional care that nursing homes are designed to provide [6–9]. Concurrently, changing family structures and evolving societal attitudes have fueled the demand for institutional elderly care [10,11]. Despite efforts by the Chinese government to expand and improve nursing home services, challenges persist, particularly in the spatial distribution and resource allocation of these facilities, leading to inequities in access to high-quality care.

Extensive research has been conducted on the spatial distribution of nursing homes, covering aspects such as spatial characteristics [12–14], accessibility [15–17], and facility allocation [18–22]. Despite progress, regional disparities remain due to differences in economic development, healthcare infrastructure, and the proportion of elderly populations. Achieving spatial equity in nursing home accessibility is crucial to ensuring that elderly individuals, particularly those in economically disadvantaged or remote areas, have equal access to essential healthcare services [23].

Spatial equity in public services has attracted significant attention in recent years [24–28]. Unlike mere uniform distribution, spatial equity emphasizes the fair allocation of public resources based on demographic, socioeconomic, and geographic factors [29–31]. In the context of an aging society, ensuring equitable access to elderly care services is essential for public health planning and social cohesion. However, existing studies have primarily focused on the spatial distribution of nursing homes themselves, while little attention has been given to the accessibility of emergency medical service (EMS), which is vital during health emergencies [15,32,33]. The increasing demand for EMS in nursing homes underscores the importance of addressing spatial disparities [34,35]. Timely EMS access is crucial for safeguarding elderly residents' health, yet unequal access can place vulnerable individuals at risk [36–39]. Despite its significance, research on the spatial equity of EMS access for nursing homes remains limited.

Extensive research has examined the various factors influencing EMS response times and service satisfaction, encompassing policy frameworks, internal system operations (e.g., staffing levels and vehicle dispatch efficiency), transportation infrastructure, resource distribution, and patient-related characteristics [40–42]. However, extreme weather events driven by climate change, such as flooding, present growing challenges to the resilience of EMS systems [43], raising widespread concerns [44]. Floods can severely disrupt urban transportation networks, damage infrastructure, reduce traffic capacity, and cause delays, all of which can weaken the overall emergency response system [45–47]. In severe cases, road blockages may completely halt EMS operations in certain areas, further widening disparities in access to medical assistance for nursing homes and preventing timely healthcare delivery to elderly residents. Therefore, it is crucial to comprehensively investigate the impact of urban flooding on the spatial equity of EMS access for nursing homes. Such an investigation is essential not only for optimizing resource allocation but also for strengthening healthcare system resilience and ensuring the safety and well-being of the elderly during disasters. Despite its importance, this issue remains underexplored.

To address these gaps, this study examines the spatial equity of EMS accessibility for nursing homes in Shanghai, considering the impacts of urban flooding. Using ordinary least squares (OLS) and geographically weighted regression (GWR) models, the study assesses accessibility patterns at the township level and investigates key influencing factors, including road network characteristics and flood severity levels. The findings aim to provide strategic insights for optimizing healthcare infrastructure, strengthening flood resilience, and ensuring equitable healthcare access for elderly populations.

Although this research focuses on Shanghai, its methodology and findings are applicable to other flood-prone urban areas, including coastal cities affected by storm surges and inland regions prone to river floods. These areas share common challenges, such as aging populations and complex urban networks vulnerable to service disruptions.

Additionally, the study offers insights and adaptable frameworks that can be extended to other disruption scenarios, such as traffic congestion and natural disasters.

The remainder of this paper is organized as follows: Section 2 outlines the data sources and methodological framework, Section 3 presents the study findings and a discussion, and Section 4 concludes with policy recommendations and future research directions

2. Study Area and Data

2.1. Study Area

As depicted in Figure 1, the study area, Shanghai, is a significant urban center located at the Yangtze River estuary in China, covering an approximate area of 6340 square kilometers and with an average elevation of 2.19 m above sea level. It shares its western boundary with Jiangsu and Zhejiang provinces and is bordered by water on its eastern, southern, and northern fronts. Shanghai's coastal location, well-developed transportation infrastructure, and expansive economic hinterland have established it as a pivotal hub in the international economy, finance, trade, shipping, and science and technology sectors [48]. However, Shanghai is also confronting multiple challenges posed by population aging, rapid urbanization, and climate change.

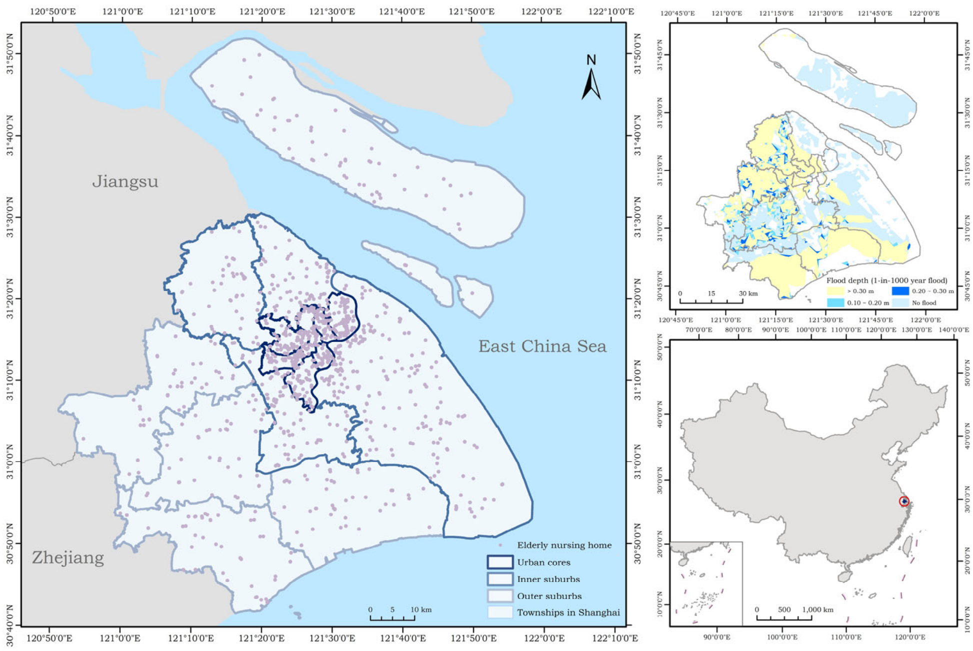


Figure 1. The study area of Shanghai.

The city's climate is predominantly subtropical monsoon, characterized by frequent interactions of warm and cold air masses. Shanghai is susceptible to multiple types of flooding due to its low elevation, coastal proximity, and urban development [49,50]. The major types of floods include river floods caused by the overflow of rivers such as the Huangpu River, typically occurring during heavy rainfall upstream or storm surges, coastal flooding due to strong winds and low atmospheric pressure induced via storm surges and typhoons, and flash floods resulting from intense, short-duration rainfall events, often exacerbated by Shanghai's high percentage of impervious surfaces and inadequate drainage capacity in some areas [51]. The duration of flood-induced inundation varies, depending on the flood type and severity. Flash floods typically subside within hours to a few days, whereas river or coastal flooding can persist for days. Historical flood records for Shanghai highlight the increasing frequency and intensity of flood events. For instance, Typhoon Gloria in 1949 breached a 25-km seawall in Shanghai, resulting in severe flooding with inundation depths of up to 2 m, the collapse of over 18,000 houses, and 1670 fatalities across urban and suburban areas [52]. More recently, during Typhoon Winnie in 1997, the occurrence of a "triple threat"—typhoon rainstorms, storm surges, and astronomical tides—caused record-high water levels at major tidal stations along Shanghai's coast and rivers, leading to widespread flooding and affecting over 150,000 people with severe losses [53]. In 2007, Typhoon Wipha led to significant coastal flooding, with water levels surpassing warning thresholds. In 2013, Typhoon Fitow brought an unprecedented daily rainfall of 156 mm, paralyzing road and subway traffic during peak hours [54]. In 2019, Typhoon Lekima caused cumulative rainfall of 150 to 250 mm in most areas of Shanghai, resulting in 43 underpass inundations, 389 road waterlogging cases, and 409 flooded residential communities [55]. In 2021, extreme rainfall resulted in urban waterlogging in low-lying areas. These flooding events not only result in significant property damage but also paralyze urban infrastructure and hinder socioeconomic development. In this context of increasingly frequent extreme weather events, the resilience of urban infrastructure, particularly the EMS system, is under significant strain.

In addition, Shanghai is the first Chinese city to transition into an aging society, with one of the highest levels of aging in the country. Recent demographic data reveal that the population aged 65 or above in Shanghai has reached 4.3792 million, representing 28.8% of the city's total population, a figure that continues to rise [56]. Furthermore, by the end of 2023, the elderly dependency ratio in the city had reached 47.8%, markedly exceeding the national average. The combination of aging, a declining birth rate, smaller household sizes, and a rising proportion of elderly living alone or in "pure" elderly households has resulted in escalating social and familial burdens, with growing demands for elderly care services and healthcare support. While Shanghai has been a leader in addressing the challenges of aging [57], there is still considerable room for improvement in its elderly care system, particularly in terms of the equitable allocation of elderly care resources. Several studies and reports have highlighted the pronounced regional disparities in the distribution of nursing homes within Shanghai, leading to inequity of access to elderly care services for regional populations [39,58]. These disparities not only affect the daily care of the elderly but may also be exacerbated during extreme weather events, potentially leading to shortages of EMS and delays in response in certain regions, thereby threatening the health and safety of the elderly.

Therefore, this study focuses on elderly residents of nursing homes in Shanghai who require EMS. Using a newly proposed framework for equity measurement and evaluation, this study analyzes the spatial equity of access to EMSs among nursing homes under different flood scenarios.

2.2. Data

The datasets employed in this research include data on nursing homes, emergency centers, floods, and road networks. Specifically, the data on nursing homes and emergency centers were obtained from the Search Service API of AutoNavi Map [59], which provides detailed information on different types of points of interest, including the name, address, and geographic coordinates (latitude and longitude) of facilities. To further enhance data completeness and accuracy, we supplemented this dataset with additional information on nursing homes sourced from the official website of the Shanghai Civil Affairs Bureau [60]. Specifically, we conducted a thorough comparison and integration of the two datasets. Missing information in the AutoNavi API data, such as facility types, was systematically supplemented using authoritative data from the Civil Affairs Bureau. After careful geo-coding and validation, 1081 nursing homes and 152 emergency centers were identified in this study. The road network shapefiles were sourced from

OpenStreetMap [61] and reflect the state of Shanghai's road network characteristics. The three datasets reflect the infrastructure as of 2023, ensuring temporal consistency.

Flood data were obtained from the World Resources Institute's Aqueduct Floods tool [62], which provides raster datasets of flood inundation depths under different scenarios. The data were produced based on the Global Flood Risk with IMAGE Scenarios (GLOFRIS). The GLOFRIS model integrates climate data from multiple global climate models, including GFDL-ESM2M, enhancing the diversity and scientific robustness of flood risk projections. By incorporating SSP-RCP climate scenarios, the model provides a comprehensive assessment of future climate change impacts on flood risks. However, GLOFRIS does not explicitly incorporate local flood protection infrastructure (e.g., drainage systems), which may lead to an overestimation of flood risk in well-protected areas. It also relies on assumptions about future climate scenarios, introducing uncertainties, particularly regarding the frequency and intensity of extreme precipitation events. Despite these limitations, the model demonstrates significant advantages in simulating large-scale flood risks under various climate scenarios. It is particularly suitable for assessing flood risks in flood-prone urban areas such as Shanghai.

Given that global warming and rapid urbanization have intensified climate system instability—significantly increasing the frequency and severity of extreme flood events—this study focuses on 25-year, 100-year, and 1000-year riverine floods. The flood predictions were derived for the year 2030 under the SSP-RCP 245 scenario. We chose SSP-RCP 245 mainly because SSP-RCP 245 represents a "middle-of-the-road" scenario combining moderate socioeconomic development and greenhouse gas mitigation. This scenario aligns with Shanghai's current climate policies and development trajectory, which aim for balanced growth while addressing climate change risks. The scenario provides flood predictions that are realistic and actionable for urban environments of rapidly urbanizing cities like Shanghai. Additionally, the flood data under SSP-RCP 245 were readily available and provided robust predictions of flood inundation for a range of return periods (25-year, 100-year, and 1000-year floods). This allowed for consistent modeling and analysis across scenarios.

The flood database only provides projections for the years 2030, 2050, and 2080, with a baseline year of 2010. For the purpose of this study, we utilized the 2030 projection, which best aligns with the timeframe of the other datasets (2023). Additionally, while this dataset represents a future projection, its use was justified by the need to model potential impacts under climate change scenarios. The 2030 flood projections align with the study's focus on planning for EMS accessibility. The flood data were overlaid onto the road network shapefiles using GIS tools to identify flood-impacted road sections. Previous research such as that of Yu et al. [44] and Pregnolato et al. [63] indicates that, at a depth of 30 cm, most vehicles lose stability and begin to float, making safe driving impossible; hence, this study considered flood depths exceeding 30 cm as a significant impedance to road functionality.

3. Methodology

The methodological framework of this study, as illustrated in Figure 2, consists of three primary components: spatial accessibility, spatial equity, and influencing factors of spatial equity. First, this study employs accessibility analysis to evaluate the capacity of nursing homes to access EMSs under different weather conditions, including normal and flood scenarios. Subsequently, spatial equity is assessed from both global and local perspectives using the Lorenz curve and Gini coefficient, as well as location entropy to capture disparities in EMS access among nursing homes. Finally, this study applies OLS and GWR models to identify the factors influencing spatial equity and to investigate the impact of flooding on the spatial equity of access to EMS.

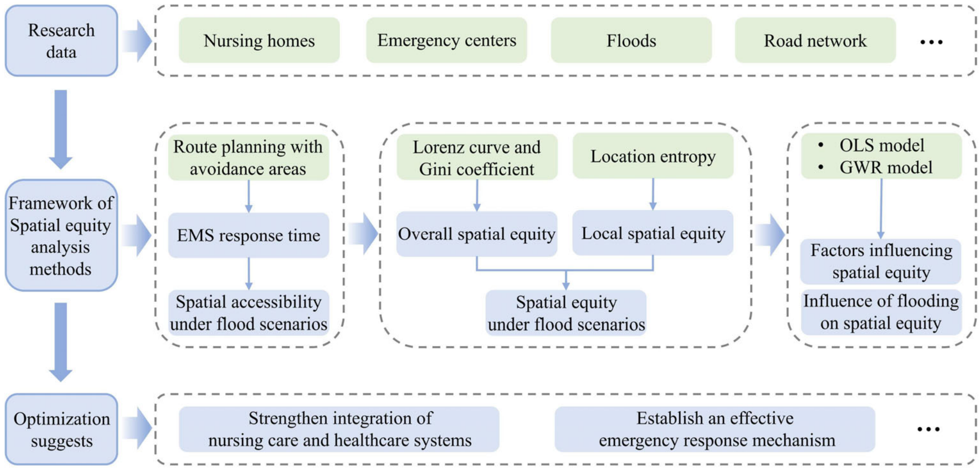


Figure 2. Research framework.

3.1. Measurement of EMS Accessibility

Accessibility fundamentally refers to the ease with which one can travel from one location to another. Based on the urgency of the services provided, public facilities are typically categorized into emergency and non-emergency types [64]. Given that emergency centers fall under the category of emergency facilities, for which response time is critical, selecting indicators that accurately reflect timeliness is essential. Commonly used methods for measuring accessibility include the proportional method [65], the nearest distance method [66], the cumulative opportunity method [67], and the spatial interaction-based method [68]. For facilities with high timeliness demands, such as emergency centers, the nearest distance method has been widely applied due to its effectiveness in evaluating spatial accessibility. Therefore, this study adopts the shortest travel time as the core indicator to measure EMS accessibility.

This study calculates the EMS response time under normal weather and various flood scenarios to measure EMS accessibility. Currently, the drainage capacity in Shanghai's urban area is 36 mm/h, designed to withstand a one-in-a-year rainfall event. In the central business district areas, drainage systems are designed for 49.6 mm/h or 56.3 mm/h, capable of handling three-year or five-year rainfall events [69,70]. However, due to the increase in extreme weather in recent years and land subsidence caused by urban development, the drainage system's functionality has deteriorated. This has significantly weakened Shanghai's ability to respond to sudden flood disasters. For this study, we assume a worse-case duration of inundation, with areas inundated for more than 30 cm treated as having significant access impedance and drainage capacity set to 36 mm/h. The term "normal weather" refers to non-flood conditions under which the EMS system operates without significant disruption caused by extreme weather events such as heavy rainfall, riverine flooding, or coastal flooding. Specifically, it represents a baseline scenario where no significant inundation (flood depths >30 cm) is observed within the road network and accessibility to EMS facilities is only influenced by standard road network characteristics, traffic flow patterns, and facility distribution.

We utilized AutoNavi Map's Path Planning API to determine the fastest driving routes from emergency centers to nursing homes, acknowledging the critical importance of timeliness in emergencies. The API allows users to define impedance. Under flood scenarios, areas submerged more than 30 cm deep were treated as impedance. The flooded road sections were identified by overlaying the road network with flood data. In cases where severe flooding obstructed all routes, the response time was estimated by predicting the time required for floodwaters to recede until at least one travel route could be detected [69].

3.2. Measurement of Spatial Equity

The study assesses the spatial equity of EMS accessibility based on the emergency response times from emergency centers to nursing homes. The evaluation relies on two stages. The first stage involves using the Lorenz curve and Gini coefficient to quantify the overall spatial equity of EMS accessibility under different scenarios. The Lorenz curve is plotted using the cumulative percentage of nursing homes against their cumulative capacity to access EMSs. The Gini coefficient can be further calculated using the Lorenz curve, which is calculated as follows:

$$Gini = 1 - \sum_{k=1}^{n} (A_k - A_{k-1})(B_k + B_{k-1}) \tag{1}$$

where A_k is the accumulative percentage of nursing homes, $k = 0, \ldots\ldots, n,\ A_0 = 0,\ A_n = 1$; B_k is the accumulative percentage of the capacity of nursing homes to obtain EMSs, $k = 0, \ldots\ldots, n,\ B_0 = 0,\ B_n = 1$. The Gini coefficient value ranges from 0 to 1. A value closer to one indicates greater inequity.

In the second stage of spatial equity evaluation, location entropy is applied to assess the degree of spatial matching between nursing homes and emergency centers at the township level. Townships are administrative units widely used in Shanghai for urban planning and resource allocation. They represent the operational level at which many healthcare and emergency services are managed. The use of township-level analysis ensures that the findings are directly relevant to decision-makers and can be easily integrated into policy planning and disaster preparedness strategies.

Location entropy is an index used to measure the spatial distribution of specific elements within a region and their relative importance or role within a larger area. It is widely applied in analyzing the spatial equity patterns of public service facilities. In this study, location entropy is employed to assess the spatial matching between nursing homes and emergency medical centers at the township level, thereby evaluating the spatial equity of access to EMS among nursing homes. The premise of the location entropy is that longer or shorter rescue times indicate greater deviation from the average level of access to EMS. Specifically, a location entropy value close to 1 indicates that the accessibility of EMS for nursing homes in a given area is consistent with the overall average level across the entire study region, reflecting a higher degree of spatial equity. Conversely, the greater the deviation of the location entropy value from 1, the more significant the disparity in EMS accessibility for nursing homes in that area compared to the regional average, indicating lower spatial equity. The formula of location entropy is as follows:

$$LQ_i = \begin{cases} (T_i/P_i)/(\mathrm{T}/m), if\ (T_i/P_i)/(\mathrm{T}/m) \geq 1 \\ (\mathrm{T}/m)/(T_i/P_i), if\ (T_i/P_i)/(\mathrm{T}/m) < 1 \end{cases} \tag{2}$$

where LQ_i is the location entropy of the spatial unit (i.e., township) $i,\ i = 1, \ldots\ldots, m$. T_i is the accumulative capacity of nursing homes to obtain EMSs in a spatial unit i. P_i is the number of nursing homes in the spatial unit i. T is the accumulative capacity of nursing homes to obtain EMSs in the whole study area. m is the number of nursing homes in the whole study area.

Compared to the Lorenz curve and the Gini coefficient, which primarily reflect overall equity, location entropy provides a more detailed analysis of the specific spatial matching patterns between nursing homes and emergency centers. Therefore, this study adopts location entropy to analyze the spatial equity of EMS accessibility for nursing homes, offering a more intuitive and in-depth reflection of equity disparities across different regions.

3.3. Analysis of Factors Influencing Spatial Equity

This study employs both OLS and GWR for analyzing factors influencing spatial equity. The former is widely used as a foundational approach due to its simplicity and ability to reveal general trends across the study area; it was selected as the baseline model to provide an overview of the global relationships between the independent variables and the dependent variable. The latter was employed to account for spatial heterogeneity in the relationships observed in the OLS model; it offers localized insights into how the influencing factors of spatial equity differ across townships in Shanghai.

3.3.1. Variables

This study employs location entropy values under different weather scenarios as dependent variables. The independent variables are designed to capture areal features, with a primary focus on the characteristics of the road network. Key variables include *NoEMS* (the number of EMS centers), *NoNH* (the number of nursing homes), *RdLen* (road length), and *JunRd* (junction density). To further investigate the influence of varying flood severities on spatial equity, this study incorporates flood inundation depth under different return periods as additional independent variables, including *Dep25*, *Dep100*, and *Dep1000*. Their descriptive statistics are shown in Table 1.

Table 1. Descriptive statistics of independent variables.

Variable Name	Description	Min	Max	Avg	Std.
NoEMS	No. of EMS centers	0	5	0.71	1.05
NoNH	No. of nursing homes	1	20	5.28	3.35
RdLen	Length of roads (1000 km)	15.70	951.03	155.34	92.23
JunRd	No. of junctions per 1000 km of roads	0.64	16.65	4.26	2.46
Dep25	The average depth of inundation under 1-in-25-year flood (m)	0.00	0.44	0.10	0.11
Dep100	The average depth of inundation under 1-in-100-year flood (m)	0.00	0.63	0.15	0.16
Dep1000	The average depth of inundation under 1-in-1000-year flood (m)	0.00	0.87	0.22	0.24

3.3.2. Ordinary Least Squares Regression

This study uses the OLS regression to model spatial equity and identify influencing factors. The specification of linear regression is as follows:

$$y_i = \beta_0 + \sum_{k=1}^{p} \beta_k x_{ik} + \varepsilon_i \quad (3)$$

where y_i is the location entropy, β_0 is the intercept, β_k is the coefficient for predictor k, and ε_i is the random error.

3.3.3. Geographically Weighted Regression

The GWR model is introduced in this research to account for spatial heterogeneity. The formula of the GWR model is as follows [71,72]:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \quad (4)$$

where y_i is the location entropy, u_i and v_i are the coordinates of the centroid of spatial unit i, $i = 1, \ldots\ldots, m$. $\beta_0(u_i, v_i)$ is the local intercept, $\beta_k(u_i, v_i)$ is the local coefficient for predictor k at spatial unit i, and ε_i is the random error.

GWR is more sensitive to the bandwidth than the weight function. In this study, we used the Adaptive Bi-square, the Golden section search, and the corrected Akaike information criterion to obtain the optimal bandwidth value. The formula of the bi-square function is as follows:

$$w_{ij} = \begin{cases} \left[1 - \left(d_{ij}/b\right)^2\right]^2, & if\ d_{ij} < b \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

where d_{ij} is the Euclidean distance between (X_i, Y_i) and (X_j, Y_j), b is the bandwidth. GWR4 software was employed to establish the model.

4. Results and Discussion

4.1. EMS Accessibility

The EMS response time was calculated for each nursing home under different scenarios to assess their accessibility. Based on the response time, nursing homes were categorized into five levels of EMS accessibility: high, relatively high, middle, relatively low, and low. This classification was determined using threshold response times of 8, 12, 15, and 30 min. This study adopted 8-min, 12 min, 15 min, and 30 min thresholds to classify EMS accessibility levels based on international standards and local policies. Specifically, the 8 min threshold is widely recognized as the "golden response time" for pre-hospital emergency care, which is critical for improving survival rates and reducing mortality among critically ill patients [73]. This benchmark has been adopted by numerous EMS systems worldwide as a key indicator for evaluating EMS response performance. Additionally, at the local policy level, the Shanghai Municipal Health Commission released the Shanghai 13th Five-Year Plan for the Development of Pre-hospital Medical Emergency in 2016, setting a target for the average EMS response time to be within 12 min by 2020 [74]. Data indicate that, by 2019, Shanghai's average EMS response time had been reduced to 15 min [70]. Furthermore, the 14th Five-Year Plan for Shanghai's Health Development (2021) reinforced this goal by mandating that the average EMS response time should be consistently maintained within 12 min, aiming to improve the efficiency and coverage of EMS services [75]. Lastly, the 30 min threshold was established to evaluate the extreme limit of EMS accessibility under severe conditions, such as major flooding. This threshold accounts for the impact of extreme weather and disasters on the urban transportation network and emergency medical systems, allowing for the identification of areas with inadequate resource allocation. Figure 3 illustrates the average EMS accessibility for nursing homes in each Shanghai township under normal weather conditions and varied flood scenarios.

The analysis reveals a marked variance in accessibility across different scenarios. Under normal conditions, about 80% of Shanghai's townships are able to meet the 12 min response time standard, as specified in Ref. [74]. However, EMS accessibility tends to decrease from the central urban area towards the inner and outer suburbs. Approximately 85% of the townships in the central urban area achieve EMS response times within 8 min. In contrast, only 43% of the inner suburbs and 24% of the outer suburbs meet this criterion. This finding underscores the stark contrast in EMS resource allocation between central urban areas and suburban regions, with the latter facing disproportionately greater pressure in meeting EMS demands.

The spatial distribution of EMS accessibility exhibits substantial changes with increasing flood severity. During a 1-in-25-year flood scenario, accessibility is notably diminished, especially in northwest Shanghai. The count of townships where nursing homes face response times exceeding 30 min surges to 60, a stark contrast to the three townships classified as low-accessibility under normal conditions. This implies that approximately 30% of townships experience a significant deterioration in EMS accessibility under this scenario, with delayed services posing a potential threat to the health and safety of the elderly in nursing homes. The situation further deteriorates in the 1-in-100-year flood scenario, with southern Shanghai also experiencing a notable decline in EMS accessibility. Compared to normal conditions, the townships capable of accessing EMSs within 12 min plummet from 157 to 82, while those unable to receive services within 30 min rise by 47%, indicating the intensifying spatial and scale-related challenges posed by flooding to EMS accessibility. In the most severe flood scenario, the increase in inundation depth significantly impedes road capacity. This leads to only 63 townships, that is, 47% under normal conditions, maintaining high or relatively high levels of EMS accessibility. The decline in this proportion reflects the systemic pressure that flooding places on the EMS resource distribution and service capacity, posing a potential risk of widening regional equity disparities.

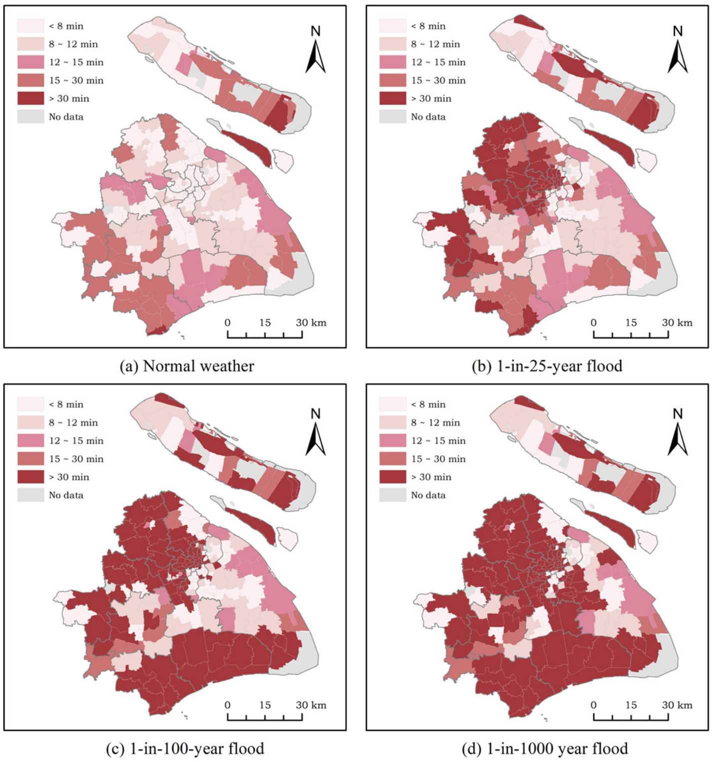


Figure 3. EMS accessibility for nursing homes under different scenarios: (**a**) normal weather; (**b**) 1-in-25-year flood; (**c**) 1-in-100-year flood; (**d**) 1-in-1000-year flood.

4.2. Spatial Equity of EMS Accessibility

4.2.1. Overall Evaluation of the Spatial Equity

This study utilized the Lorenz curve and Gini coefficient to evaluate the spatial equity of access to EMSs among nursing homes. The Lorenz curve, illustrated in Figure 4, represents the cumulative percentage of townships on the horizontal axis against the cumulative response time on the vertical axis. Under normal weather conditions, the Lorenz curve is relatively close to the diagonal, with a Gini coefficient of 0.295, indicating a relatively equitable and reasonable spatial distribution of EMS accessibility among nursing homes. This suggests that most nursing homes across different regions are able to access EMS with a comparable level of efficiency.

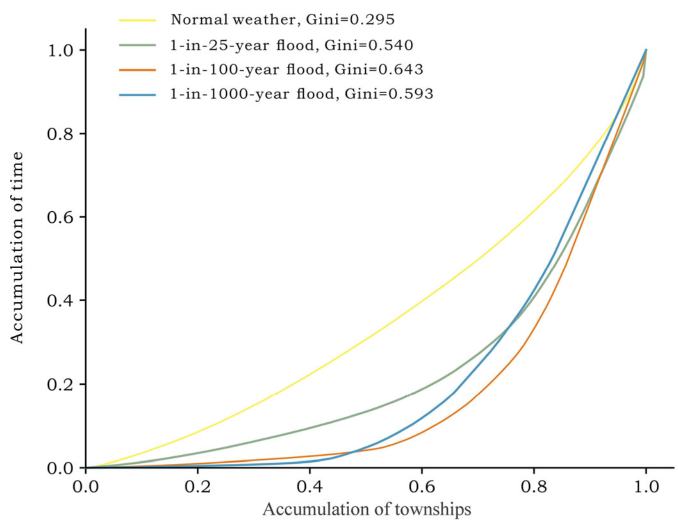


Figure 4. Lorenz curve for spatial equity of access to EMSs among nursing homes under different scenarios.

However, flood scenarios alter the situation significantly. In the 1-in-25-year flood scenario, the Gini coefficient rises to 0.540, reflecting a substantial reduction in overall equity among nursing homes. This inequity peaks in the 1-in-100-year flood scenario, with the Gini coefficient reaching its highest at 0.643, indicating an extreme spatial disparity. EMS resources become increasingly concentrated in a few regions, leaving many townships with nursing homes unable to access even basic EMS. Under such circumstances, the allocation of resources can be characterized as severely inequitable. In the 1-in-1000-year extreme flood scenario, the Gini coefficient slightly reduces to 0.593, indicating a marginal improvement in spatial equity, mainly because the flood inundation is widespread and severe, impacting a large proportion of the study area. This results in a generalized decline in EMS accessibility across most townships. As accessibility levels become uniformly poor, the relative differences between townships are reduced, leading to a lower Gini coefficient. In other words, while accessibility worsens across the board, the equity in poor accessibility increases due to the leveling effect of extreme disruption. The decrease in the Gini coefficient does not indicate improved service quality or equity in a positive sense. Instead, it reflects an "equalization" of disadvantage caused by extensive disruptions to EMS accessibility across all townships. This nuanced understanding reinforces the importance of addressing both equity and absolute service quality in disaster preparedness planning. The finding reveals the limitations of existing EMS infrastructure in responding to extreme flood scenarios, highlighting the need for resilient and adaptive systems.

Overall, the increase from 0.295 under normal weather conditions to 0.643 in the extreme flood scenario vividly illustrates the intensifying inequity in EMS accessibility for nursing homes caused by flooding. This impact is particularly evident in the trend of service centralization and the complete loss of EMS access in certain areas, posing significant challenges for EMS planning in flood-prone regions.

4.2.2. Spatial Equity at the Township Level

While the Lorenz curve and Gini coefficient provide an overview of overall equity, they do not detail the specific spatial matching patterns between nursing homes and emergency centers. To address this, location entropy was employed to analyze the spatial equity pattern of EMS access from nursing homes. We classified the location entropy values into five grades, with intervals set to 2, 3, 4, and 5, corresponding to the spatial equity levels of high, relatively high, middle, relatively low, and low.

As depicted in Figure 5, the distribution maps of location entropy under different weather scenarios further reveal distinct changes in the spatial equity of access to EMS among nursing homes. Under normal weather conditions (Figure 5a), the location entropy values of most townships are close to 1, with 161 townships (about 80%) falling into the highest equity grade, suggesting a relatively balanced distribution of EMS accessibility among nursing homes. This aligns with the Gini coefficient of 0.295, reflecting the relative equity of access to EMS in nursing homes. However, it is noteworthy that, despite the high concentration of elderly care and EMS resources in the central urban area, there are still individual townships with relatively low levels of spatial equity. This is counterintuitive and reveals a mismatch between resources and demand, indicating that the current resource allocation is still insufficient to meet the growing elderly care and healthcare needs driven by population aging.

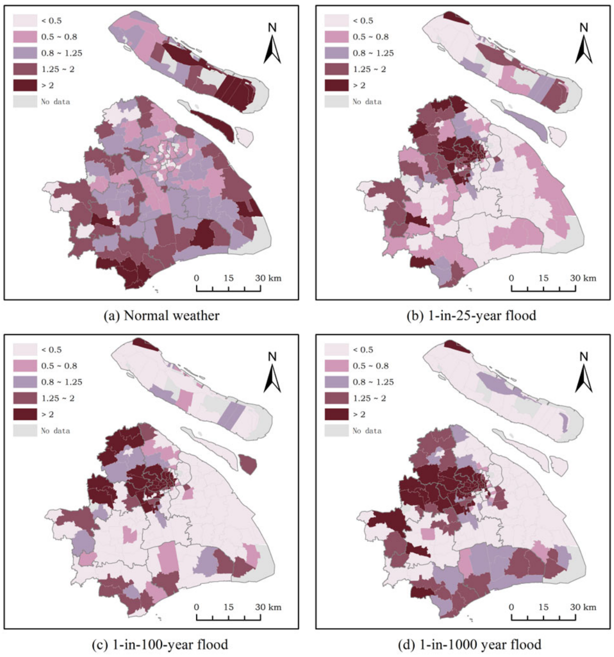


Figure 5. Location entropy distribution of access to EMSs from nursing homes under different scenarios: (**a**) normal weather; (**b**) 1-in-25-year flood; (**c**) 1-in-100-year flood; (**d**) 1-in-1000-year flood.

As flood severity increases (Figure 5b–d), the number of townships with lower location entropy values noticeably increases, and the inequity between regions intensifies. This trend underscores the impact of flood events on EMS accessibility, amplifying the spatial disparity in healthcare resource distribution. For instance, in the 1-in-25-year flood scenario (Figure 5b), only 70 streets remain in the high equity grade, while the count of townships in the relatively low and low equity grades rises from 3 to 97, marking a 46.53% increase from normal weather conditions. This change corresponds to the significant increase in the Gini coefficient from 0.295 to 0.540, indicating that flood events exacerbate the inequity in EMS access for nursing homes. In the 1-in-100-year flood scenario (Figure 5c), EMS access inequity worsens further. Most townships experience a greater deviation from 1 in location entropy. 52% of townships fall into the relatively low and low equity grades, which aligns with the Gini coefficient rising to 0.643, reflecting extreme inequity. Furthermore, in this scenario, the spatial distribution of townships in lower equity grades shifts significantly toward the eastern and central parts of Shanghai. This indicates that flooding significantly alters both the spatial distribution and the intensity of each location entropy grade. Flood interference in resource distribution causes EMS resources to concentrate in a few areas, while nursing homes in most townships face significant barriers to accessing EMS, highlighting the vulnerability of these regions. In the 1-in-1000-year extreme flood scenario (Figure 5d), the number of townships in the relatively low and low equity grades decreases from 52% in the 1-in-100-year flood scenario to 41%. This aligns with the Gini coefficient, which drops from 0.643 to 0.593. It is important to note that this apparent "improvement" is not an indication of better service equity but, rather, a result of the intensified flooding. The extensive inundation in this extreme scenario reduces EMS accessibility across a broad area to critically low levels, narrowing the relative disparities between regions, albeit without actual improvements in service availability.

Overall, these findings reinforce that flooding significantly exacerbates the inequity of access to EMS among nursing homes. The central urban area of Shanghai, along with townships in the northwest and south, retain relatively high levels of equity under various weather conditions, showing robust flood resilience and resource availability. In contrast, many townships in eastern and central Shanghai exhibit considerable vulnerability. The disruption caused by flooding not only affects the allocation of EMS resources but also exacerbates regional disparities in spatial equity. This highlights the severe challenges that floods pose to both regional equity and EMS planning. To mitigate these challenges, it is imperative to develop more targeted and flexible strategies for EMS resource allocation and post-disaster response.

4.3. Factors Influencing the Spatial Equity of EMS Accessibility

This study incorporates four independent variables, namely *NoEMS* (the number of EMS centers), *NoNH* (the number of nursing homes), *RdLen* (road length), and *JunRd* (junction density), into every model. Additionally, the independent variable Dep indicates the average depth of inundation under a specific circumstance. The VIF values of independent variables range from 1.03 to 1.23, indicating small collinearity. The dependent variable is location entropy, calculated under different weather scenarios, to assess the spatial equity of access to EMS among nursing homes. The analysis is conducted at the township level, with each township serving as a unit of analysis, where the spatial equity of EMS access and the associated variables are assessed.

4.3.1. Ordinary Least Squares Regression Results

Table 2 delineates the outcomes derived from OLS regression models. Under normal conditions, the variables *NoEMS*, *RdLen*, and *JunRd* exhibit significant impacts on spatial equity. The coefficients for *NoEMS* and *JunRd* are negative, indicating that an increase in the number of EMS centers and junction density markedly diminishes location entropy, thereby enhancing spatial equity. When variables pertinent to EMS centers, nursing homes, and junction density are held constant, it is observed that townships with more extensive road networks face disparities in accessing EMS.

Table 2. Results of ordinary least squares regression models.

Variable	Model Type							
	Normal		1-in-25-Year-Flood		1-in-100-Year-Flood		1-in-1000-Year-Flood	
	Coefficient	Sig.	Coefficient	Sig.	Coefficient	Sig.	Coefficient	Sig.
NoEMS	−1.21 ***	0.000	−0.24	0.287	0.034	0.908	−0.20	0.337
NoNH	−0.29	0.291	−0.27	0.303	−0.10	0.783	−0.10	0.685
RdLen	1.83 ***	0.000	−0.04	0.900	−0.55	0.160	−0.10	0.724
JunRd	−1.03 ***	0.000	0.12	0.699	0.81 **	0.044	1.03 ***	0.000
Dep	-	-	2.29 ***	0.000	3.51 ***	0.000	3.02 ***	0.000
(Constant)	1.19 ***	0.000	0.51 ***	0.000	0.07	0.672	0.06	0.588
R^2	0.40		0.45		0.54		0.65	

Note: ** $p < 0.05$; *** $p < 0.01$.

In the context of flood scenarios, the variable representing the average depth of inundation exerts a significant and positive influence on location entropy. This finding underscores that flooding exacerbates spatial inequity in EMS accessibility. Notably, in the 1-in-100-year and 1-in-1000-year flood scenarios, *JunRd* remains a significant determinant of location entropy. However, contrary to the normal condition model, its coefficient values are positive. This suggests that, in severe flood situations, townships with a higher junction density encounter increased challenges in accessing EMS services.

4.3.2. Geographically Weighted Regression Results

Table 3 presents the outcomes from the GWR models. The R^2 values from these models indicate a notable improvement in performance when employing the GWR technique, with the exception of the model for the 1-in-1000-year flood scenario.

Table 3. Results of geographically weighted regression models.

Model Type	Variable	Townships at the 95% Significance Level or Above (%)	Min	Max	Median
Normal (R^2: 0.66)	*NoEMS*	68.3	−2.003	−0.309	−0.491
	NoNH	3.5	−0.765	0.239	0.009
	RdLen	93.6	0.284	3.680	1.276
	JunRd	25.2	−2.835	−0.100	−0.234
1-in-25-year-flood (R^2: 0.58)	*NoEMS*	0.0	−0.474	0.026	−0.279
	NoNH	0.0	−0.720	0.446	−0.413
	RdLen	3.0	−1.091	1.287	−0.030
	JunRd	0.0	−0.761	1.008	−0.294
	Dep	96.5	0.495	2.764	2.552
1-in-100-year-flood (R^2: 0.60)	*NoEMS*	0.0	−0.191	0.306	−0.107
	NoNH	0.0	−0.544	0.512	−0.180
	RdLen	11.9	−1.214	−0.201	−0.793
	JunRd	20.3	−0.089	1.964	0.311
	Dep	100.0	3.160	3.924	3.694
1-in-1000-year-flood (R^2: 0.65)	*NoEMS*	0.0	−0.249	−0.186	−0.230
	NoNH	0.0	−0.252	−0.032	−0.189
	RdLen	0.0	−0.253	0.172	−0.090
	JunRd	100.0	0.756	1.209	0.920
	Dep	100.0	2.968	3.108	3.064

The variation in coefficients across the study area highlights the presence of spatial heterogeneity in how different factors influence the spatial equity of EMS accessibility among nursing homes across various townships in Shanghai. Specifically, under normal conditions, the number of emergency centers (*NoEMS*) and junction density (*JunRd*) exhibited significant negative correlations with location entropy in 68.3% and 25.2% of the townships, respectively. This suggests that increasing the number of emergency centers and enhancing road connectivity effectively improve EMS accessibility in certain regions, particularly in suburban areas where EMS resources are scarce. However, this effect was less pronounced in central urban areas, where the concentration of EMS facilities leads to diminishing marginal benefits from additional resources. In contrast, during flood scenarios, especially in the 1-in-100-year and 1-in-1000-year flood conditions, the average flood depth (*Dep*) became a dominant factor, significantly impacting spatial equity in 100% of the townships. This finding indicates that severe flooding disproportionately disrupts EMS accessibility, particularly in low-lying and flood-prone areas.

The spatial distribution of GWR coefficients suggests that the influence of independent variables varies across regions. For instance, while improved road connectivity enhances EMS accessibility under normal conditions, this advantage diminishes or even reverses during severe floods due to road network disruptions. Such spatial patterns highlight the need for region-specific strategies in EMS resource allocation and infrastructure planning, especially in areas more vulnerable to flooding.

4.4. Discussion

4.4.1. The Urban–Rural Divide Under Normal Weather

The analysis reveals that EMS accessibility under normal weather conditions is the most equitable among the four scenarios. This finding aligns with existing research, which indicates that transportation ease and supporting infrastructure are crucial in influencing the spatial differentiation of nursing homes [76]. However, the GWR results indicate that this relationship does not uniformly apply across all townships, particularly for the variables *NoEMS* and *JunRd*. Figures 6 and 7 illustrate the distribution and significance levels of these two variables. Townships exhibiting insignificant changes in *NoEMS* are predominantly situated in the urban core. In contrast, increasing the number of EMS centers in the outer suburbs appears to have a more pronounced effect on enhancing equity compared to inner urban areas. This disparity suggests a relative scarcity of EMS for the elderly in nursing homes in peripheral regions.

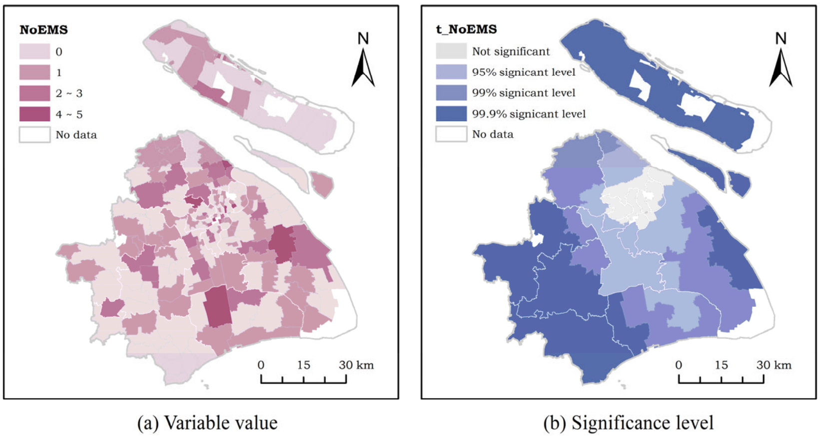


Figure 6. The variable value and significance level of *NoEMS* in the normal model: (**a**) variable value; (**b**) significance level.

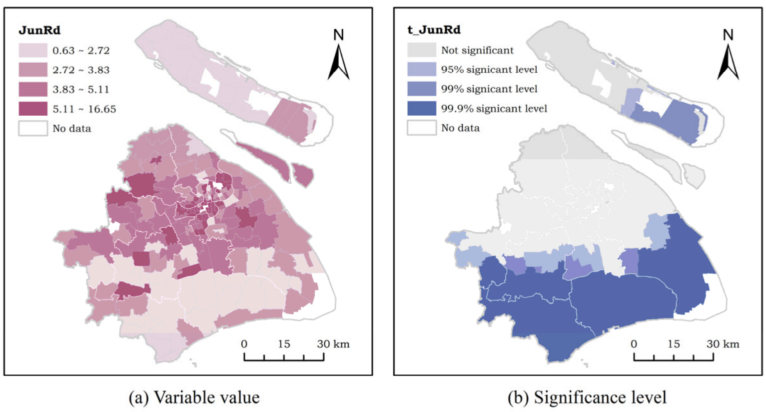


Figure 7. The variable value and significance level of *JunRd* in the normal model: (**a**) variable value; (**b**) significance level.

A similar divide is observed in the analysis of *JunRd*. Figure 7 reveals that townships with negative and significant *JunRd* values are mostly located in the southern outskirts of the study area, where junction density is comparatively lower.

4.4.2. Influence of Floods

Figures 8 and 9 provide pivotal insights into the influence of floods on spatial equity in nursing care, highlighting the significant findings of studies like Ref. [44]. Figure 8 displays the average flood inundation levels for each township under different flood scenarios, while Figure 9 details their corresponding significance levels and coefficients.

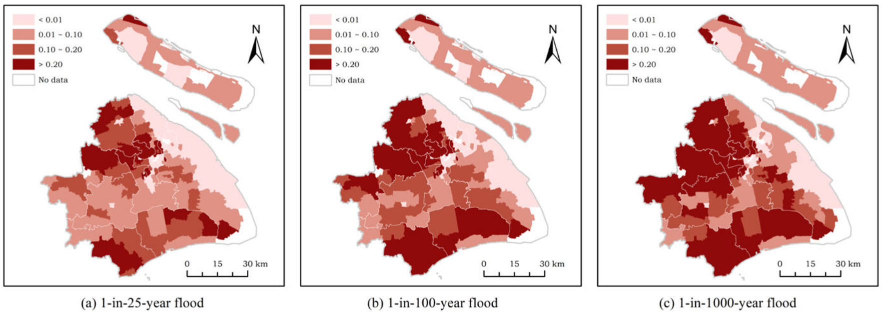


Figure 8. The variable value of *Dep*: (**a**) *Dep25*; (**b**) *Dep100*; (**c**) *Dep1000*.

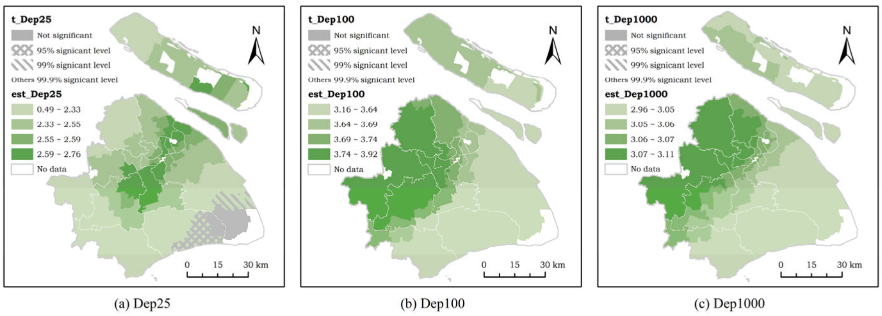
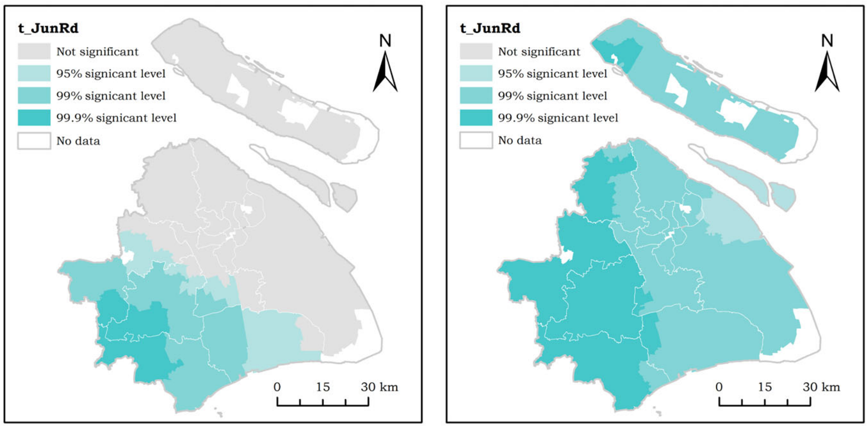


Figure 9. The significance level and coefficient values of *Dep*: (**a**) 1-in-25-year flood; (**b**) 1-in-100-year flood; (**c**) 1-in-1000-year flood.

The data indicate notable spatial heterogeneity in response to varying flood scenarios. In the 1-in-25-year flood scenario, townships within the urban core appear least affected by flood inundation, as illustrated in Figure 8a. Nevertheless, the distribution of coefficients in Figure 9a indicates a high sensitivity of EMS accessibility to flooding in these areas. As the severity of flooding escalates, the vulnerability of nursing homes to EMS accessibility issues becomes more pronounced, particularly in northwestern townships where flood inundation levels are substantial. This trend suggests the increasing risk faced by nursing homes in these regions as they struggle to maintain access to essential EMSs during severe flood events.

Flood events have a profound impact on road networks, significantly affecting their functionality and connectivity [69]. Under normal weather conditions, enhancing road connectivity is instrumental in improving spatial equity, as it facilitates better EMS accessibility for nursing homes, particularly in townships with limited road infrastructure (see Figure 7). However, this relationship inversely shifts under severe flood conditions, where improved road connectivity can lead to increased location entropy. Figure 10, which presents the significance levels under the 1-in-100-year and 1-in-1000-year flood scenarios, highlights this dynamic. The data reveal the heightened vulnerability of road systems during extreme flood events, particularly in suburban areas. This vulnerability underscores the challenges in ensuring EMS accessibility in these regions during severe floods, as even well-connected road networks may become impediments rather than facilitators of EMS response.



(a) 1-in-100-year flood (b) 1-in-1000-year flood

Figure 10. The significance level of *JunRd*: (**a**) 1-in-100-year flood; (**b**) 1-in-1000-year flood.

4.4.3. Limitations

While this study provides valuable insights into the spatial equity of EMS accessibility for nursing homes in Shanghai, certain limitations must be acknowledged. One notable limitation is the reliance on a single SSP-RCP scenario (SSP-RCP 245) for modeling flood impacts. Different SSP-RCP scenarios may produce differing predictions of flood inundation depth, extent, and frequency. To address this, future studies should incorporate a comparative analysis across multiple SSP-RCP scenarios, such as SSP-RCP 126 (low emissions) and SSP-RCP 585 (high emissions), to explore the variability in flood impacts and assess the robustness of EMS accessibility strategies under varying conditions. Additionally, the study assumes a static urban and road network, which may not reflect potential future developments or changes in infrastructure. Incorporating dynamic projections of urban growth, road network expansions, and demographic shifts in future research could enhance the applicability of the findings to long-term planning.

The primary objective of this study was to assess the equity of access to EMS among nursing homes under flood conditions. To achieve this, a simplified analytical approach was adopted, utilizing a binary classification of road accessibility—categorizing roads as either passable or impassable. This approach facilitated a focused evaluation of changes in equity and service coverage across varying flood scenarios. Furthermore, the analytical framework was designed to be adaptable and flexible, allowing for modifications to incorporate more complex flood scenarios. However, a notable limitation of this approach is its inability to capture nuanced factors, such as speed reductions and increased travel times due to partial road inundation. These dynamic elements could provide a more comprehensive understanding of flood impacts on EMS accessibility. Future research should aim to integrate such complexities to enhance the robustness of the analysis.

In this study, accessibility was measured based on the assumption of an immediate EMS response. However, in reality, response times depend on demand and EMS system capacity. Future research incorporating data on facility capacity could yield a more accurate assessment of accessibility. Additionally, as analyzing facility distribution and configurations can help identify opportunities for optimizing resource placement and guiding future infrastructure development, future research can focus on detailed spatial analyses of facility distribution to identify clusters or underserved areas and an assessment of the impacts of potential reconfigurations or additions to EMS infrastructure on accessibility and equity.

Another limitation is the modeling of factors influencing the spatial equity of EMS. The R^2 coefficients range from approximately 0.4 to 0.6, which are relatively moderate. Shanghai is a highly urbanized and heterogeneous city, with variations in infrastructure and geographic features. This complexity likely introduces non-linear interactions that are not fully captured by the linear models used in this study. Future research efforts can be dedicated to the enhancement of model accuracy, such as integrating more variables on network connectivity with machine learning in dealing with non-linear relationships between variables.

This study performed its analysis at the township level. However, analyses conducted at the mesh level (e.g., grid level) may yield finer-scale insights into spatial inequities. Mesh-level analysis can capture localized variations in EMS accessibility, such as within-township disparities caused by uneven road networks or facility clustering. These fine-scale insights are valuable for hyper-local interventions. Moreover, an increased sample size may further support the application of machine learning models, enabling a more effective capture of complex nonlinear relationships among variables. Therefore, it is worthwhile exploring mesh-level analyses and comparing findings with township-level results to better understand spatial equity at multiple scales.

5. Conclusions

In an era marked by rapidly aging populations and escalating demands on elderly care services, ensuring the equitable allocation of resources for nursing homes has become a critical issue. This necessity stems not only from the imperative to uphold the rights of the elderly but also to foster sustainable social development. Our study recognizes nursing homes as significant demanders of EMSs, a particularly crucial aspect in an aging society. This research extends this perspective by evaluating spatial equity in EMS accessibility for nursing homes, specifically considering the compounding effects of urban flooding.

The results indicate that, under normal weather conditions, EMS accessibility at the township level in Shanghai exhibits relative equity but reveals potential for enhancement. Notably, a discernible decline in accessibility is observed from the central urban areas to the inner and outer suburbs. Moreover, the study highlights the exacerbation of inequity in EMS accessibility during flood events. This situation poses a grave threat to the well-being of elderly individuals requiring emergency medical intervention. Our analysis also suggests that the road network has a significant and spatially heterogeneous influence on the spatial equity of access to EMS among nursing homes. Furthermore, flood events further amplify the impact of road connectivity on spatial equity, particularly in vulnerable areas.

Based on the findings of this study, policymakers should prioritize integrated planning and the spatial optimization of emergency centers and nursing homes, especially in underserved suburban and flood-prone areas. This includes increasing emergency facilities in regions with poor accessibility and strategically locating flood-resilient nursing homes in safer areas to ensure medical responsiveness and protect vulnerable elderly populations.

Strengthening flood control infrastructure is essential for uninterrupted EMS operations during severe flooding. Key measures include improving drainage systems, elevating critical road networks, and reinforcing frequently used roads with flood-resilient materials, elevated roadways, and flood barriers.

For long-term planning, scenario-based models should assess the impacts of road network development strategies and facility placement under varying climate and urbanization scenarios. Implementing a multi-level emergency alert and response system that integrates nursing homes, EMS providers, and local governments is crucial for rapid communication and resource deployment during disasters.

Lastly, fostering collaboration among urban planners, healthcare authorities, and disaster management agencies is vital to enhancing EMS accessibility and strengthening disaster preparedness, ensuring resilient and equitable emergency services in the face of climate-related challenges.

Author Contributions: Conceptualization, X.Z. and S.Y.; methodology, X.Z. and S.W.; validation, L.F.; formal analysis, X.Z. and S.Y.; resources, S.W.; data curation, X.Z.; writing—original draft preparation, X.Z., S.W. and S.Y.; writing—review and editing, L.F.; visualization, X.Z.; supervision, S.W., S.Y. and L.F. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China, grant number W2412140, and East China Normal University, grant number 1002021036-1002021006.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

EMS	Emergency medical service
OLS	Ordinary least squares
GWR	Geographically weighted regression

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