https://doi.org/10.5194/nhess-2024-88
Preprint. Discussion started: 5 August 2024

Natural Hazards and Earth System Sciences
Discussions

Flood relief logistics planning for coastal cities: a case study in Shanghai, China

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Abstract: Coastal cities are becoming more vulnerable to flood risks due to climate change, rising sea levels, intense storm surges, population growth, and land subsidence. Developing emergency preparedness and response strategies can reduce the impact of coastal flooding and enhance a city's resilience. This article presents a flood relief logistics planning aimed at providing decision-makers with a feasible framework. The framework integrates geographic information system (GIS) network analysis and resource allocation optimization models. Considering the fairness of resource allocation, a biobjective allocation model that minimizes the total transportation cost and maximum unsatisfied rate is developed. This flood relief logistics planning approach is applied to Shanghai, China to presents feasible distribution strategies. And, the case study indicates that the current capacity of emergency flood shelters (EFSs) and the supplies stored in emergency reserve warehouses (ERWs) are adequate to meet the demand of the elderly population if affected by a 100-year coastal flood scenario. However, they would not be sufficient to cover the demand in a 1000-year coastal flood scenario and could only serve half of the affected elderly people. The results also suggest that the city-level ERW in Jiading District and the branch warehouse in Minhang District play a crucial role in distribution. Additionally, the study highlights the importance of increasing resource investments to tackle the inherent unfairness caused by resource shortages. This study provides a scientific reference for developing flood relief logistics plans in Shanghai, and it presents a transferable framework that is applicable to other coastal cities.

Keywords: Coastal flooding; Flood relief logistics planning; Relief distribution; NSGA-II; Biobjective allocation mode; Emergency flood shelters; Emergency reserve warehouses.

1. Introduction

Flooding is among the most frequent and catastrophic natural hazards, causing substantial global casualties and losses (Douben 2006). In particular, coastal cities, where population and assets are concentrated, have been severely affected by storm-induced flooding(Cook and Merwade 2009). For example, Hurricane Katrina-induced flooding overwhelmed 80% of New Orleans in 2005, resulting in approximately 1833 fatalities, displacing approximately 770,000 residents, and causing over $100 billion in losses (Kates et al. 2006; Townsend 2006). Hurricane Sandy, which made landfall near Atlantic City in 2012, triggered a catastrophic storm surge in New York City, causing disruptions of city's systems and 43 deaths and approximately $19 billion in losses (Bloomberg 2013). Furthermore, sea level rise and storm surge intensification, driven by climate change, exacerbate the risk of coastal flooding (Field et al. 2014), and the frequency of coastal flooding is predicted to double in the next few decades (Vitousek et al. 2017). Moreover, the trend of rapid urbanization in coastal zones is expected to continue in the future (Hallegatte et al. 2013), which may further amplify the impact of flooding (Jongman 2018). Hence, as the most crucial pathway for enabling governmental actors to respond to this threat, the operational implementation of coastal flooding adaptations in emergency management must be examined.

In recent decades, the increase in the frequency and intensity of coastal flooding has attracted growing attention from the public, researchers and decision-makers worldwide (Burzel et al. 2010; Oumeraci et al. 2012). In response, society has sought to reduce the coastal flooding risk, with global policy frameworks and national strategies gradually emerging to address the threat. In the 21st century, disaster preparedness and emergency response have been emphasized as the priorities of the Hyogo Framework for Action 2005-2015 and the Sendai Framework for Disaster Reduction 2015-2030, respectively (ISDR 2005; UN/ISDR 2015). In emergency management, disaster relief logistics is essential to save human life and reduce damage (Qin and Liu 2017). However, there are many deficiencies in disaster relief logistics systems, such as a shortage of resources, ineffective communication regarding supply and demand information, and improper allocation of resources(L. Zhang 2016; Hu et al. 2019). During the Hurricane Katrina, numerous American citizens experienced profound levels of physical and psychological distress while ensconced in shelters for extended durations, devoid of sufficient provisions such as water, food, and medical attention (Brodie et al. 2006). In the aftermath of the Great East Japan Earthquake, the failure of certain systems, unreasonable warehouse placements, and other issues resulted in the irrational distribution of emergency supplies and a state of chaos (Ranghieri and Ishiwatari 2014). Thus, developing disaster relief logistics strategies to ensure the availability of adequate supplies and capacity is essential to prepare for coastal flooding and achieve effective emergency management.

The mechanism of disaster relief logistics plays a vital role in ensuring the efficiency of emergency response efforts (İvgin 2013). In past decades, numerous studies have been conducted in the field of disaster relief logistics, with the majority focusing on developing mathematical optimization models to solve this problem (Rawls and Turnquist 2010; Wang et al. 2019). Previous relevant research mostly focuses on facility location, stock pre-positioning, and relief distribution (Caunhye et al. 2012; Kundu et al. 2022). For example, Rawls et al. (2010) developed an emergency response planning tool that used a two-stage stochastic mixed-integer programming model to determine the location and quantities of multiple types of emergency supplies to be prepositioned. Zhang et al. (2022) proposed a distributional robust optimization model to determine the optimal location of emergency facilities and make resource allocation decisions. Jana et al. (2022) proposed a probabilistic fuzzy goal programming model for making decisions to manage the supply of emergency relief materials. The goal of disaster relief logistics decision-making is primarily focused on improving the effectiveness and fairness of an emergency response. For instance, Fiedrich et al. (2000) developed a dynamic combinatorial optimization model to allocate available resources with the goal of minimizing fatalities. Huang et al. (2015) developed a triobjective allocation network model with a focus on life-saving utility, delay costs and equity. Additionally, Halit Üster et al. (2017) designed a strategic emergency preparedness network that aimed to minimize the maximum travel distance for an evacuee and the overall system cost.

https://doi.org/10.5194/nhess-2024-88
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While considerable research has been performed in the field of disaster relief logistics, less attention has been given to flood relief logistics modeling. Only a few studies have combined the use of a geographical information system (GIS) with an optimization model to conduct analyses. Rodríguez-Espíndola et al. (2015) used GIS to create flood maps and developed a multiobjective optimization model to determine the locations of emergency facilities, assess the allocation of prepositioned goods, and establish a distribution plan based on the flood pattern. Christopher Mejia-Argueta et al. (2018) evaluated flood hazards using GIS and proposed a multicriteria optimization model that considered evacuation and distribution flow-time and budget usage to evacuate people and distribute relief supplies. Additionally, considering uncertainties in the scale and impact of flooding, Garrido et al. (2015) proposed a stochastic programming model to optimize the inventory of emergency supplies as well as vehicle availability in flood emergency logistics. However, these studies lack consideration of future extreme flooding scenarios under climate change. And, few studies have focused on the issue of how to distribute supplies equitably when there is a shortage of supplies in disaster relief logistics planning.

In this paper, we propose a scenario-based approach to flood relief logistics planning for coastal cities through a combination of GIS analysis and resource allocation models. GIS-based analysis is used to estimate facility availability and relief resource demand under coastal flooding scenarios. Then, resource allocation models based on the estimation of supply and demand are developed and implemented to determine the locations of active warehouses and to support resource allocation planning. This approach is applied to the metropolitan region of Shanghai, which, globally, is one of the coastal cities that is most exposed to flooding (Balica et al. 2012). Specifically, based on future coastal flood mapping, we use GIS and resource allocation models to analyze flood relief logistics schemes under various scenarios. This study provides scientific and technical support for improving contingency plans for coastal megacities. The rest of this paper is organized as follows. In Section 2, the modeling methodology is presented. Section 3 describes the case study results. The conclusions are summarized in Section 4.

2. Methodology

2.1. Problem description

As storm-induced flooding poses a significant threat to coastal cities, emergency authorities may be required to respond by evacuating vulnerable populations to emergency flood shelters (EFSs) and providing them with necessary supplies. In distributing these resources, emergency responders must assess the needs of evacuees to develop an effective allocation plan. When supply exceeds demand, emergency managers tend to focus on maximizing efficiency to optimally allocate resources. Conversely, if supply cannot meet demand, managers must consider both efficiency and fairness in their resource allocation schemes to avoid the humanitarian inequalities that are caused by unbalanced allocation. In this study, we propose a flood relief logistics planning framework (Fig. 1) that can assist decision-makers in addressing the challenge of distributing resources to vulnerable populations affected by coastal flooding at the city level. The methodology integrates GIS with resource allocation models to present a planning framework based on coastal flood mapping. We evaluate available candidate facilities, the remaining road network and affected people and obtain information regarding basic population needs and the shortest path through GIS analysis. Then, the obtained information is used in allocation models to determine which emergency reserve warehouses (ERWs) to activate and how to supply resources to the activated shelters.

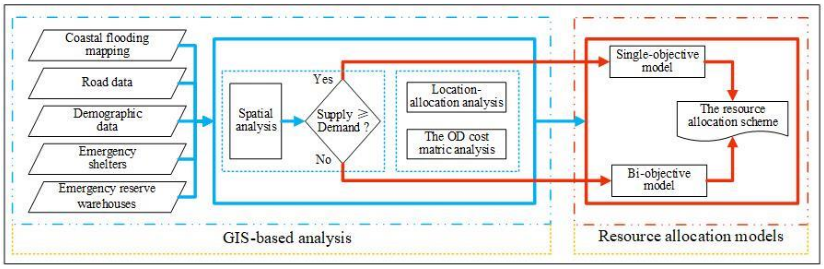

Fig. 1. The flood relief logistics planning framework.

2.2 Assumptions

In the development of the proposed methodology, to simplify the model, the following assumptions were made:

A1: The numbers, locations and capacities of emergency facilities such as warehouses and shelters are known.

A2: Pedestrians and vehicles are not allowed to use roads with a flood inundation depth greater than 30 cm, which is the common standard for urban roads closed due to waterlogging (Yin et al. 2016).

A3: Flooded EFSs will be set as invalid shelters. ERWs located in areas with flood inundation depths above 30 cm or that cannot be reached by vehicles are set as invalid warehouses.

A4: Only the needs of the elderly population in the affected areas are considered. This is because these individuals are often most vulnerable to flood disasters due to their limited ability to acquire information, make rapid judgments and take action.

A5: Resources refer to daily living supplies (e.g., water and food). A kit of goods can meet the requirements of a person during a flood evacuation.

A6: Resources are only transported from ERWs to EFSs and not separately to any other areas.

A7: There is no limitation on vehicle number, and each vehicle can transport one hundred kits.

A8: Any allocation of resources in the city is within 12 hours of an individual arriving at a shelter. Notably, the Ministry of Civil Affairs promises that affected people will have their basic living needs met within 12 hours.

A9: The affected elderly population is allowed to go to shelters in advance following a flood warning. The authorities can then establish strategies for distributing goods after evaluating the effects of flooding.

2.3 GIS-based analysis

Based on coastal flood mapping, the locations of available ERWs and EFSs as well as unsubmerged road networks and affected communities can be determined through GIS-based spatial and network analysis. Additionally, the number of elderly individuals in each affected community can be calculated using the following formula.

$$AP = \frac{IA}{A} * P \tag{1}$$

where AP represents the number of affected elderly people in the community; IA is the inundation area in the community; A is the total area in the community; and P is the total number of elderly people in the community.

Then, according to GIS-based location-allocation analysis, the locations of activated EFSs and the number of elderly individuals in the activated EFSs can be identified. Specifically, all available shelters are candidate sites for activated shelters, and all affected community centroids are considered demand points and used to assign affected elderly people in the community to shelters by minimizing the total distance traveled considering shelter capacity constraints. In this way, we determine the number of affected elderly people at each activated shelter. This information is used to determine how many kits of goods should be distributed to each shelter in subsequent resource allocation models. In addition, the matrix of the shortest path between available warehouses and activated shelters affected by flooding is used as an input for the resource allocation models, and this information is calculated based on OD (origin-destination) cost matrix analysis in GIS with the objective of minimizing the total route length.

2.4. Resource allocation models

Based on the above description and assumptions, models for resource allocation are designed. The following resource allocation models are used to establish allocation plans and their components, such as the number of activated ERWs that need to provide supplies and the quantity of kits that must be transported from ERWs to activated EFSs. Considering that emergency responders encounter two cases, namely, sufficient or insufficient supplies, a resource allocation model with two case outcomes is established.

2.4.1 Notations and definitions

The full mathematical model uses the following notation.

Indices and sets

I: set of available ERWs, indexed by $i \epsilon I$

J: set of activated EFSs, indexed by $j \epsilon J$

Parameters

c_{ij}: the unit transportation cost per unit distance per hundred kits transported between available ERW i and activated EFS j

d_{ij}: the shortest path between available ERW i and activated EFS j

P_i: the inventory of available ERW i

Q_j: the demand of activated EFS j

ω: the lowest satisfaction rate for each activated EFS

decision variables

X_{ij}: a binary value of 0 or 1, representing whether available ERW i serves activated EFS j or not

Y_{ij}: a nonnegative variable, representing the quantity of allocated resources from available ERW i to activated EFS j

R_j: the satisfaction rate, representing the quantity of elderly individuals receiving supplies as a percentage of the total elderly population at each activated EFS j

2.4.2 Sufficient supply scenario

In a sufficient supply situation, the total available supplies in the city can meet the total demand of the refugee population during flooding. That is, everyone can obtain sufficient resources. Therefore, we establish a single-objective allocation model considering only the efficiency objective. It aims to optimize system efficiency by minimizing the total transportation cost. The objective function can be defined as:

$$min f = \sum_{j\in J}\sum_{i\in I} c_{ij} d_{ij} Y_{ij} \tag{1}$$

Subject to:

$$\sum_{i\in I} Y_{ij} = Q_j \qquad \forall j \in J \tag{2}$$

$$\sum_{j\in J} Y_{ij} \leq P_i \qquad \forall i \in I \tag{3}$$

Objective function (1) minimizes the total transportation cost. Then, to satisfy the demand of each EFS, the related constraint function is expressed in Equation (2) to ensure that the resources received are equal to the demand for each EFS. Equation (3) ensures that the supplies allocated from each ERW are less than its overall inventory.

2.4.3 Insufficient supply scenario

During times of catastrophic coastal flooding, we assume that the relief supplies of available ERWs are inadequate and thus cannot meet the demand of all evacuees. To consider both efficiency and fairness, a biobjective programming model with a trade-off between efficiency and fairness is established to provide decision-makers with different options for resource allocation. Specifically, our model includes two possible objectives: objective (f1), minimizing the total transportation cost as the efficiency goal, and objective (f2), minimizing the maximum unsatisfied rate as the fairness goal. The objective function can be defined as:

$$min f1 = \sum_{j\in J}\sum_{i\in I} c_{ij} d_{ij} Y_{ij} \tag{1}$$

$$min f2 = max(1 - R_j) \tag{2}$$

$$\sum\nolimits_{i\in I} Y_{ij} \Big/ Q_j = R_j \qquad \forall j \in J \tag{3}$$

Subject to:

$$\sum_{j\in J} Y_{ij} = P_i \qquad \forall i \in I \tag{4}$$

$$\sum_{i\in I} Y_{ij} \leq Q_j \qquad \forall j \in J \tag{5}$$

$$R_j \geq \omega \qquad \forall j \in J \tag{6}$$

Equation (3) is the formula for calculating the satisfaction rate R_j, which equals the total allocated resources as a percentage of the total demand at each EFS. Equation (4) ensures that the resources allocated from ERWs do not exceed the total inventory of ERWs. Additionally, the supplies received should be less than the demand for each EFS, and the constraint function is expressed in Function (5). Function (6) ensures that the minimum satisfaction rate is met for each EFS.

3. Case study

3.1. Study area

A case study is conducted in Shanghai, China. Shanghai is located on the west coast of the Pacific Ocean and is located in a part of the floodplain of the Yangtze River Delta. This city is one of the financial centers of China, and its gross domestic product (GDP) is among the top 10 in the world. It has a total population of over 24 million, with 16.3% of residents being aged 65 and over (Shanghai Municipal Statistics Bureau 2021).

Coastal flooding has historically been a frequent issue in Shanghai. For example, Typhoon Winnie in 1997 resulted in RMB 635 million in economic losses and approximately 15000 affected people (Quan 2014). In response, Shanghai has built emergency shelters and prepared relief supplies in emergency reserve warehouses. By the end of 2020, Shanghai had built 117 emergency shelters to provide basic security protection for affected people. This work continues, and the goal of 1.5 m^2 of shelter space per capita is expected to be met by 2025 (General Office of the Shanghai Municipal People’s Government 2021). Currently, Shanghai has over 200 emergency warehouses at three levels: the city level, district level and township level. There is one city-level warehouse, with the main depot in Jiading District and a branch depot in Minhang District.

3.2. Data sources

Data such as flood inundation maps, road data, demographic data, emergency warehouse information and emergency shelter information are obtained from different sources for this study.

Future flood inundation scenarios in Shanghai are derived from Yin et al. (Yin et al. 2020). In previous work, the coastal flood inundation induced by overtopping and dike breaching was simulated using a 2-D flood inundation model (FloodMap-Inertial) with a fine-resolution DEM for three representative return periods (10, 100, and 1000 years) under current and future climate scenarios (RCP 8.5). We use future scenarios of flood inundation, a 100-year return period and a 1000-year return period under the RCP8.5 scenario in 2030. The RCP8.5 scenario represents high radiative forcing and worst-case climate impacts. Thus, these two future scenarios represent extreme flood inundation.

The road network data are from the 2013 Shanghai Traffic Navigation GIS dataset. It includes approximately 243,000 road sections with attributes such as road name, type, function, direction, and length. Referring to the “Technical Standards for Highway Engineering of the People’s Republic of China (JTG B01-2003)”, the roads are divided into five grades: superhighway, highway, main road, secondary road and branch road.

Shanghai's demographic data are from the Sixth National Population Census, which was conducted in 2010 through a household-level survey, and the main results were published by the Chinese government in 2011. The dataset provides the most detailed information on demographics at the basic administrative level—community or village. According to these data, we calculated the elderly population (over 65 years old) in each community.

The emergency warehouse data for this study are from the Shanghai Emergency Management Bureau. We obtained location information for 169 emergency warehouses. After filtering by facility name, 25 warehouses were identified as potential emergency reserve warehouses that could provide daily living supplies for 281K affected people. Based on surveys and Standard for the Construction of Relief Goods Reserve Warehouses

(Ministry of Civil Affairs of the People’s Republic of China 2009), it was assumed that city-level warehouses can meet the basic needs of 200K affected people, district-level warehouses can meet the needs of 5K people, and township-level warehouses can meet the needs of 3K people.

The data for emergency shelters used in this paper are from the statistics of the Shanghai Emergency Management Bureau. This includes 117 emergency shelters with attributes such as name, capacity, and level. They are divided into three classes: class 1, class 2, and class 3. Generally, class 1 and class 2 are fixed emergency shelters; class 1 facilities have the capacity to hold more than 5K people, and class 2 facilities can accommodate 1K to 5K people. Considering the nature of coastal flooding, 74 shelters with indoor venues, such as schools, could be emergency flood shelters. These EFSs can accommodate approximately 330K people.

3.3. Results

3.3.1. GIS-based results

Figure 2 illustrates the spatial distribution of ERWs, EFSs and activated EFSs across Shanghai, as well as the affected areas in 100- and 1000-year coastal flood scenarios. Table 1 shows statistical information regarding emergency facilities and disaster situations in two coastal flood scenarios, including the number of available facilities, number of activated EFSs, number of affected communities and population of affected elderly, etc.

During the 100-year flood scenario, all 25 ERWs and 71 EFSs (96% of total EFSs) are available. The available ERWs have the capacity to provide daily supplies for 281K individuals, and the available EFSs can accommodate up to 313,299 elderly people, accounting for 95% of the total capacity of EFSs. The impact of flooding is most pronounced in areas such as Chongming Island and Baoshan, Huangpu, and Xuhui districts. In this scenario, there are 562 affected communities with approximately 145K exposed elderly individuals. Thus, only 26 EFSs need to be activated to accommodate the impacted elderly population. The EFSs can house approximately 146,000 people, which represents 47% of the total available capacity.

As expected, the 1000-year flood scenario involves more extensive and severe flood inundation in the city. A total of 1,820 communities are exposed to coastal flooding, with approximately 534K elderly individuals in need of relocation to EFSs. In terms of critical facilities, only 21 ERWs and 61 EFSs (82% of total EFSs) are available in the 1000-year flood scenario. The available supplies can meet the needs of 265K people (50% of total demand), and the available EFSs have the capacity to accommodate 280,919 individuals. Thus, all 61 available EFSs need to be activated to accommodate the affected elderly population. Only 53% of the total affected elderly individuals can be accommodated at these EFSs.

Table 1. Statistics for emergency facilities and disaster situations in two coastal flood scenarios.

Flood Scenarios	**Available ERWs**		**Available EFSs**		**Activated EFSs**		**Affected Communities**	**Affected elderly**
	number	**stock**	**number**	**capacity**	**number**	**capacity**	**number**	**number**
100-year	25	281,000	71	313,299	26	145,981	562	145,197

1000-year	21	265,000	61	280,919	61	280,919	1,820	534,079

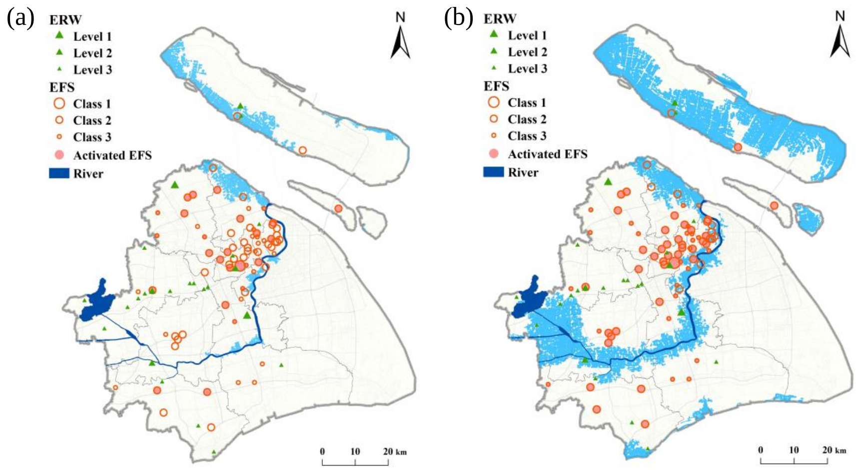

Figure 2. Spatial distribution of the emergency reserve warehouse (ERW) and emergency flood shelter (EFS) in 100-year (a) and 1000-year (b) flood scenarios in 2030. (Level 1/2/3 represent city/district/township)

3.3.2. Resource allocation in two coastal flood scenarios

For the 100-year flood scenario, the total amount of available supplies stockpiled in Shanghai can cover the needs of all affected elderly individuals (Table 1). Therefore, a single-objective model is employed to determine the resource allocation scheme in this scenario. The resource allocation network comprises 25 available ERWs and 26 activated EFSs in total. In terms of the main model parameter, the unit transportation cost (c_{ij}) is assumed to be 1 RMB, which prevents data unavailability issues. The results indicate that activating 17 ERWs could meet the needs of all elderly people at 26 EFSs. The relative transportation cost is 22,764 RMB. Figure 3 and Table 2 show the resource allocation scheme and the service capacity of the activated ERWs in the 100- and 1000-year flood scenarios in 2030, respectively.

As shown in Figure 3a, the demand of activated EFSs can almost entirely be provided by the nearest ERW. The city-level ERW in Jiading District (No. 24) and the branch warehouse in Minhang District (No. 25) play prominent roles in emergency resource provision. In contrast, ERWs located in the western region of Shanghai are mostly inactive. For example, the city-level ERW and the branch warehouse provide emergency resources for 8 and 11 EFSs in Shanghai, accounting for 28.6% and 39.6% of the total demand, respectively (Table 2). Furthermore, Figure 3a indicates that EFSs in the central areas of Shanghai demonstrate significantly higher demand than those in the suburbs; thus, the branch warehouse (No. 25), which is near downtown, provides most of the supplies. The result also shows a cross-river supply route from the branch warehouse to an EFS (No. 26) located on a nearshore island, which is the longest route identified in the scenario.

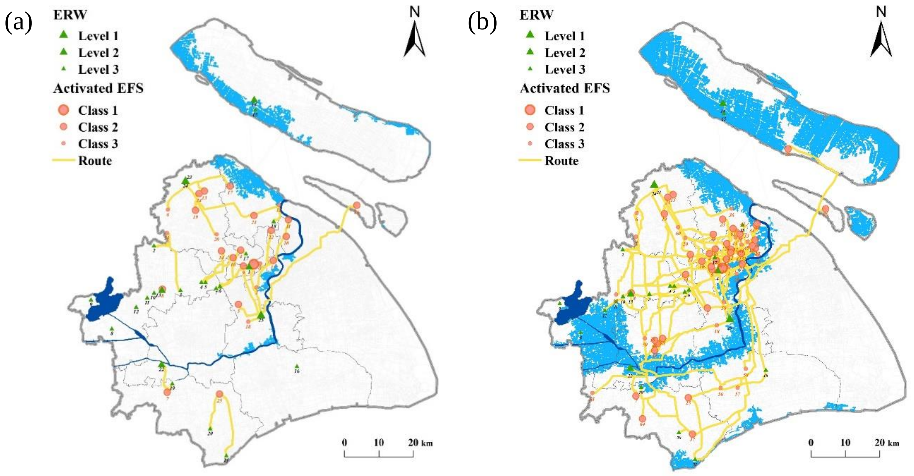

Figure 3. The resource allocation scheme in 100-year (a) and 1000-year (b) flood scenarios in 2030.

Table 2. The service capacity of the activated ERWs in two coastal flooding scenarios.

Level	**ID**	**100-year**		**1000-year**	
		EFSs served	**Supplies (^10^2)**	**EFSs served**	**Supplies (^10^2)**
Level 1	24	8 (30.8%)	416 (28.6%)	20 (32.8%)	1000 (35.6%)
	25	11 (42.3%)	574 (39.5%)	34 (55.7%)	1000 (35.6%)
Level 2	1	1 (3.8%)	50 (3.4%)	1 (1.6%)	50 (1.8%)
	13	1 (3.8%)	50 (3.4%)	5 (8.2%)	50 (1.8%)
	22	1 (3.8%)	14 (1.0%)	1 (1.6%)	50 (1.8%)
	23	1 (3.8%)	50 (3.4%)	2 (3.3%)	50 (1.8%)
Level 3	2	1 (3.8%)	30 (2.1%)	4 (6.6%)	30 (1.1%)
	3	1 (3.8%)	10 (0.7%)	1 (1.6%)	30 (1.1%)
	4	1 (3.8%)	30 (2.1%)	5 (8.2%)	30 (1.1%)
	5	2 (7.7%)	30 (2.1%)	1 (1.6%)	30 (1.1%)
	6	1 (3.8%)	30 (2.1%)	2 (3.3%)	30 (1.1%)
	7	3 (11.5%)	30 (2.1%)	4 (6.6%)	30 (1.1%)
	10	-	-	1 (1.6%)	30 (1.1%)
	11	-	-	1 (1.6%)	30 (1.1%)
	12	-	-	1 (1.6%)	30 (1.1%)
	16	-	-	2 (3.3%)	30 (1.1%)
	17	1 (3.8%)	30 (2.1%)	5 (8.2%)	30 (1.1%)
	18	1 (3.8%)	30 (2.1%)	1 (1.6%)	30 (1.1%)
	19	1 (3.8%)	30 (2.1%)	1 (1.6%)	30 (1.1%)
	20	1 (3.8%)	30 (2.1%)	1 (1.6%)	30 (1.1%)
	21	1 (3.8%)	20 (1.4%)	2 (3.3%)	30 (1.1%)

Note: The proportion of EFSs served to the total number of activated EFSs and the proportion of supplies provided to the total demand are given in parentheses.

In terms of the 1000-year flood scenario, the total available supplies in Shanghai are insufficient to meet the demand of affected elderly people. To ensure fairness in the allocation of limited supplies, a biobjective model is employed to determine the resource allocation scheme. This scenario involves the allocation of supplies from 21 available ERWs to meet the basic needs of 265K affected people at 61 activated EFSs; these EFSs can accommodate approximately 281K of the affected elderly individuals. The minimum level of rate of satisfaction ω for each EFS is set to 1%. This biobjective model is implemented by the NSGA-II algorithm which is used to obtain Pareto optimal solution in multi-objective optimization problems(Deb et al. 2002).

Figure 4 presents the Pareto front for the resource allocation scheme obtained with the proposed biobjective framework. This Pareto front depicts the relationship between the relative transportation cost and the maximum rate of unsatisfied demand, with a total of 200 nondominated solutions. The resource allocation schemes that prioritizes fairness, resulting in low maximum degrees of unsatisfied demand, correspond to solutions that plot close to the x-axis. Conversely, the resource allocation schemes that prioritize efficiency, resulting in lower relative transportation costs, correspond to solutions that plot close to the y-axis. The results provide a variety of strategies to the decision maker, and which solution to choose depends on the decision-maker's preference between relative transportation cost and the degree of demand satisfaction.

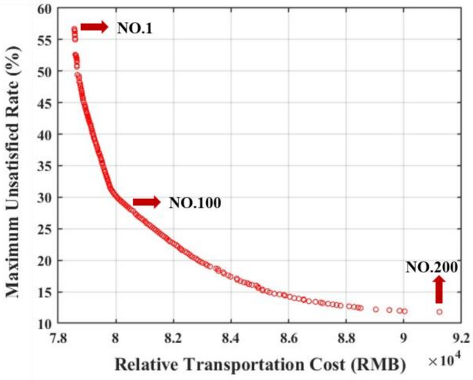

Figure 4. The Pareto front for relative transportation cost and maximum rate of unsatisfied demand in the 1000-year flood scenario.

Fig. 4 also shows the objective values for three representative solutions (i.e., No. 1, No. 100, and No. 200). These solutions demonstrate different trade-offs between the relative transportation cost and maximum rate of unsatisfied demand. Solution No. 1 yields the lowest relative transportation cost and the highest maximum rate of unsatisfied demand, totaling 56.7%. Solution No. 200 achieves the lowest maximum rate of unsatisfied demand (11.8%), and the relative transportation cost is the highest of all values in the solution set. However, solution No. 200 increases the relative transportation cost by 16% compared with that for solution No. 1 but achieves a 44.9% reduction in the maximum rate of unsatisfied demand. The objective value of solution No. 100 is between the values of the other two solutions, with a moderate transportation cost and a maximum rate of unsatisfied demand of 29.8%.

As mentioned above, the choice of resource allocation scheme depends on the decision-maker's priorities. If the decision maker emphasizes efficiency, solution No. 1, with a low transportation cost, may be adopted. Conversely, if the decision maker prioritizes equity, solution No. 200, with a low maximum rate of unsatisfied demand, can be employed. Moreover, for a balanced consideration of both efficiency and equity, a middle-ground solution between No. 1 and No. 200 can be selected, such as efficient solution No. 100.

Figure 3b and Table 2 present the spatial patterns of the resource allocation scheme and the service capacity of the activated ERWs for solution No. 100 in the 1000-year flood scenario. All available supplies are distributed (Table 2). The branch ERW (No. 25) provides services to a large number (34) of EFSs, serving 56% of all activated EFSs. Moreover, Figure 3b reveals that there are relatively few ERWs and that they cannot meet the large demand of EFSs in the central areas of Shanghai. Furthermore, the result shows three cross-river supply routes from the city-level ERW (No. 24) to EFS No. 26 and from the branch ERW to EFSs No. 26 and No. 39. The former is also the longest of the routes in this scheme. In addition, the result suggests that the resource demands of 79% of EFSs are met in the solution No. 100. Among the remaining EFSs with unmet demands, EFS No. 36, located in the urban center, displays the maximum rate of unsatisfied demand, totaling 29.8%.

3.3.3. Analysis of demand variability in the 1000-year flood scenarios

Given the capacity limitations of each EFS, it is impossible to accommodate all affected elderly people in the 1000-year flood scenario. As a result, the activated EFS demand (Q_j) in the optimization model includes only the number of elderly people assigned to EFSs in Section 3.3.2. To investigate the results of demand variability, it is assumed that the capacity of each EFS can be moderately adjusted to accommodate more elderly people and that each EFS's demand is increased by 10%, 50%, and 100% (Scen. 1, Scen. 2, and Scen. 3), respectively. The other parameters in the biobjective optimization model and in the NSGA-II algorithm are consistent with those in Section 3.3.2 (baseline scenario). The Pareto front for the four scenarios is obtained, and the results are presented in Figure 5. Table 5 illustrates the objective values of the endpoint solutions of the Pareto frontiers.

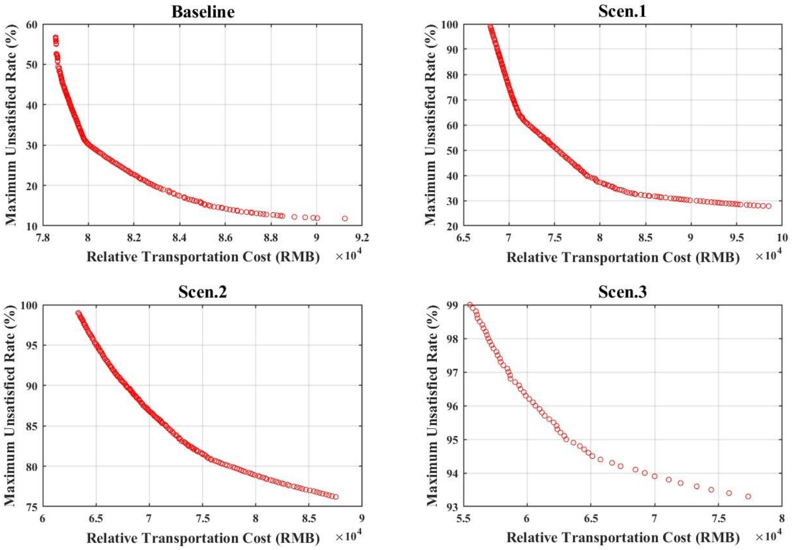

Figure 5. The Pareto fronts for the relative transportation cost and maximum rate of unsatisfied demand in four scenarios.

Table 5. The objective values of the endpoint solutions of the Pareto fronts in four scenarios.

The efficient solution		Relative transportation cost (RMB)	Maximum unsatisfied rate (%)
Top point	Baseline	78563.8	56.7
	Scen.1	67961.0	99
	Scen.2	63324.5	99
	Scen.3	55510.5	99
Bottom point	Baseline	91237.4	11.8
	Scen.1	98501.0	27.8
	Scen.2	87516.5	76.2
	Scen.3	77328.8	93.3

Comparing the results of the four scenarios, Figure 5 shows that the baseline scenario yields the highest satisfaction rate, with maximum rates of unsatisfied demand ranging from 11.8% to 56.7% (Table 5). Scenario 3 exhibits a significantly higher rate of unsatisfied demand, falling between 93.3% and 99%. This indicates that a fair allocation scheme can be achieved by reducing the gap between supply and demand. Furthermore, the results demonstrate that Scenario 3 yields a better solution than the others in terms of relative transportation costs, i.e., a lower value. Moreover, the relative transportation cost declines gradually from the baseline scenario to Scenario 3, potentially due to the expanding gap between supply and demand, which presents challenges for optimizing the maximum rate of unsatisfied demand. Therefore, there is more room for optimization in terms of relative transportation cost.

Overall, the results show that significant gaps between supply and demand indicate resource shortages, resulting in a high degree of unfairness in the allocation plan. The implication is that solely relying on optimal allocation strategies is inadequate to address the unfairness issue. Increasing resource inputs is a crucial fundamental approach to alleviate the unfairness related to resource allocation. These findings aid in understanding the fairness involved in resource allocation decisions.

4. Conclusions

Flood relief logistics planning is a critical component of flood management that directly impacts the livelihood and security of affected populations. In this study, we presented a comprehensive framework for flood relief logistics planning using a combination of GIS network analysis and resource allocation optimization models. By integrating these methodologies, we achieved a synergistic outcome that leverages the strengths of both approaches. The framework was implemented in Shanghai, China, to explore the availability of ERWs and EFSs as well as the flood relief logistics plans in future coastal flood scenario.

Such flood relief logistics planning could contribute to enhancing the efficiency and fairness of emergency management strategies. The framework proposed in this study can also be adopted for applications in other coastal cities worldwide. However, to arrive at more robust conclusions, future studies could be directed to the following aspects: 1) our demand estimation of supplies relies entirely on the affected elderly population and is biased to some extent. A more accurate approach would consider the willingness of various individuals impacted by flooding to reside in shelters at varying flood levels. 2) it is assumed that roads are closed when the water limit of 30 cm is reached, and the speed at which vehicles can safely navigate a flooded road network is not considered. More complex traffic scenarios should be considered in future work. 3) our research predominantly presents a static perspective of the supply-demand relationship. Recognizing that disaster situations are dynamic and evolve over time, there is a pressing need for the development of multiphase emergency resource allocation models. These models should capture the continuous and multistage nature of emergency response decisions, ensuring a holistic approach.

Furthermore, in this study, the disaster situation is explored in ArcGIS, and the resource allocation models are developed in MATLAB. Therefore, future efforts could focus on developing accessible, comprehensive decision-support systems and large models that integrate disaster assessment with relief resource allocation models. These systems have the potential to provide decision-makers with predictive analytics and scenario-based simulations, thus enabling proactive decision-making rather than reactive response. By filling these research gaps, the future of effective flood relief logistics planning can be ensured, providing more resilient and adaptive emergency responses in coastal cities worldwide.

Competing interests

The contact author has declared that none of the authors has any competing interests.

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Financial support

This paper was supported by the National Natural Science Foundation of China (grant no. 42371076).

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