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 improve a city's resilience. This article presents a flood relief logistics planning approach 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 equity of resource allocation, a bi-objective 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 present feasible distribution strategies. 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, such capacity and supplies would not be sufficient to cover the demand in a 1000-year coastal flood scenario and would be able to serve only 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 crucial roles in distribution. Additionally, the study highlights the importance of increasing resource investments to tackle the inherent inequity 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; Bi-objective allocation model; Emergency flood shelters; Emergency reserve warehouses.

1. Introduction

Flooding is among the most frequent and catastrophic natural hazards, causing substantial global casualties and losses. Over the past two decades, the number of major flood events has more than doubled, claiming approximately 1.2 million lives and impacting over 4.03 billion people (Mizutori and Guha-Sapir, 2020). 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

40   landfall near Atlantic City in 2012, triggered a catastrophic storm surge in New York City, causing disruptions of

41   city systems, 43 deaths, and approximately \$19 billion in losses (Bloomberg, 2013). Although the threat is already

42   considerable, various ongoing trends could greatly amplify flood risks in the coming years. Sea level rise (SLR)

43   and storm surge intensification, driven by climate change, exacerbate the risk of coastal flooding (Field et al.,

44   2014), and the frequency of coastal flooding is predicted to double in the next few decades (Vitousek et al., 2017).

45   Moreover, the trend of rapid urbanization in coastal zones is expected to continue in the future (Hallegatte et al.,

46   2013), which may further amplify the impact of flooding (Jongman, 2018). Disaster risk management systems

47   face increasing challenges in adapting to evolving risk profiles (IPCC, 2023). Hence, as the most crucial pathway

48   for enabling governmental actors to respond to this threat, the operational implementation of coastal flooding

49   adaptations in emergency management must be examined.

50

51   In recent decades, the increase in the frequency and intensity of coastal flooding has attracted growing attention

52   from the public, researchers and decision-makers worldwide (Moftakhari et al., 2017; Couasnon et al., 2020). In

53   response, society has sought to address this threat, with global policy frameworks and national strategies gradually

54   emerging to reduce coastal flooding risk. In the 21 century, disaster preparedness and emergency response have

55   been emphasized as the priorities of the Hyogo Framework for Action 2005-2015 and the Sendai Framework for

56   Disaster Reduction 2015-2030, respectively (ISDR, 2005; UN/ISDR, 2015). Moreover, the New Urban Agenda

57   outlines actions to strengthen cities' capacities to reduce disaster risk and mitigate their impacts (Habitat III, 2017).

58   The Making Cities Resilient 2030 (MCR2030) initiative advocates for incorporating climate risk projections into

59   disaster risk reduction and resilience strategies (UNDRR, 2022). Yin et al. (2024) demonstrated the improved

60   performance of risk-informed, strategic evacuation planning in advance of coastal flooding.

61

62   In disaster management, disaster relief logistics are essential to save human lives and reduce damage (Qin and

63   Liu, 2017). However, disaster relief logistics systems have many deficiencies, such as resource shortage,

64   ineffective communication regarding supply and demand information, and improper allocation of resources(Hu

65   et al., 2019; Zhang, 2016). During Hurricane Katrina, numerous American citizens experienced profound levels

66   of distress while ensconced in shelters, devoid of sufficient provisions (Brodie et al., 2006). In the aftermath of

67   the Great East Japan Earthquake, the failure of certain systems, unreasonable warehouse placements, and other

68   issues resulted in the irrational distribution of emergency supplies and a state of chaos (Ranghieri and Ishiwatari,

69   2014). Thus, developing disaster relief logistics strategies to ensure the availability of adequate supplies and

70   capacity is essential to prepare for coastal flooding and effectively manage emergencies.

71

72   The mechanism of disaster relief logistics plays a vital role in ensuring the efficiency of emergency response

73   efforts (İvgin, 2013). In past decades, numerous studies have been conducted in the field of disaster relief logistics,

74   with the majority focusing on developing mathematical optimization models to solve this problem (Rawls and

75   Turnquist 2010; Wang et al. 2019). Previous relevant research has focused primarily on facility location, stock

76   prepositioning, and relief distribution (Caunhye et al., 2012; Kundu et al., 2022). For example, Rawls et al. (2010)

77   developed an emergency response planning tool that uses a two-stage stochastic mixed-integer programming

78   model to determine the locations and quantities of multiple types of emergency supplies to be prepositioned.

79   Zhang et al. (2022) proposed a distributional robust optimization model to determine the optimal location of

80　emergency facilities and resource allocation. Jana et al. (2022) proposed a probabilistic fuzzy goal programming

81　model for making decisions to manage the supply of emergency relief materials. The goal of disaster relief

82　logistics decision-making is primarily to improve the effectiveness and fairness of an emergency response. For

83　instance, Huang et al. (2015) developed a tri-objective allocation network model with a focus on life-saving utility,

84　delay costs and equity. Additionally, Halit Üster et al. (2017) designed a strategic emergency preparedness

85　network that aimed to minimize the maximum travel distance for an evacuee and the overall system cost. And,

86　Ghasemi et al. (2022) proposed a scenario-based stochastic multi-objective model to minimize the expected total

87　cost, maximum unsatisfied demand for relief personnel, and total probability of unsuccessful evacuations.

88

89　Despite considerable research in the field of disaster relief logistics, only a few studies have examined the impact

90　of floods on resource distribution logistics, particularly the disruptions caused by the inundation of emergency

91　facilities and roads. For example, Rodríguez-Espíndola et al. (2015) used GIS to create flood maps and developed

92　a multiobjective optimization model to determine the locations of emergency facilities, assess the allocation of

93　prepositioned goods, and establish a distribution plan based on flood patterns. Christopher Mejia-Argueta et al.

94　(2018) evaluated flood hazards using GIS and proposed a multicriteria optimization model that considered

95　evacuation and distribution flow-time and budget usage to evacuate people and distribute relief supplies.

96　Additionally, considering uncertainties in the scale and impact of flooding, Garrido et al. (2015) proposed a

97　stochastic programming model to optimize the inventory of emergency supplies as well as vehicle availability in

98　flood emergency logistics. However, it is noteworthy that these existing studies were primarily based on historical

99　flood scenarios and did not adequately consider the potential increased risks posed by extreme flood events under

100　future climate scenarios. Moreover, most of these studies focused on optimizing the efficiency of resource

101　distribution, whereas relatively little research has focused on ensuring equity in the allocation process.

102

103　In this paper, we introduce a scenario-based approach to flood relief logistics planning for coastal cities through

104　a combination of GIS analysis and resource allocation models. GIS-based analysis is used to estimate facility

105　availability and relief resource demand under future coastal flood scenarios. Then, resource allocation models

106　based on the estimation of supply and demand are developed and implemented to determine the locations of active

107　warehouses and to support resource allocation planning. This approach has been applied to the metropolitan region

108　of Shanghai, which is one of the coastal cities that is most exposed to flooding in the world (Balica et al., 2012).

109　This study aims to provide scientific and technical support for enhancing contingency plans for coastal megacities,

110　and to offer new insights into operational emergency management decisions for major coastal cities facing

111　significant flood risks. The rest of this paper is organized as follows. In Section 2, the modelling methodology is

112　presented. Section 3 describes the case study results. The conclusions are summarized in Section 4.

113

114　**2. Methodology**

115　**2.1. Problem description**

116　As storm-induced flooding poses a significant threat to coastal cities, emergency authorities may be required to

117　respond by evacuating vulnerable populations to emergency flood shelters (EFSs) and providing them with

118　necessary supplies. In distributing these resources, emergency responders must assess the needs of evacuees to

119　develop an effective allocation plan. In this study, we propose a flood relief logistics planning framework (Fig. 1)

120 that can assist decision-makers in addressing the challenge of distributing resources to vulnerable populations
121 affected by coastal flooding at the city level. The methodology integrates GIS with resource allocation models to
122 present a planning framework based on coastal flood mapping. We evaluate available candidate facilities, the
123 remaining road network and affected people and obtain information regarding basic population needs and the
124 shortest path through GIS analysis. Then, the obtained information is used in allocation models to determine which
125 ERWs to activate and how to supply resources to the activated shelters.

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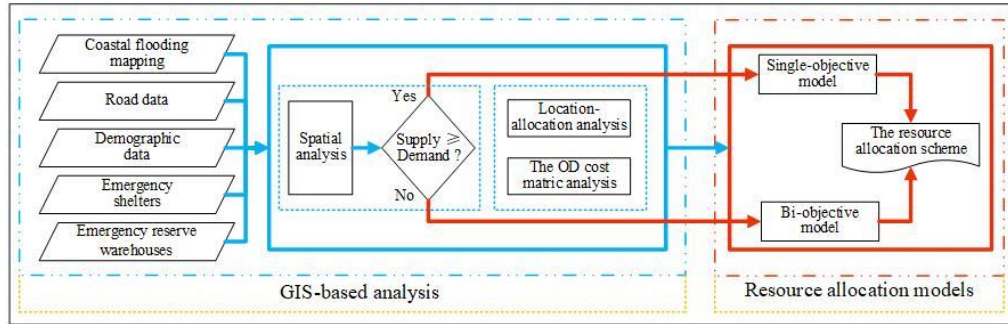
127 Fig. 1. The flood relief logistics planning framework.

128

129 **2.2 Assumptions**

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

  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 flood inundation depths greater than 30 cm,
    which is the common standard for urban roads that are closed due to waterlogging (Yin et al., 2016b).

  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 considered invalid warehouses.

  A4: Only the needs of the elderly population in the affected areas are considered because these individuals
    are often most vulnerable to flood disasters given their limited ability to acquire information, make rapid
    judgements 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 transported only from ERWs to EFSs and not separately to other areas.

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

  A8: Any resource allocation within the city can be completed within 12 hours. Notably, the 14th Five-Year
    National Comprehensive Disaster Prevention and Mitigation Plan in China stipulates that the basic living
    needs of affected individuals will be met within 12 hours.

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

149

150 **2.3 GIS-based analysis**

151 Based on coastal flood mapping, the locations of available ERWs and EFSs as well as unsubmerged road networks
152 and affected communities can be determined through GIS-based spatial and network analysis. Additionally, owing
153 to the lack of more detailed spatial distribution data for the elderly population, this study assumes a uniform

154 distribution within the community. The number of elderly individuals in each affected community can be
155 calculated using Equation 1.

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

157 where AP represents the number of affected elderly people in the community, IA is the inundation area in the
158 community, A is the total area in the community, and P is the total number of elderly people in the community.
159
160 Then, according to GIS-based location-allocation analysis, the locations of activated EFSs and the number of
161 elderly individuals in the activated EFSs can be identified. Specifically, all available shelters are candidate sites
162 for activated shelters, and all affected community centroids are considered demand points and used to assign
163 affected elderly people in the community to shelters by minimizing the total distance travelled while considering
164 shelter capacity constraints. In this way, we determine the number of affected elderly people at each activated
165 shelter. This information is used to determine how many kits of goods should be distributed to each shelter in
166 subsequent resource allocation models. In addition, the matrix of the shortest path between available warehouses
167 and activated shelters affected by flooding is used as an input for the resource allocation models, and this
168 information is calculated on the basis of origin–destination (OD) cost matrix analysis in GIS with the objective to
169 minimizing the total route length.
170

171 **2.4. Resource allocation models**
172 Based on the above description and assumptions, models for resource allocation are designed. The following
173 resource allocation models are used to establish allocation plans and their components, such as the number of
174 activated ERWs that need to provide supplies and the quantity of kits that must be transported from ERWs to
175 activated EFSs. Considering that emergency responders encounter two cases, namely, sufficient or insufficient
176 supplies, a resource allocation model with two case outcomes is established.
177

178 **2.4.1 Notations and definitions**
179   The full mathematical model uses the following notation.
180   **Indices and sets**
181   I: set of available ERWs, indexed by $i \in I$
182   J: set of activated EFSs, indexed by $j \in J$
183   **Parameters**
184   c_{ij}: the unit transportation cost per unit distance per hundred kits transported between available ERW i and
185   activated EFS j
186   d_{ij}: the shortest path between available ERW i and activated EFS j
187   P_i: the inventory of available ERW i
188   Q_j: the demand of activated EFS j
189   ω: the lowest satisfaction rate for each activated EFS
190   **decision variables**
191   X_{ij}: a binary value of 0 or 1, representing whether available ERW i serves activated EFS j
192   Y_{ij}: a nonnegative variable, representing the quantity of allocated resources from available ERW i to

5

193   activated EFS j

194   R_j: the satisfaction rate, representing the quantity of elderly individuals receiving supplies as a percentage

195   of the total elderly population at each activated EFS j

196

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 a flood. That is, everyone can obtain sufficient resources. Therefore, we establish a single-objective allocation model that considers only the efficiency objective. This method 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. 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. When supply is insufficient to meet demand, emergency managers should ensure that resources are distributed fairly across regions to avoid the humanitarian inequalities that result from unbalanced allocation. To consider both efficiency and equity, a bi-objective programming model with a trade-off between efficiency and equity is established to provide decision-makers with different options for resource allocation. Specifically, our model includes two possible objectives: objective (f1), which minimizes the total transportation cost as the efficiency goal, and objective (f2), which minimizes the maximum unsatisfied rate as the equity goal. The maximum unsatisfied rate refers to the highest unmet demand rate among these regions. By minimizing this rate, we aim to reduce disparities in unmet demand across regions, ensuring that no area experiences extreme shortages. The objective function can be defined as:

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

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

$$\left. \sum_{i \in I} Y_{ij} \middle/ Q_j \right. = R_j \qquad \forall j \in J \tag{3}$$

subject to:

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

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

$$R_j \geq \omega \qquad \forall j \in J \qquad\qquad (6)$$

227

228 Equation (3) is the formula for calculating the satisfaction rate R_j, which equals the total allocated resources as a

229 percentage of the total demand at each EFS. Equation (4) ensures that the resources allocated from ERWs do not

230 exceed the total inventory of ERWs. Additionally, the supplies received should be less than the demand for each

231 EFS, and the constraint function is expressed in Function (5). Function (6) ensures that the minimum satisfaction

232 rate is met for each EFS.

233

234 **3. Case study**

235 **3.1. Study area**

236 A case study is conducted in Shanghai, China. Shanghai is located on the west coast of the Pacific Ocean and is

237 in the floodplain of the Yangtze River Delta. This city is one of the financial centres of China, and its gross

238 domestic product (GDP) is among the top 10 in the world. Its a total population is over 24 million, and 16.3% of

239 its residents are 65 years old or older (Shanghai Municipal Statistics Bureau, 2021).

240

241 Coastal flooding has historically been a frequent issue in Shanghai. For example, Typhoon Winnie in 1997

242 resulted in RMB 635 million in economic losses and approximately 15000 affected people (Quan, 2014). In

243 response, Shanghai has built emergency shelters and prepared relief supplies in ERWs. By the end of 2020, 117

244 emergency shelters had been built in Shanghai to provide basic security protection for affected people. This work

245 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

246 Shanghai Municipal People's Government, 2021). Currently, Shanghai has emergency warehouses at three levels:

247 the city level, district level and township level. There is one city-level warehouse, with the main depot in Jiading

248 District and a branch depot in Minhang District.

249

250 **3.2. Data sources**

251 Data such as flood inundation maps, road data, demographic data, emergency warehouse information and

252 emergency shelter information are obtained from different sources for this study (Table 1).

253

254 Table 1. Data Source Information.

Data Type	Source	Description
Flood Inundation Maps	Yin et al. (2020)	Simulated coastal flood inundation scenarios for 100-year and 1000-year return periods under the RCP 8.5 scenario.
Road Network	Key Laboratory of the Ministry of Education at East China Normal University.	Comprises approximately 243,000 road sections with attributes.
Demographic	Shanghai Municipal Bureau of Statistics	Detailed demographic information at the community level.

Data Type	Source	Description
Emergency Warehouse	Shanghai Emergency Management Bureau	Includes information from 169 emergency warehouses
Emergency Shelter	Shanghai Emergency Management Bureau	Includes 117 emergency shelters divided into three classes.

Future flood inundation scenarios in Shanghai are derived from Yin et al (2020). In their previous work, coastal flood inundation caused by overtopping and dike breaching was simulated via 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). The study considered climatically driven absolute SLR by using probabilistic, localized SLR projections at the Lvsi gauge station located in the Yangtze River Delta, provided by Kopp et al. (2014). This projection accounts for climatic factors such as ice sheet melting, glacier and ice cap melting, and ocean thermal expansion. In addition, FloodMap-Inertial, developed from FloodMap (Yu and Lane, 2006), has been thoroughly tested and applied in Shanghai (Yin et al., 2016a, 2019), showing reliable performance in flood prediction. This model uses a computationally efficient inertial algorithm to solve the 2-D shallow water equations (Bates et al., 2010), using the Forward Courant-Friedrichs-Lewy (CFL) condition for the calculation of time steps. A complete description of the model structure and parameterization can be found in Yu and Lane (Yu and Lane, 2006). In this study, we focused on the 2030 scenarios with 100- and 1000-year return periods under the RCP 8.5 scenario. The RCP 8.5 scenario represents high radiative forcing and worst-case climate impacts. Thus, these two future scenarios represent extreme flood inundation. The 2030 projections are the closest to the present, making them relevant for near-term planning.

The road network data are from the 2013 Shanghai Traffic Navigation GIS dataset. Data are included on approximately 243,000 road sections with attributes such as road name, type, function, direction, and length. In accordance with the "Technical Standards for Highway Engineering of the People's Republic of China (JTG B01-2003)", the roads are divided into five grades: superhighways, highways, main roads, secondary roads and branch roads.

Shanghai's demographic data were collected during the Sixth National Population Census of China, which utilized a household-level survey. 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 (65 years old or older) 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 ERWs that could provide daily living supplies for 281K affected people. Based on surveys and the 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 (Level 1) warehouses can meet the basic needs of 200K affected people, district-level (Level 2) warehouses can meet the needs of 5K people, and township-level (Level 3) warehouses can meet the needs of 3K people.

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The data for the emergency shelters used in this paper are from the statistics of the Shanghai Emergency
Management Bureau[1]. Data on 117 emergency shelters are included, with attributes such as name, capacity, and
level. The shelters 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 distributions of ERWs, EFSs and activated EFSs across Shanghai, as well as the
affected areas in 100- and 1000-year coastal flood scenarios. Table 2 provides 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 the 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 the total EFSs) are available
in the 1000-year flood scenario. The available supplies can meet the needs of 265K people (50% of the 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 2. 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

9

Figure 2. Spatial distributions of the emergency reserve warehouses (ERWs) and emergency flood shelters (EFSs) in 100-year (a) and 1000-year (b) flood scenarios in 2030. (Levels 1, 2, and 3 represent city-level, district-level, and township-level ERWs, respectively)
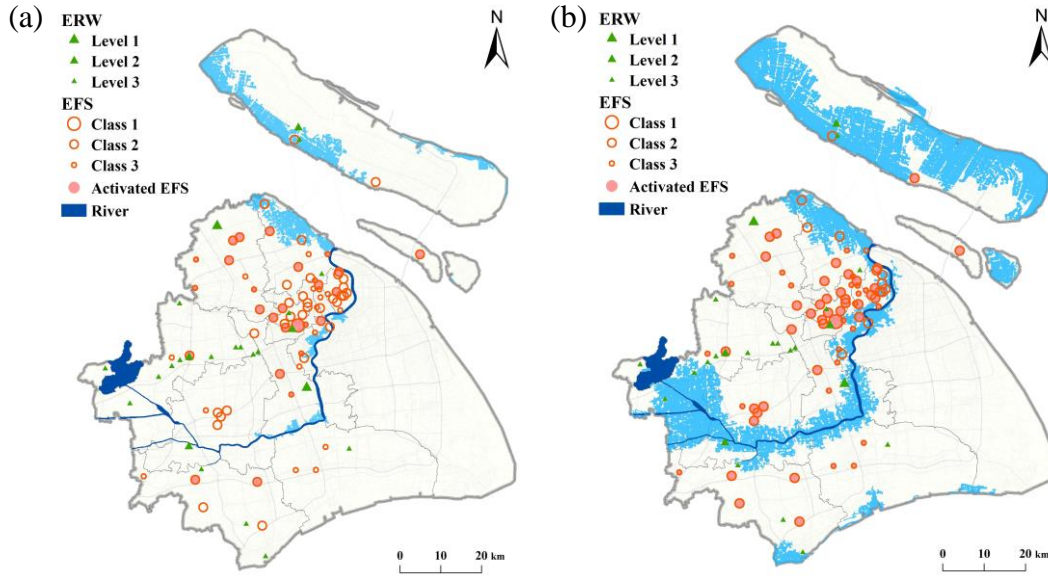
3.3.2. Resource allocation in two coastal flood scenarios

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 2). 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 to prevent 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 3 show the resource allocation scheme and the service capacity, respectively, of the activated ERWs in the 100- and 1000-year flood scenarios in 2030.

As shown in Figure 3a, the demand for 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, the ERWs located in the western region of Shanghai are mostly inactive. For example, the city-level ERW and 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 3). 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 results also show a cross-river supply route from the branch warehouse to an EFS (No. 26) located on a nearshore island; this route is the longest route identified in the scenario.
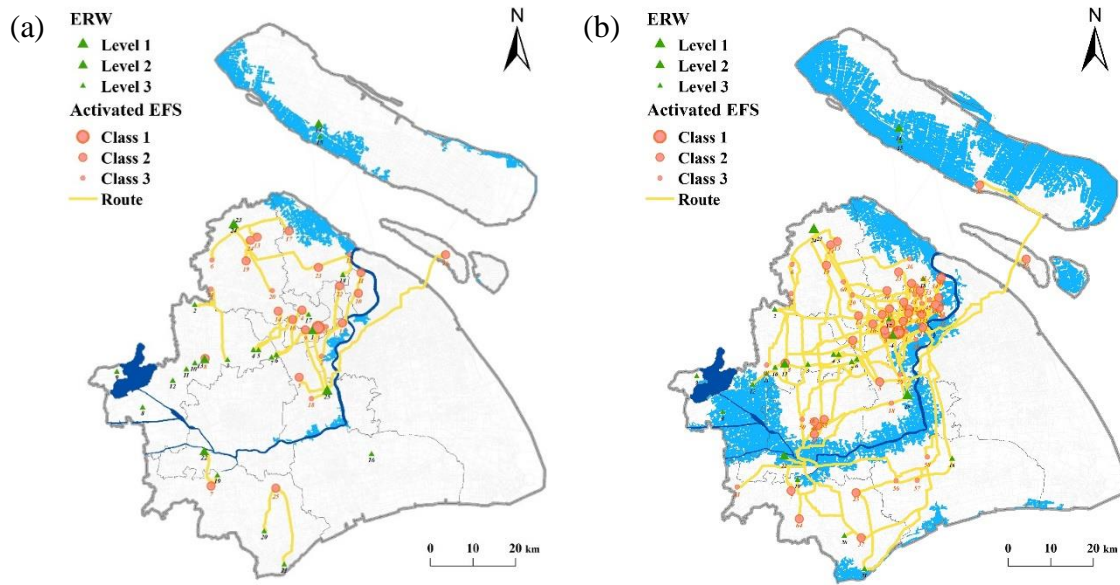
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348   Figure 3. Resource allocation scheme for the 100-year (a) and 1000-year (b) flood scenarios in 2030.

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350   Table 3. Service capacity of the activated ERWs in two coastal flood scenarios.

Level	ID	100-year		1000-year	
		EFSs served	Supplies (^{2})	EFSs served	Supplies (^{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%)

351   Note: The proportion of EFSs served to the total number of activated EFSs and the proportion

352   of supplies provided to the total demand are given in parentheses.

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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 equity in the allocation of limited supplies, a bi-objective 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 rate of satisfaction ω for each EFS is set to 1%. This bi-objective mathematical model is solved via the nondominated sorting genetic algorithm II (NSGA-II), which is used to obtain a Pareto optimal solution in multiobjective optimization problems (Deb et al., 2002). NSGA-II is an advanced multiobjective evolutionary algorithm that maintains population diversity across generations through nondominated sorting and promotes a uniform distribution of solutions along the Pareto front using a crowding distance measure. The NSGA-II algorithm is widely used in selected combinatorial optimization problems and has the advantages of fast convergence speed, low computational complexity, and high robustness (Ma et al., 2023; Verma et al., 2021). The corresponding algorithm settings for the solution in this study are shown in Table 4.

Table 4. Optimization parameter settings for NSGA-II

Parameter	Population Size	Maximum Number of Iterations	Pareto Fraction	Crossover Probability
Value	500	3,000	0.4	0.8

Figure 4 presents the Pareto front for the resource allocation scheme obtained with the proposed bi-objective 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 prioritize equity, resulting in low maximum degrees of unsatisfied demand, correspond to solutions that are plotted close to the x-axis. Conversely, the resource allocation schemes that prioritize efficiency, resulting in lower relative transportation costs, correspond to solutions that are plotted close to the y-axis. The results indicate a variety of strategies for decision-makers; the choice of solution depends on the decision-maker's preference between the relative transportation cost and the degree of demand satisfaction.
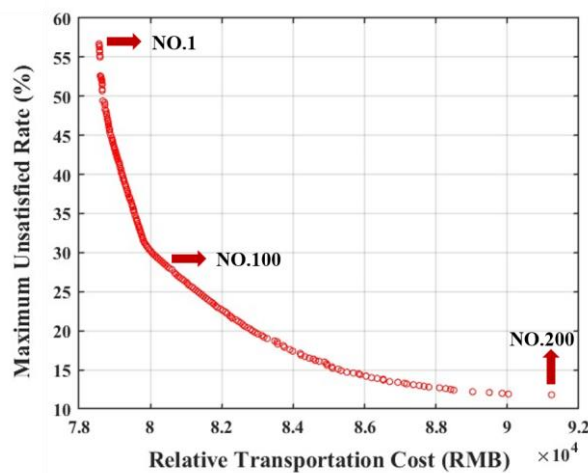
Figure 4. Pareto front for relative transportation cost and maximum rate of unsatisfied demand in the 1000-year flood scenario.

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 the maximum rate of unsatisfied demand. Solution No. 1 yields the lowest relative transportation cost and the highest maximum rate of unsatisfied demand, totalling 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 may be adopted, with its low transportation cost. Conversely, a decision-maker that prioritizes equity can employ, solution No. 200, with a low maximum rate of unsatisfied demand. 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 3 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 3). 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 for EFSs in the central areas of Shanghai. Furthermore, the results show 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 route in this scheme. In addition, the results suggest that the resource demands of 79% of EFSs are met in solution No. 100. Among the remaining EFSs with unmet demand, EFS No. 36, located in the urban centre, shows the maximum rate of unsatisfied demand, totalling 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% (scenario 1, scenario 2, and scenario 3, respectively). The other parameters in the bi-objective 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 lists the objective values of the endpoint solutions of the Pareto frontiers.
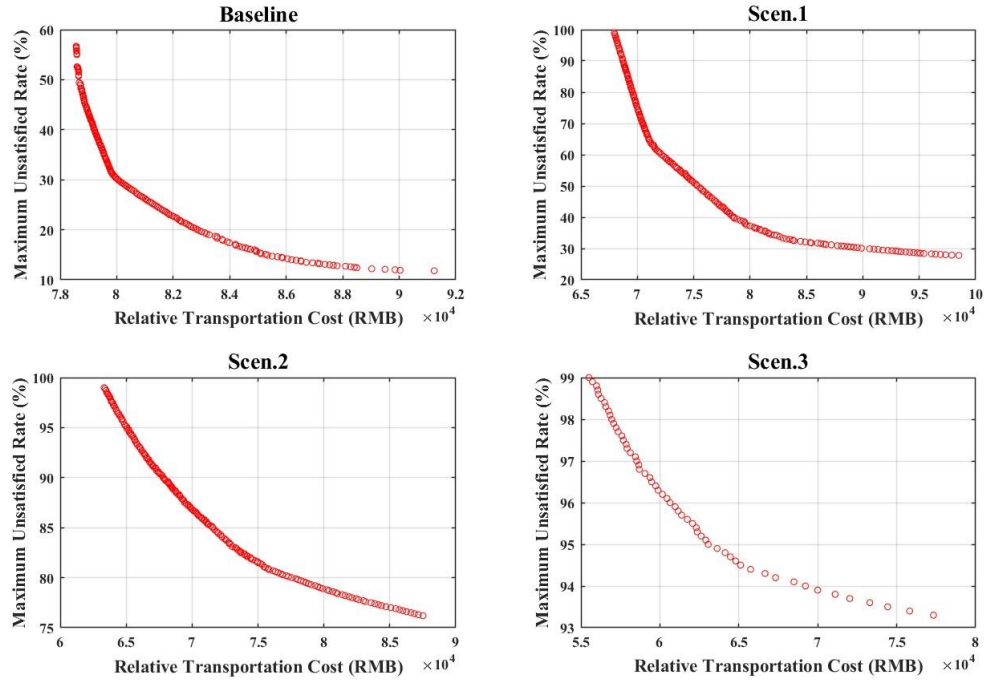
Figure 5. Pareto fronts for the relative transportation cost and maximum rate of unsatisfied demand in the four scenarios.

Table 5. Objective values of the endpoint solutions of the Pareto fronts in the 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

In a comparison of the results for 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 results in 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 other scenarios do 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, the relative transportation cost can be further optimized.

Overall, the results show that significant gaps between supply and demand indicate resource shortages, resulting in a high degree of inequity in the allocation plan. The implication is that solely relying on optimal allocation

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strategies is inadequate to address the inequity issue. Increasing resource inputs is a crucial fundamental approach to alleviate the unfairness related to resource allocation. These findings aid in understanding the level of equity 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 scenarios.

Our work can assist emergency managers in better understanding the inadequacies of existing emergency facilities and highlights the importance of incorporating climate risk information into exhaustive government flood relief logistics plans. The framework in this study can also be adopted for applications in other coastal cities worldwide. However, to arrive at more robust conclusions, future studies could focus on the following aspects: 1) Demand estimation: Given issue of ageing in Shanghai, the elderly population is likely to increase significantly by 2030, which is highly likely to lead to greater scarcity of shelter resources and supplies. Therefore, future research should focus on obtaining more detailed data on the elderly population to better understand the spatial distribution and temporal changes in the affected elderly population. 2) Traffic scenarios: Currently, the model assumes that roads are closed when the water level reaches 30 cm. Future work should incorporate more complex traffic scenarios, such as variable speeds at which vehicles can safely navigate flooded areas, to better simulate real-world conditions. 3) Model validation: This study has not yet incorporated a formal validation of the proposed models. Comparing model outputs with historical flood event data or established decision models would provide a more comprehensive validation and enhance the robustness of the framework. Future work should prioritize these comparisons to improve the model.

Furthermore, in this study, the disaster situation was explored in ArcGIS, and the resource allocation models was developed in MATLAB. Therefore, future efforts could focus on developing comprehensive decision-support systems and large models that integrate disaster assessment with relief resource allocation models. Such systems can offer predictive analytics and scenario-based simulations, enabling proactive decision-making. By filling these research gaps, researchers can contribute to optimizing effective flood relief logistics planning in the future, providing more resilient and adaptive emergency responses in coastal cities worldwide.

Code and Data Availability

The optimization models for resource allocation in this study were developed utilizing MATLAB's Optimization Toolbox with MatlabR2022a. The disaster scenarios were visualized and analyzed within ArcGIS. The source code for our models is available upon request from the corresponding author. The emergency shelter data for Shanghai can be publicly accessed (https://gfdy.sh.gov.cn/yjbncs/). Other datasets are not open-source. We have obtained all necessary permissions for the use of these datasets in our research.

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