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Emergency resource allocation considering the heterogeneity of affected areas during the COVID-19 pandemic in China

Yanyan Wang¹✉, Mingshu Lyu²✉ & Baiqing Sun²✉

The scientific allocation of emergency resources is crucial to ensure the success of COVID-19 relief operations. However, the heterogeneity of epidemic areas has an important impact on the allocation of emergency resources. Although it is a crucial topic, there has been limited research that considers the heterogeneity of affected areas in the emergency resource allocation. To bridge the gap, this study proposes a multi-period optimal allocation model of emergency resources considering the heterogeneity of affected areas, which aims to make the allocation of resources more equitable, efficient and economical. Then, a typical and representative case of emergency medical resource allocation in Hubei Province, China (where the epidemic occurred earlier and was seriously affected by COVID-19), was selected for a simulation study to verify the effectiveness and feasibility of the proposed model and method. The study finds that considering the heterogeneity such as disaster coefficient and demand urgency in different disaster stricken areas in emergency resource allocation can minimize the negative impact of resource shortfalls, especially in the early period of relief operations with insufficient resource supply. In addition, the proposed model can optimize multi-period emergency resource allocation by simultaneously considering time (efficiency criterion), cost (economic criterion), and loss (equity criterion), which is in line with the actual needs of emergency rescue to the COVID-19 epidemic. The results of this study can be effectively applied to the multi-period optimal allocation of emergency resources for large-scale public health emergencies, and providing insights for the government and relevant management departments to formulate emergency resource allocation policies and plans.

¹Faculty of Humanities and Social Sciences, Harbin Institute of Technology, Harbin, China. ²School of Management, Harbin Institute of Technology, Harbin, China. ✉email: wyy@hit.edu.cn; 19b306005@stu.hit.edu.cn; baiqingsun@hit.edu.cn

Introduction

The COVID-19 pandemic is devastating the world (World Health Organization 2023; as shown in Fig. 1), resulting in significant human casualties and socio-economic losses (Bonaccorsi et al. 2020; Camporesi et al. 2022; Jeong 2022; Lewandowsky et al. 2021; Oberndorfer et al. 2022; Pollack 2020; Spennemann and Whitsed 2023). Faced with the impact of the epidemic, the governments of all countries highly value the selection of scientific emergency management and rescue decisions (Mastropietro et al. 2020; Murphy and Lakoma 2023; Pan et al. 2019; Tanislav and Kostev 2022; Zhang et al. 2023). Emergency resources are an important guarantee for reducing casualties and losses. The allocation of emergency resources is a crucial component of emergency response, and it significantly affects the success of the entire epidemic emergency rescue operation (Aalami and Kattan 2018; Kovacs and Spens 2009; Liu et al. 2020; Mannelli 2020; Wan et al. 2023). However, COVID-19 occurs suddenly and spreads rapidly, usually requiring multiple time periods to effectively control it (this can be regarded as a multi-period emergency rescue effort). Especially in the early period of the epidemic, a large amount of emergency relief resources were needed simultaneously at multiple affected areas. How to scientifically allocate limited emergency resources to different demand sites is a highly challenging task (Wang and Zhu 2022).

In fact, affected by the COVID-19 epidemic, there is usually a certain degree of heterogeneity in multiple disaster-affected areas, that is, different disaster-affected areas have different characteristics. The heterogeneity of disaster-affected areas is manifested in multiple aspects. In this paper, disaster coefficient and demand urgency are selected to describe the heterogeneity of different disaster-affected areas from two perspectives: disaster degree and demand degree. On the one hand, the disaster coefficient of affected area in a period of time reflects the impact and damage degree of the location caused by the epidemic, which can be measured by factors such as epidemic intensity and disaster carrying capacity (i.e., mortality and infection rates); the larger the value of the disaster coefficient, the greater the potential loss caused by the destruction and impact of the epidemic on the affected areas. On the other hand, the urgency of resource demand in affected areas over a period of time can be comprehensively determined based on the characteristics of victims

(vulnerability, age) and infection rates; the higher the value, the more urgent the demand for such resources in the affected areas. It can be seen that considering the heterogeneity of disaster-affected areas (disaster coefficient and demand urgency) has an important impact on the allocation of emergency resources. For example, the amount and type of rescue resources required are limited, and if the limited resources are allocated to areas with severe disasters and high urgent needs, it will help to prevent the spread of the epidemic and treat the injured to a certain extent, thus improving the entire effectiveness of emergency resource allocation. On the contrary, if allocated indiscriminately, it can lead to major infections and losses in severely affected areas. Therefore, under the constraints of limited resources and transportation capacity, it is extremely necessary to fully consider the heterogeneity of different disaster-affected areas for the equitable, efficient, and economic allocation of emergency resources in multiple periods.

This paper introduces disaster coefficient and demand urgency to describe the heterogeneity of disaster-affected areas, and establishes an optimal multi-period emergency resource allocation model that considers efficiency, economy, and equity criteria simultaneously, making contributions to existing literature. In particular, it emphasizes the impact of heterogeneity in affected areas on emergency resource allocation and explores the balance between the three decision-making criteria of efficiency, economy, and equity. This study not only verified the effectiveness and feasibility of the proposed model, but also provided insights for the policy formulation and scheme selection of the optimal allocation of emergency resources for the epidemic by conducting a simulation study on the allocation of emergency resources in response to the COVID-19 in Hubei Province, China.

The remainder of this paper is organized into the following sections: A review of relevant research, a description of the research method, an analysis of simulation study. The final section presents conclusions and discussions based on the study findings.

Literature review

Emergency resource allocation in humanitarian logistics has received increasingly more attention in recent research due to the increased frequency and destructive impact of disasters

Global Situation

771,820,937

confirmed cases

6,978,175

deaths

Source: World Health Organization

Data may be incomplete for the current day or week.

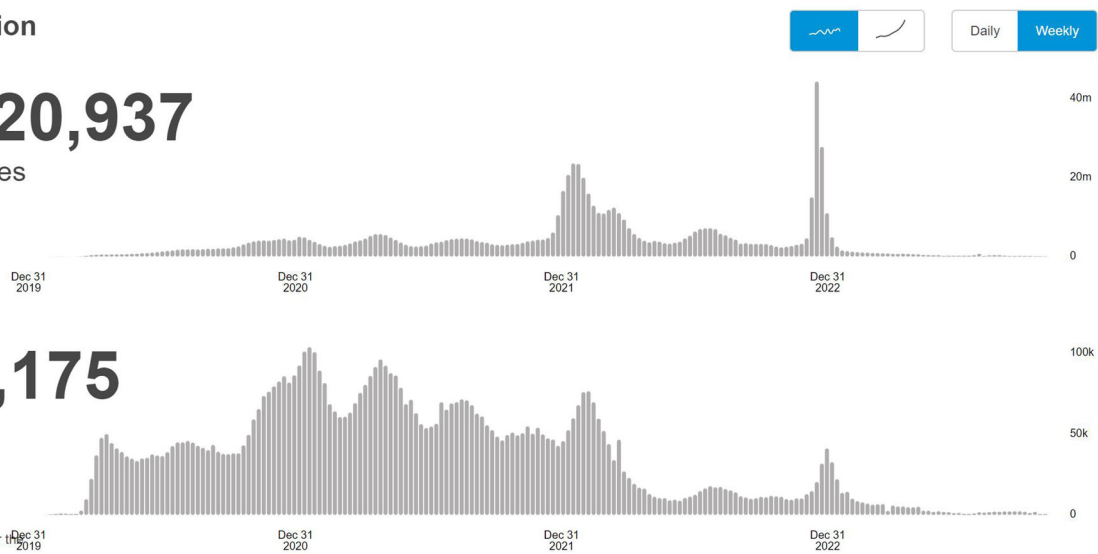


Fig. 1 WHO Coronavirus (COVID-19) Dashboard. (Globally, as of 6:15 pm CET, 8 November 2023, there have been 771,820,937 confirmed cases of COVID-19, including 6,978,175 deaths, reported to WHO.)

(Agarwal et al. 2019; Farahani et al. 2020; Galindo and Batta 2013; Hoyos et al. 2015; Moreno et al. 2016). Most of the existing studies on emergency resource allocation typically derive resource allocation schemes by constructing optimization models (Mete and Zabinsky 2010; Özdamar and Ertem 2015). However, various models for allocating emergency resources focus on different decision objectives/criteria. Generally speaking, these objectives/criteria can be roughly divided into three categories: efficiency-oriented criterion (pursuing the shortest delivery time), economy-oriented criterion (pursuing the lowest allocation cost), and equity-oriented criterion (pursuing the minimum system loss) (Banomyong et al. 2019; Ferrer et al. 2018; Kou and Wu 2014; Sabbaghorkan et al. 2020).

Therefore, this work is related to the following research streams: (1) the efficiency criteria in emergency resource allocation; (2) the economy criteria in emergency resource allocation; (3) the equity criteria in emergency resource allocation; and (4) the combination of different decision criteria in emergency resource allocation.

The efficiency criterion in emergency resource allocation. Since the primary goal of post-disaster emergency rescue is to minimize casualties, most studies have used efficiency-oriented objectives as the first decision criterion. This is generally described by the shortest delivery time of emergency resource allocation (Altay 2013; Berkoune et al. 2012). For example, Campbell et al. (2008) minimize the maximum or average arrival time of humanitarian aid routes to ensure that critical supplies can be delivered to all affected individuals as soon as possible. Yan and Shih (2009) presented an optimization model for allocating disaster emergency materials. The objective was to minimize the total distribution time, which includes both route transportation time and road repair time. Wex et al. (2014) developed an emergency resource allocation model aimed at minimizing the total time and obtained corresponding resource optimization allocation schemes by analyzing actual natural disaster cases. Tang and Ye (2021) proposed an emergency medical supplies distribution model for multiple relief centers and multiple demand sites. The goal of the model is to minimize the total time required for loading, unloading, and transportation.

The economy criterion in emergency resource allocation. In addition to the efficiency-oriented criterion, some researchers focus on the economy-oriented criterion in emergency resource allocation, which is generally measured by the lowest cost of emergency resource allocation (Arrubla et al. 2014; Minas et al. 2015; Özdamar et al. 2004; Yi and Özdamar 2007; Han et al. 2021). For example, Barbarosoglu et al. (2002) presented a two-stage emergency resource allocation stochastic programming model with the goal of minimizing total cost. Cotes and Cantillo (2019) constructed a humanitarian emergency facility resource positioning and allocation model for responding to flood disasters, where objective is measured by the lowest total social costs (including facilities costs, deprivation costs, inventory costs, and transportation costs). Zhou and Erdogan (2019) proposed a two-stage integer stochastic programming model for resource allocation in wildfire disaster relief, which aims to minimize the total cost of resource allocation operations.

The equity criterion in emergency resource allocation. In addition to efficient and economical allocation of resources, some studies have gradually realized that equitable allocation of available resources is also crucial in post disaster emergency rescue (Erbeyoglu and Bilge 2020; Kovacs and Spens 2009). Neglecting the equity criterion in emergency resource allocation may lead to

dissatisfaction and social unrest among disaster victims, increasing the burden of additional rescue work and negative social impacts (Ahmadi et al. 2022). The key to effectively reducing casualties and losses in the post disaster emergency rescue process lies in the equitable allocation of various emergency resources (Huang and Rafiei 2019). Holguin-Veras et al. (2013) introduced the concept of deprivation cost into the emergency decision-making process of humanitarian logistics, with the goal of maximizing equity in the allocation of relief resources by minimizing deprivation costs. Wang et al. (2019) used the minimization of disutility loss caused by resource shortage to measure the equity of distribution, aiming to achieve equitable distribution of emergency resources in multiple demand sites affected by earthquake disasters. Zolfaghari and Peyghaleh (2015) developed a two-stage stochastic planning model for equitable allocation of emergency resources to reduce major disaster losses.

The combination of different decision criteria in emergency resource allocation. With the need of emergency rescue in reality, some researches begin to focus on the combination of different decision criteria to obtain a more scientific and reasonable emergency resource allocation scheme (Salmerón and Apte 2010; Sheu 2007; Wang 2021). For example, some studies have explored the combination of efficiency and economy criteria (Xue et al. 2020), as well as the combination of efficiency and equity criteria (Fu and Chen 2018). Xue et al. (2020) proposed a multi-objective decision-making model for emergency material allocation based on capacity constraints. This model aims to optimize two objectives: minimizing the total network cost and average waiting time. Fu and Chen (2018) proposed a dual-objective model for allocating the first batch of emergency resources after a disaster. In this model, efficiency is measured by the delivery time, while equity is measured by the unmet demand for resources in the disaster-stricken areas.

However, there are also studies on emergency resource allocation that consider both efficiency, economy, and equity criteria (Tzeng et al. 2007; Bozorgi-Amiri and Khorsi, 2016), but such studies are relatively rare. For example, Tzeng et al. (2007) constructed an emergency resource allocation model for earthquake disaster relief operations with the goal of minimizing the total cost and the total travel time, and maximizing the minimal satisfaction during the emergency planning period. Bozorgi-Amiri and Khorsi (2016) proposed a dynamic multi-objective location-routing model for earthquake disaster relief logistic planning. The model features three objectives: minimizing the maximum amount of shorfalls among the affected areas in all emergency periods, the total travel time, and total costs. Finally, a case study was conducted to verify the potential applicability of the model in emergency resource allocation planning for earthquake scenarios in the megacity of Tehran. However, it should be noted that although Tzeng et al. (2007) and Bozorgi-Amiri and Khorsi (2016) considered three decision criteria simultaneously, their research mainly focused on the allocation of emergency resources for natural disasters. Compared with natural disasters, the COVID-19 epidemic has obvious differences: Firstly, the COVID-19 spreads rapidly, and if the emergency resources are not allocated in a timely and unreasonable manner, it will lead to large-scale infection and spread; Natural disasters such as earthquakes do not cause mutual transmission among populations. Secondly, Second, the types of emergency resources required are different, and the medical resources needed by the COVID-19 are less replaceable. Thirdly, in the process of allocating resources for COVID-19 emergencies, transportation conditions are generally relatively good, while in the process of

emergency resource allocation for natural disasters such as earthquakes, the road transportation conditions are usually poor, and the accessibility of the road network needs to be focused and considered. Therefore, the experience learned in allocating resources for natural disasters cannot be fully replicated in responding to the COVID-19 pandemic.

In summary, the above studies provide a solid theoretical foundation for this work. A brief review of relevant research indicates that it is crucial to consider various decision criteria (e.g. efficiency, economy, and equity) in emergency resource allocation. However, there are still gaps in the current research.

On the one hand, previous researches on emergency resource allocation mostly pursue a single decision criterion. Although some studies have begun to consider the combination of different decision criteria, such as the combination of economic and efficiency criteria, and the combination of efficiency and equity criteria, there are very few studies on emergency resource allocation that simultaneously consider the three decision criteria of efficiency, economy and equity, and they are mostly applied to natural disasters.

On the other hand, previous researches rarely consider the heterogeneous characteristics of different affected areas (e.g. disaster coefficients and urgency of demand) in the process of emergency resource allocation, which easily leads to the failure to achieve optimal allocation of emergency resources.

Therefore, this study attempts to propose a multi-period optimization allocation model of emergency resources specifically designed for COVID-19 rescue operations. The proposed model can simultaneously consider capture efficiency criteria (allocation time), economic criteria (allocation cost), and equity criteria (system loss). The main contributions of this work can be summarized as follows:

- A multi-period optimal model for emergency resource allocation is developed that simultaneously considers efficiency, economy and equity, and the balance between these three decision criteria is explored.
- Disaster coefficient and urgency of demand are introduced to describe the heterogeneity of disaster-affected sites, and the impact of heterogeneity on emergency resource allocation in different affected areas is discussed.
- A simulation study of emergency resource allocation in response to COVID-19 epidemic in Hubei Province, China was conducted, which demonstrated the benefits of balancing various decision criteria and considering the heterogeneity of the affected areas to improve the efficiency and effectiveness of resource allocation, and provided enlightenment for policy formulation and scheme selection of optimal allocation of emergency resources for the epidemic.

Methods

Study design. On the basis of paying attention to the heterogeneity of disaster affected areas, this paper proposes a multi-period optimization model for emergency resource allocation, which simultaneously considers equity, efficiency and economic criteria, and then conducts a simulation study on the allocation of emergency medical resources in response to the COVID-19 epidemic in Hubei Province, China.

The notation listed in Table 1 (sets, indices, parameters, and variables) is used in model formulation.

Objective function:

The objective function (1) minimizes the total loss due to resource shortfall during all time periods and represents the equity criterion. The objective function (2) minimizes the total

delivery time of resource allocation during all time periods, representing the efficiency criterion. The objective function (3) minimizes the total cost of allocation during entire time periods and stands for the economic criterion.

$$\min Z_1 = \sum_{d \in D} \sum_{m \in M} \sum_{n \in N} \lambda_{dmn} \cdot (L_{dmn})^{\delta_{dn}} \tag{1}$$

$$\min Z_2 = \sum_{r \in R} \sum_{d \in D} \sum_{n \in N} T_{rd} \cdot K_{rdn} \cdot \delta_{rdn} + \sum_{r \in R} \sum_{d \in D} \sum_{m \in M} \sum_{n \in N} T_{rdmn} \cdot x_{rdmn} \tag{2}$$

$$\min Z_3 = \sum_{r \in R} \sum_{d \in D} \sum_{n \in N} CF_{rdn} \cdot K_{rdn} + \sum_{r \in R} \sum_{d \in D} \sum_{n \in N} CV_{rdn} \cdot K_{rdn} + \sum_{r \in R} \sum_{d \in D} \sum_{m \in M} \sum_{n \in N} (C_{mnn} + C_{rdmn}) \cdot x_{rdmn} \tag{3}$$

The constraints of the proposed model are as follows:

Demand constraint:

$$\sum_{r \in R} x_{rdmn} \leq P_{dmn} + L_{dm,n-1} \quad \forall d \in D, m \in M, n \in N \tag{4}$$

Supply constraint:

$$\sum_{d \in D} x_{rdmn} \leq Q_{rmn} + B_{rm,n-1} \quad \forall d \in D, m \in M, n \in N \tag{5}$$

Resource satisfaction rate constraint:

$$\sum_{r \in R} x_{rdmn} \geq \eta_{dmn} \cdot (P_{dmn} + L_{dm,n-1}) \quad \forall d \in D, m \in M, n \in N \tag{6}$$

Transport capacity constraint:

$$\sum_{m \in M} x_{rdmn} \leq U_{rdn} \quad \forall r \in R, d \in D, n \in N \tag{7}$$

Inventory capacity constraints in the supply center:

$$\sum_{m \in M} \left[(Q_{rmn} + B_{rm,n-1}) - \sum_{d \in D} x_{rdmn} \right] \cdot V_m \leq G_{rm} \quad \forall r \in R, n \in N \tag{8}$$

Expression of the number of vehicles used to allocate emergency resources in each time period in the case of resource mixed loading:

$$K_{rdn} = \sum_{m \in M} \frac{x_{rdmn}}{H_m} \quad \forall r \in R, d \in D, n \in N \tag{9}$$

Expression of resource shortfall at the end of each time period:

$$L_{dmn} = P_{dmn} + L_{dm,n-1} - \sum_{r \in R} x_{rdmn} \quad \forall d \in D, m \in M, n \in N \tag{10}$$

Constraint to satisfy as much demand as possible. If the available supply is adequate to meet all demand in a given time period, then all demand is satisfied; conversely, if the demand exceeds supply, then all available supply is sent. As follows:

$$\sum_{r \in R} \sum_{d \in D} x_{rdmn} = \begin{cases} \sum_{r \in R} (Q_{rmn} + B_{rm,n-1}) - \sum_{d \in D} (P_{dmn} + L_{dm,n-1}) < \sum_{d \in D} (P_{dmn} + L_{dm,n-1}) \\ \sum_{d \in D} (P_{dmn} + L_{dm,n-1}) - \sum_{r \in R} (Q_{rmn} + B_{rm,n-1}) > \sum_{d \in D} (P_{dmn} + L_{dm,n-1}) \end{cases} \tag{11}$$

Nonnegativity constraints of the decision variables:

$$L_{dmn} \geq 0 \quad \forall r \in R, d \in D, m \in M, n \in N \tag{12}$$

$$x_{rdmn} \geq 0 \quad \forall r \in R, d \in D, m \in M, n \in N \tag{13}$$

Solution method. The emergency resource allocation model proposed in this paper is a multi-objective optimization model. Many methods have been developed to solve multi-objective optimization problems (Marler and Arora 2004). In this paper, the weighted sum method is used to integrate the three objectives,

Table 1 Notation for a multiperiod public health emergency resource allocation model.

Sets and Indices

- D Set of affected areas indexed by $d \in D$
- R Set of rescue centers indexed by $r \in R$
- N Set of time periods indexed by $n \in N$
- M Set of types of relief resources indexed by $m \in M$

Parameters

- P_{dmn} New demand for emergency resource $m \in M$ at affected area $d \in D$ at the beginning of each time period $n \in N$
- Q_{rnm} Latest amount of resource $m \in M$ raised at rescue center $r \in R$ at the beginning of each time period $n \in N$
- T_{rdmn} Loading and unloading time for allocating unit resource $m \in M$ from the rescue center $r \in R$ to the affected area $d \in D$ during time period $n \in N$
- CF_{rdn} Fixed cost required for the single transit time for each vehicle allocating resources from the rescue center $r \in R$ to the affected area $d \in D$ during time period $n \in N$
- CV_{rdn} Variable cost required for the single transit time for each vehicle allocating resources from the rescue center $r \in R$ to the affected area $d \in D$ during time period $n \in N$
- C_{mn} Unit purchasing cost of emergency resource $m \in M$ during time period $n \in N$
- C_{rdmn} Loading and unloading cost of unit resource $m \in M$ allocated from the rescue center $r \in R$ to the affected area $d \in D$ during time period $n \in N$
- λ_{dmn} Urgency of the demand for emergency resource $n \in M$ at affected area $d \in D$ during time period $n \in N$, and it can be determined comprehensively based on characteristics of victims (vulnerability, age) and infection rate. $\lambda_{dmn} \geq 1$, the higher the value, the more urgent the demand for such resource at the affected area
- ∂_{dn} Disaster coefficient of affected area $d \in D$ during time period $n \in N$ reflects the impact and damage degree of the location caused by the epidemic, which can be measured by factors such as epidemic intensity and disaster carrying capacity (i.e., mortality and infection rates). $\partial_{dn} \geq 1$, the larger the value of the disaster coefficient, the greater the potential loss caused by the destruction and impact of the epidemic on the affected areas
- T_{rd} Single transit time for each vehicle allocating resources from the rescue center $r \in R$ to the affected area $d \in D$ in a non-disaster relief situation
- δ_{rdn} Disturbance coefficient of the time required to allocate resources from the rescue center $r \in R$ to the affected area $d \in D$ in disaster relief situation, $\delta_{rdn} \geq 1$, the larger the value is, the greater the fluctuation of the road transportation time of emergency resources due to the impact of disasters
- K_{rdn} Number of vehicles used to allocate emergency resources from the rescue center $r \in R$ to the affected area $d \in D$ during time period $n \in N$ in the case of combined vehicle distribution, and its value is an integer
- η_{dmn} Minimum demand satisfaction rate, which can be obtained and set in advance based on the actual rescue experience of policymakers and emergency experts
- H_m Maximum loading capacity of resource $m \in M$ of each vehicle each time
- U_{rdn} Maximum amount of resource $m \in M$ that can be transported from the rescue center $r \in R$ to the affected area $d \in D$
- B_{rnm} Residual amount of resource $n \in M$ at rescue center $r \in R$ at the end of each time period $n \in N$
- V_m Volume of per unit resource $m \in M$
- G_r Available inventory capacity of the rescue center $r \in R$ at the end of each time period $n \in N$

Variables

- x_{rdmn} Amount of resource $n \in M$ allocated to affected area $d \in D$ from rescue center $r \in R$ during time period $n \in N$
- L_{dmn} Shortfall of emergency resource $m \in M$ at the affected area $d \in D$ at the end of time period $n \in N$

and the multi-objective optimization problem is transformed into a single-objective programming problem (Cohon 1978). As shown in Eq. (14):

$$\min Z = \sum_{y=1}^t \omega_y \cdot z_y^* \tag{14}$$

Where, ω_y is the weight coefficient of each objective function. In practical multi-objective optimization problems, how to determine the weights among various objectives to obtain satisfactory decision is a major issue in the application of weighted sum method (Huang et al. 2015). Existing literature has conducted in-depth research on the method of determining the weight of each objective (Belton and Stewart 2002; Mendoza and Martins 2006). Based on the analysis and reference of the existing research, the weights ω_y of the objective functions in this paper are determined by the decision-makers and experts according to the factors such as the vulnerability of the disaster victims, the urgency of demand and the situation of supply and demand in each emergency period.

For objective functions with different dimensional units, the (0-1) interval transformation method is adopted for normalization, as shown in Eqs. (15) and (16):

Cost-oriented objective function:

$$Z_y^* = \frac{\max z_y - z_y}{\max z_y - \min z_y} \tag{15}$$

Benefit-oriented objective function:

$$Z_y^* = \frac{z_y - \min z_y}{\max z_y - \min z_y} \tag{16}$$

Where, $\max Z_y$ and $\min Z_y$ are the maximum and minimum values of the objective function Z_y , respectively.

On this basis, the proposed multi-objective model can be transformed into a single objective model. Then, Lingo 12.0 software can be used to solve the transformed model.

Simulation study. To validate the proposed model and method, this section conducts a simulation study on the allocation of emergency medical resources in Hubei Province, China. Hubei Province is chosen as it is a representative and typical province that experienced an early outbreak and severe impact of the epidemic.

The allocation of emergency resources must involve a large number of affected areas and emergency rescue centers. In this study, the term ‘‘affected areas’’ refers to the locations where there is a need for emergency resources due to the impact of the epidemic, that is, the emergency resource demand points; and the ‘‘emergency rescue centers’’ are the locations where emergency resources are provided to the affected areas, that is, the emergency resource supply points. To minimize casualties and losses during the

emergency response to the epidemic, it is crucial to allocate resources from emergency rescue centers to affected areas promptly.

In this case, five cities in Hubei Province that were most seriously affected by the epidemic at that time were selected as the affected areas, including Wuhan City (WH), Huanggang City

(HG), Suizhou City (SZ), Xiaogan City (XG), and Jingzhou City (JZ). Due to the convenience of nearby rescue operations, the rescue centers were primarily selected from cities in nearby provinces, including Nanchang City (NCS) in Jiangxi Province and Zhengzhou City (ZZS) in Henan Province. According to the list of key support materials for epidemic prevention and control (medical emergency) issued by the Ministry of Industry and Information Technology of the People's Republic of China (2020), medical emergency materials are divided into six categories (drugs, reagents, disinfectant supplies, protective equipment, special vehicles, etc.). This paper selects two categories of emergency materials, protective equipment and disinfection supplies, from the above six categories of supplies as resource allocation objects. Protective clothing and disinfectant are typical representatives of these two types of resources, which are essential resources for emergency response to the epidemic, and are widely used and extremely important. Therefore, in this study, disposable protective clothing (m_1 , unit: 10^4 pieces) and disinfectant (m_2 , unit: 10^4 bottles) were selected as the urgent emergency materials in epidemic areas, which was in line with the realistic emergency rescue situation. The emergency rescue period is selected from March 1 to March 28, 2020, with 7 days as an emergency period, a total of 4 periods. The relevant data for the simulation study were chosen using a combination of real and hypothetical data, since some required data were either not published or could not be obtained through official reports. The number of accumulated confirmed cases, death cases, cured cases and existing confirmed cases in each affected area during each emergency period is shown in Table 2 (Health Commission of Hubei Province 2022), and it can provide a basis for estimating the demand for emergency resources and its fluctuation value during each emergency period in the following text.

The daily resource consumption of disposable protective clothing and disinfectant is set as follows: Disposable protective clothing can be used for up to 24 h, and each person diagnosed needs one piece per day; One bottle of disinfectant can sterilize 100 square meters, and sprayed three times a day. The new demand for emergency resources in affected areas at the beginning of each time period (Table 3) can be estimated based on the situation of the affected population (Table 2) and the per capita daily resource consumption. Since some relevant data not being officially released, the paper adopted the method of consultation to obtain relevant information. Although some of the data is estimated after consultation, it is still in line with the actual situation of emergency rescue as much as possible. For example, we first consulted with the management personnel of relevant departments and obtained the fixed and variable costs of resource transportation (Table 4), as well as the procurement costs (Table 5) of resources during the epidemic period, through the data information provided in the management process. Meanwhile, based on consultations with five staff members of the volunteer service centers who participated in the entire process of emergency resource allocation in March 2020, the resource reserve before the epidemic and the mobilization capacity during the epidemic of two

Table 2 The number of accumulated confirmed cases, death cases, cured cases and existing confirmed cases in each affected area during each emergency period.

Cases	Affected areas	Periods			
		Period 1	Period 2	Period 3	Period 4
Accumulated confirmed cases	WH	49,912	49,999	50,005	50,006
	HG	2907	2907	2907	2907
	SZ	1307	1307	1307	1307
	XG	3518	3518	3518	3518
	JZ	1580	1580	1580	1580
Death cases	WH	2370	2456	2508	2543
	HG	125	125	125	125
	SZ	43	45	45	45
	XG	125	126	128	128
	JZ	49	50	51	52
Cured cases	WH	29,770	37,632	42,354	45,418
	HG	2627	2738	2782	2782
	SZ	1077	1213	1252	1262
	XG	3024	3253	3366	3389
	JZ	1376	1483	1525	1528
Existing confirmed cases	WH	17,772	9911	5143	2045
	HG	155	44	0	0
	SZ	187	49	10	0
	XG	369	139	24	1
	JZ	155	47	4	0

Table 3 New demand for emergency resources at affected areas at the beginning of each time period.

Affected areas	Emergency resources	Period 1	Period 2	Period 3	Period 4
WH	m_1	(30 ± 5)	(40 ± 10)	(55 ± 5)	(60 ± 5)
	m_2	(55 ± 5)	(70 ± 5)	(80 ± 5)	(90 ± 5)
XG	m_1	(15 ± 5)	(18 ± 3)	(20 ± 3)	(25 ± 5)
	m_2	(35 ± 5)	(45 ± 5)	(50 ± 5)	(65 ± 5)
HG	m_1	(10 ± 5)	(13 ± 3)	(14 ± 2)	(15 ± 3)
	m_2	(30 ± 5)	(40 ± 5)	(45 ± 3)	(55 ± 3)
SZ	m_1	(7 ± 3)	(8 ± 3)	(9 ± 2)	(10 ± 2)
	m_2	(25 ± 5)	(30 ± 5)	(35 ± 3)	(45 ± 3)
JZ	m_1	(4 ± 2)	(5 ± 2)	(6 ± 1)	(7 ± 1)
	m_2	(20 ± 5)	(25 ± 3)	(30 ± 2)	(35 ± 1)

Note: The unit of disposable protective clothing (m_1) is ten thousand pieces, and the unit of disinfectant (m_2) is ten thousand bottles.

Table 4 The transit time (in non-disaster relief situation) and cost (in emergency relief situation) for a single vehicle from the rescue center to the affected area.

Rescue centers	Affected areas				
	WH	XG	HG	SZ	JZ
NCS	4; 0.6; 0.13	4.5; 0.7; 0.15	3.5; 0.5; 0.1	5.3; 0.9; 0.18	6; 1; 0.2
ZZS	6; 1; 0.2	5.3; 0.9; 0.18	6.5; 1.1; 0.22	5; 0.8; 0.17	7; 1.3; 0.25

Note: The data format in this table is (A; B; C), where A is the transit time required for a single vehicle, B and C represent the fixed cost and variable cost required for a single vehicle, respectively. The unit of A (the transit time) is hour; the units of B and C (the fixed cost and variable cost) are ten thousand yuan (10^4 CNY).

rescue centers were obtained, and then the resource supply of each rescue center was estimated accordingly, as shown in Table 6. For example, there were 100,000 disposable protective clothing stored in rescue center (Nanchang City, NCS) before the epidemic and 180,000 gathered during rescue operations, so the total supply was 280,000. The transit time required for a single vehicle from the rescue center to the affected area in a non-disaster relief situation was obtained using Baidu Maps. The volume of emergency resources can be calculated by adding up the volume of each resource. The attribute parameters of unit emergency resources (volume, loading and unloading time, loading and unloading cost) are shown in Table 7. The maximum transport capacity and disturbance coefficient of the time required for emergency resources from rescue centers to affected areas, as well as the available inventory capacity of the rescue center at the end of each period, are shown in Tables 8, 9, respectively. The outbreak of the

epidemic has caused different degrees of damage and impact on different affected areas, resulting in different heterogeneity among multiple affected areas, and the most prominent differences are reflected in the disaster coefficient (the degree of damage and the resulting vulnerability) and the urgency of demand. However, compared with only using the disaster coefficient or the urgency of demand, this paper believes that using both of them can more comprehensively describe the heterogeneity of different disaster areas. Therefore, this study selected disaster coefficient and demand urgency of each affected area in each time period to measure the heterogeneity of affected areas, as shown in Table 10. In addition, the minimum satisfaction rate for meeting the demand of emergency resources in each affected area during each period is set at 0.6. The maximum carrying capacity of a single vehicle for distributing a mix of resources is 20,000 pieces/20,000 bottles. This paper solved the computational case in Lingo 12.0 on

Table 5 Purchase cost of per unit of emergency resources (10⁴ CNY).

Emergency resources	Period 1	Period 2	Period 3	Period 4
m_1	60	55	50	50
m_2	30	25	25	20

Table 9 Available inventory capacity of rescue center at the end of each period (m³).

Rescue centers	Period 1	Period 2	Period 3	Period 4
NCS	6000	7000	8000	9000
ZZS	5000	6000	8000	10,000

Table 6 New supply of emergency resources at the supply centers at the beginning of each time period.

Rescue centers	Emergency resources	Period 1	Period 2	Period 3	Period 4
NCS	m_1	28	45	80	90
	m_2	55	70	140	150
ZZS	m_1	20	50	75	100
	m_2	40	100	130	150

Note: The unit of disposable protective clothing (m_1) is ten thousand pieces, and the unit of disinfectant (m_2) is ten thousand bottles.

Table 10 Heterogeneity of each affected areas in each time period (disaster coefficient and demand urgency).

Affected areas	Period 1	Period 2	Period 3	Period 4
WH	1.9; 1.9	1.7; 1.8	1.4; 1.5	1.2; 1.3
XG	1.6; 1.7	1.4; 1.5	1.3; 1.5	1.1; 1.2
HG	1.5; 1.6	1.2; 1.5	1.1; 1.3	1; 1
SZ	1.3; 1.5	1.2; 1.4	1.1; 1.4	1.1; 1.1
JZ	1.4; 1.6	1.3; 1.5	1.2; 1.4	1.1; 1.1

Note: The data format in this table is (J; K), where J is the disaster coefficient and K represent the the urgency of demand at each affected areas in each time period.

Table 7 Attribute parameters per unit of emergency resources.

Emergency resources	Volume (m ³)	Loading and unloading time (hour)	Loading and unloading cost (10 ⁴ CNY)
m_1	80	0.5	0.4
m_2	10	0.7	0.6

Table 8 Maximum transport capacity and disturbance coefficient of time required for emergency resources from rescue centers to affected areas in each time period.

Periods	Rescue centers	Affected areas				
		WH	XG	HG	SZ	JZ
1	NCS	100; 1.6	50; 1.5	40; 1.4	30; 1.3	25; 1.2
	ZZS	95; 1.5	45; 1.4	38; 1.3	35; 1.3	30; 1.2
2	NCS	225; 1.5	110; 1.4	95; 1.3	70; 1.2	55; 1.2
	ZZS	230; 1.4	120; 1.3	100; 1.2	75; 1.2	60; 1.1
3	NCS	365; 1.4	190; 1.3	160; 1.2	125; 1.2	95; 1.2
	ZZS	370; 1.3	200; 1.2	180; 1.2	130; 1.1	100; 1.1
4	NCS	490; 1.3	260; 1.2	230; 1.1	170; 1.1	140; 1.1
	ZZS	500; 1.2	280; 1.1	250; 1.1	180; 1.1	150; 1.1

Note: The data format in this table is (E; F), where E is the maximum transport capacity and F represent the disturbance coefficient of time required for emergency resources from rescue centers to affected areas, respectively. The unit of E (the tmaximum transport capacity) is ten thousand pieces/bottles.

a computer with an Intel(R) Core(TM)1.90 GHz processor with 16.0 GB of RAM.

Results

In this section, this paper first compare and analyze the results of resource allocation with and without heterogeneity, and then explain the advantages of balancing efficiency, economy, and equity criteria simultaneously.

Advantages of emergency resource allocation scheme considering heterogeneous characteristics of different disaster-affected areas. To test whether adding heterogeneity into account, this study compared the resource satisfaction rate under the multi-period resource allocation scheme with and without considering the heterogeneity of affected area, as shown in Fig. 2 (N: without heterogeneity, and Y: with heterogeneity). When heterogeneity is not considered, that is, the disaster coefficient and the urgency of demand are not considered in the process of emergency resource allocation, the objective function (1) becomes $\min Z_1 = \sum_{d \in D} \sum_{m \in M} \sum_{n \in N} L_{dmn}$, and then the results of emergency resource allocation under the two schemes are compared. The reason for considering the satisfaction of resource allocation is that satisfaction is an important factor to measure the effect of emergency resource allocation. The higher the satisfaction, the better the effect of resource allocation. In addition, satisfaction also implies the comprehensive consideration of total loss, total delivery time and total cost during the allocation of emergency materials.

The satisfaction rate of resource can be measured by the following formula:

$$\text{Satisfaction rate of resources} = \frac{\text{Actual amount of resources allocated}}{\text{Amount of resources actually required}} \tag{17}$$

First of all, it can be found from Fig. 2 that there are significant differences in resource satisfaction rates under the two conditions with and without considering the heterogeneity of affected areas. Whether it is resource m_1 or resource m_2 , the resource satisfaction rate of the allocation scheme considering the heterogeneity of the affected areas is almost higher than that of the case without considering heterogeneity. Considering the heterogeneity of affected areas, the satisfaction rate of emergency resources in each affected area in each period gradually increases,

and finally, all their needs are met. In the initial period of emergency relief (especially in the first time period), there were concurrent multisource demand, and not all can be satisfied at the same time immediately, but it can still provide a certain amount of resources to each affected area to the greatest extent, so as to avoid the uneven allocation of resources.

In addition, this study also found from Fig. 2 that the resource satisfaction rate of WH is always the highest among all affected areas in the case of short supply. This allocation result is both scientific and reasonable. The reason is that in all affected areas, the disaster coefficient and demand urgency coefficient of WH are the highest. If there is a serious resource shortage in WH, it will result in more severe system losses compared to other affected areas. Therefore, considering the heterogeneity of WH, limited resources are allocated to WH as much as possible.

In summary, the resource allocation scheme that considering the heterogeneity of different affected areas is more beneficial for emergency resource allocation in multiple disaster areas with simultaneous demand shortage. This scheme can help avoid the loss caused by insufficient resources to the greatest extent and establish the optimal global allocation plan. This also demonstrates the validity and feasibility of the proposed emergency resource allocation model, taking into account the heterogeneity of the affected areas.

Influence of different decision criteria on overall emergency resource allocation strategies. The values of each objective function under the equity criterion, efficiency criterion, economic criterion and balance criterion (balancing the three objectives of loss, time and cost) are calculated respectively, as shown in Fig. 3.

It can be seen from Fig. 3 that the total loss, total time and total cost of emergency resource allocation vary significantly under different decision criteria. This indicates that different decision criteria have a significant impact on the overall strategy selection for emergency resource allocation. When focusing on a specific decision criterion, the emergency resource allocation strategy based on that criterion will maximize the value of its corresponding objective function, resulting in the optimal outcome among all feasible options. For example, the equity criterion, efficiency criterion, and economic criterion respectively attach importance to the total loss, total time, and total cost of resource allocation. Under the various decision criteria mentioned above, the minimum total loss, minimum total delivery

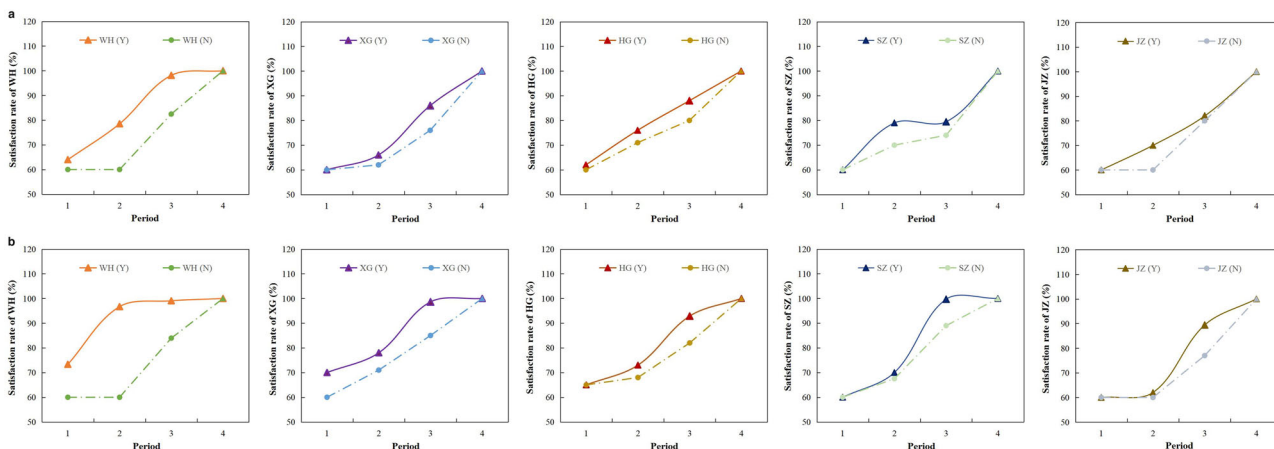


Fig. 2 Satisfaction rate of emergency resource allocation per time period with and without considering the heterogeneity of disaster affected areas. **a** Satisfaction rate of emergency resource m_1 at each affected areas per period. (a-1) Satisfaction rate of resource m_1 at WH. (a-2) Satisfaction rate of resource m_1 at XG. (a-3) Satisfaction rate of resource m_1 at HG. (a-4) Satisfaction rate of resource m_1 at SZ. (a-5) Satisfaction rate of resource m_1 at JZ. **b** Satisfaction rate of emergency resource m_2 at each affected areas per period. (b-1) Satisfaction rate of resource m_2 at WH. (b-2) Satisfaction rate of resource m_2 at XG. (b-3) Satisfaction rate of resource m_2 at HG. (b-4) Satisfaction rate of resource m_2 at SZ. (b-5) Satisfaction rate of resource m_2 at JZ.

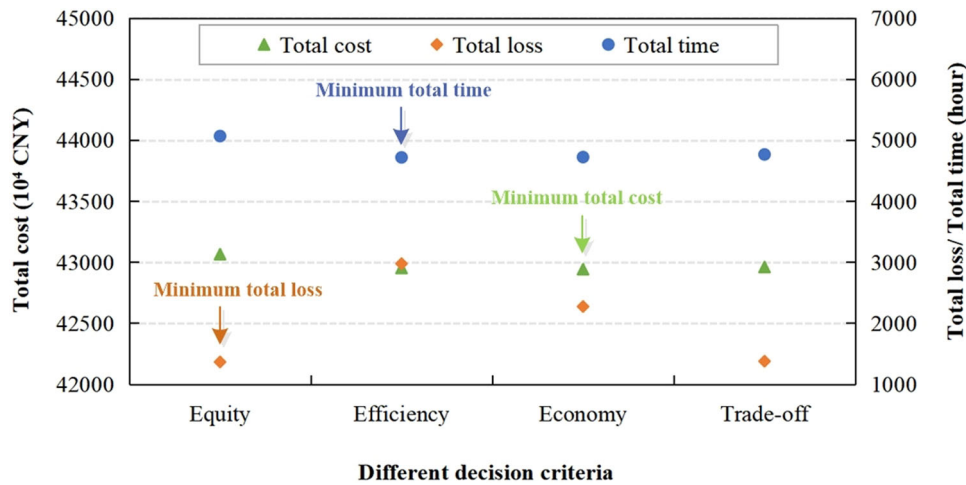


Fig. 3 Total loss, total time and total cost of emergency resource allocation under different decision criteria.

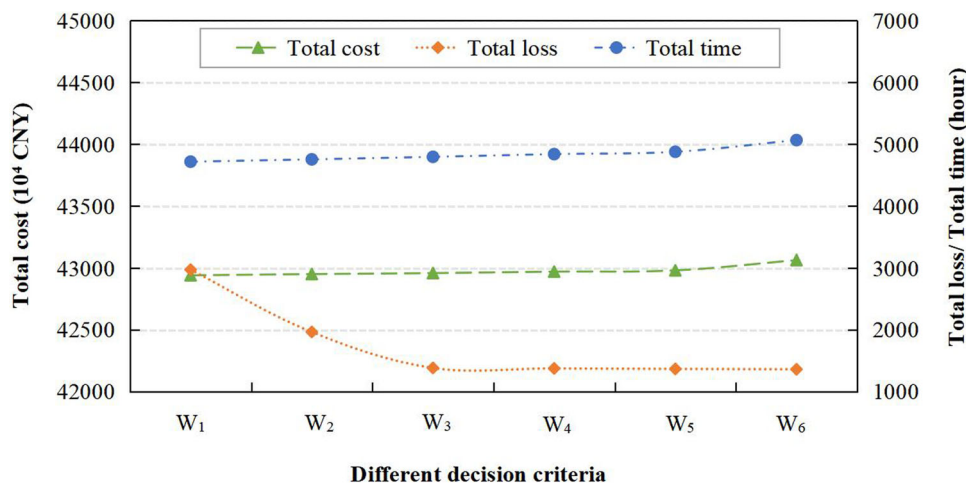


Fig. 4 Evolution trend of loss, time and cost of emergency resource allocation under different decision criteria.

time, and minimum total allocation cost are obtained, respectively.

In addition, to compare the evolution trend of loss, time and cost of resource allocation under different decision criteria (as shown in Fig. 4), different weight values are set in this paper. $W_1 = (0, 0.5, 0.5)$, $W_2 = (0.2, 0.4, 0.4)$, $W_3 = (0.4, 0.3, 0.3)$, $W_4 = (0.6, 0.2, 0.2)$, $W_5 = (0.8, 0.1, 0.1)$, $W_6 = (1, 0, 0)$. Where, W_1, W_2, W_3, W_4, W_5 and W_6 respectively represent different decision criteria. For example, in $W_1 = (0, 0.5, 0.5)$, (0, 0.5, 0.5) refers to the weight of the equity criterion (loss), the weight of the efficiency criterion (time) and the weight of the economic criterion (cost), respectively.

It can be seen from Fig. 4 that the trends of time and cost evolution are similar and consistent, while the loss deviates from their development trends. With an increase in the weight coefficient of equity decision criteria, the loss of resource allocation gradually decreases, while the time and cost gradually increase. Therefore, in the process of emergency resource allocation, it is not possible to blindly determine the best weight combination. It is crucial to scientifically balance the factors of loss, time, and cost based on the specific disaster situation and rescue information in order to achieve the optimal allocation plan.

Influence of different decision criteria on multiperiod emergency resource allocation strategy. This paper also compares the

effects of considering equity criterion, efficiency criterion, economic criterion separately, and considering these three criteria simultaneously on multi-period emergency resource allocation. Where, the situation where these three criteria are simultaneously considered is referred to as the balance criterion. The weight values under different decision criteria are set as follows: equity criterion $W_T = (1, 0, 0)$, efficiency criterion $W_E = (0, 1, 0)$, economic criterion $W_C = (0, 0, 1)$, and balance criterion $W^* = (1/3, 1/3, 1/3)$. Through calculation, the evolution trend of the loss, time and cost of emergency resource allocation in each period under the conditions of adhering to the equity criterion, efficiency criterion, economic criterion, and balance criterion is shown in Fig. 5.

As can be seen from Fig. 5, the four decision criteria all exhibit the following trend: the system loss of emergency resource allocation in each period gradually decreases until it reaches zero, while the time and cost initially increase and then decrease. The main reasons are as follows: during the early period of emergency rescue, rescue centers can offer a limited amount of emergency supplies, and the time and cost required to distribute these resources to each affected area are relatively low. However, during such times, each affected area often requires a significant quantity of emergency relief supplies. Unfortunately, due to the limited availability of relief supplies, there is a substantial loss within the system. In the middle period of rescue operations, as various emergency resources continue to be supplied, the quantity of

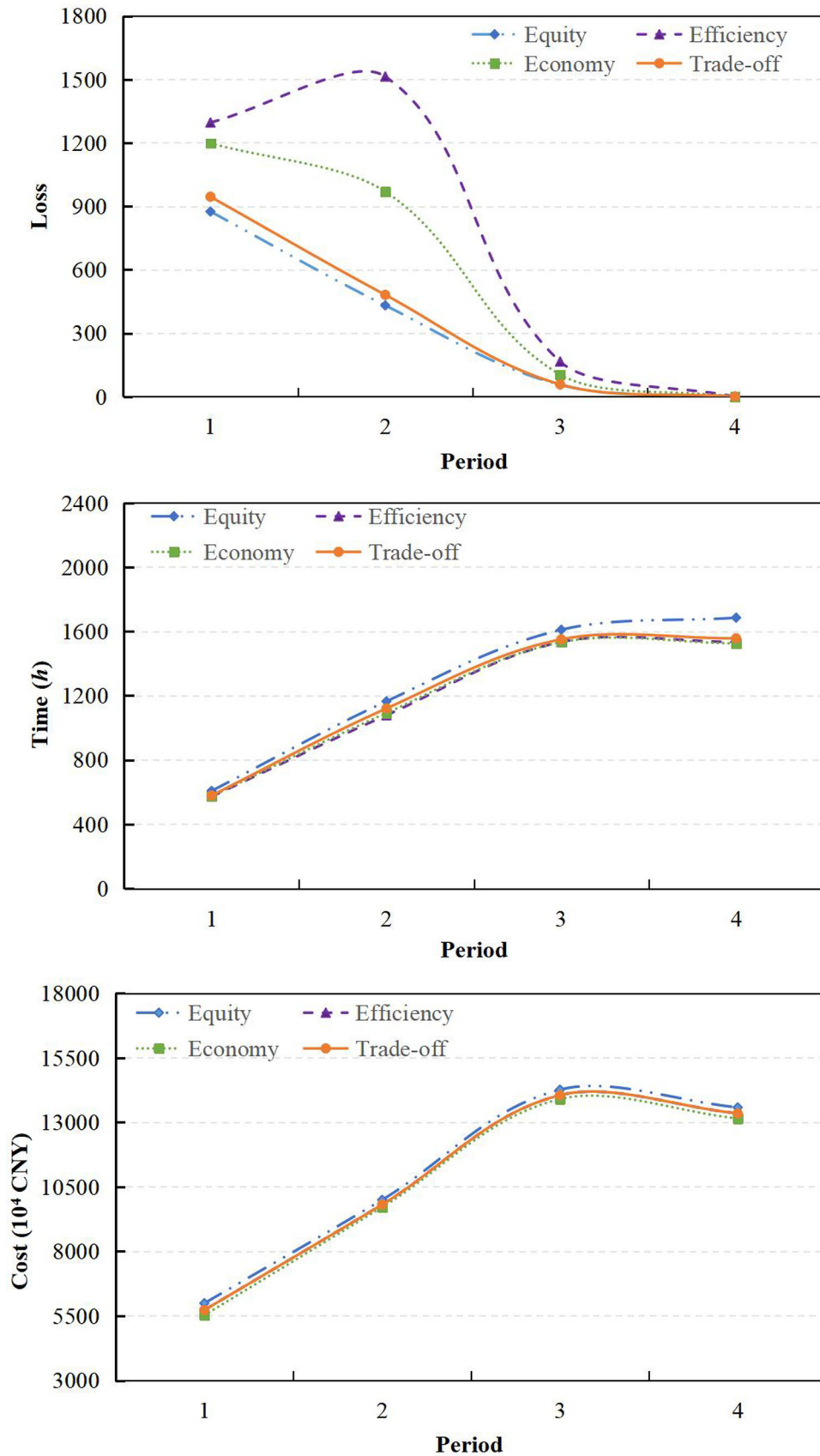


Fig. 5 Loss, time and cost of emergency resource allocation in each period under different decision criteria. a Loss of emergency resource allocation in each period under different decision criteria. **b** Time of emergency resource allocation in each period under different decision criteria. **c** Cost of emergency resource allocation in each period under different decision criteria.

resources that need to be allocated in each period gradually increases, along with the corresponding increase in time and cost of allocation. As the quantity of resources needed in each affected area gradually increases, the system loss also gradually decreases. In the late period of rescue operations, when the supply is equal to or greater than the demand, all affected areas can have their demands met, and the system loss decreases to its minimum value. This means that when the demand is fully satisfied, there is no loss caused by a shortage of resources. Meanwhile, as rescue activities progress, the disaster situation gradually improves and the demand for materials decreases. As a result, the time and cost of allocation gradually decrease. This situation aligns with the current allocation of emergency relief resources.

However, when considering long-term sustainable emergency rescue efforts, the balance criterion should be a strategy that deserves attention. The emergency resource allocation strategy, based on the balance criterion, aims to comprehensively balance different objective functions and decision indicators. It seeks to minimize system losses, reduce time and cost, and avoid focusing solely on extreme or non-global optimization of the emergency resource allocation scheme under a specific decision criterion.

Multiperiod allocation scheme of emergency resources under the balance criterion. In particular, this study analyzes the multiperiod allocation of emergency resources under the balance criteria. Here, referring to Huang et al (2015) and Wang and Sun (2023), and through expert consultation, the three objective functions of the model are compromised to obtain the optimal value, with the weight value set as $W^* = (1/3, 1/3, 1/3)$. (This paper considers a multiperiod emergency resource allocation problem. In the initial period of epidemic emergency response, resources may be allocated with less consideration for cost. However, as disaster activities continue and the situation gradually eases and is under control, this article believes that in the later periods of emergency response, factors such as loss, time, and cost should be considered simultaneously, that is, the three objectives can be achieved with equal weight). The evolution trend of the satisfaction rate of multiperiod emergency resource allocation based on the balance criterion is shown in Fig. 6. The loss caused by the shortfall, as well as the time and cost required to obtain resources at each affected area in each period, are shown in Fig. 7.

As can be seen from Fig. 6, in the allocation plan formed based on the balance criterion, the resource satisfaction rate gradually increases in each period and at the end of the entire emergency rescue work, the satisfaction rate reaches 100%, indicating that all resource needs can be fully met. This study also found that although the amount of resource shortage in the second period increased

compared with that in the first period, the actual satisfaction rate increased, which reflected the advantages of the proposed emergency resource allocation scheme based on the balance criterion.

As can be seen from Fig. 7, the multiperiod emergency resource allocation scheme formed based on the balance criterion shows that, on the whole, its losses show a gradual decline trend, and the allocation time and costs generally show a trend of first rising and then falling, which is in line with the situation of realistic multiperiod emergency resource allocation. When the demand for a certain type of resources is reduced in the affected area, the required time will be shortened accordingly, and the required cost growth will slow down. Meanwhile, system loss will gradually decrease (e.g., WH, XG, SZ, and JZ after the third period in Fig. 7). This also reflects the validity and feasibility of the proposed emergency resource allocation model.

Conclusion

The scientific and rational use of limited emergency resources is necessary to achieve efficient, economical, and equitable post-disaster relief operations. This study aims to enhance research on multiperiod emergency resource allocation in response to the COVID-19 epidemic. This paper first introduced the disaster coefficient and demand urgency to describe the heterogeneity of different disaster-affected areas. Based on this, this study constructed a multi-period emergency resource optimization allocation model that considers efficiency, economy, and equity. The goal is to optimize the resource allocation scheme by balancing these three decision criteria.

The simulation results presented here provide several insights into the allocation of emergency resources over multiple periods, taking into account the heterogeneity of the affected areas.

Firstly, the heterogeneity of the different affected areas has an important impact on the allocation of emergency resources. Especially in the early stages of emergency rescue, when multiple disaster sites require a significant amount of resources simultaneously, considering the heterogeneity of these disaster areas can help prevent resource shortages and maximize the allocation effectiveness of emergency resources. This, in turn, aids in preventing and controlling the spread of epidemics. Therefore, considering the heterogeneity of different affected areas in the process of emergency resource allocation is more in line with the practical needs of emergency rescue.

Secondly, the various decision criteria also have significant effects on the allocation of emergency resources. In the case of a resource shortage in the early period, the equity criterion has a more obvious influence on resource allocation decisions. However, as the supply gradually increases or in the case of sufficient supply, the efficiency criterion and economic

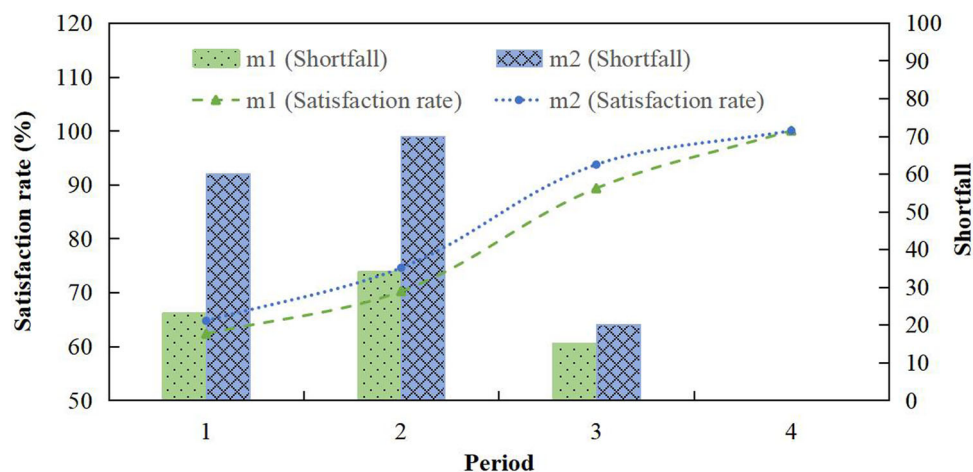


Fig. 6 The evolution trend of the satisfaction rate of multiperiod emergency resource allocation based on the trade-off criteria.

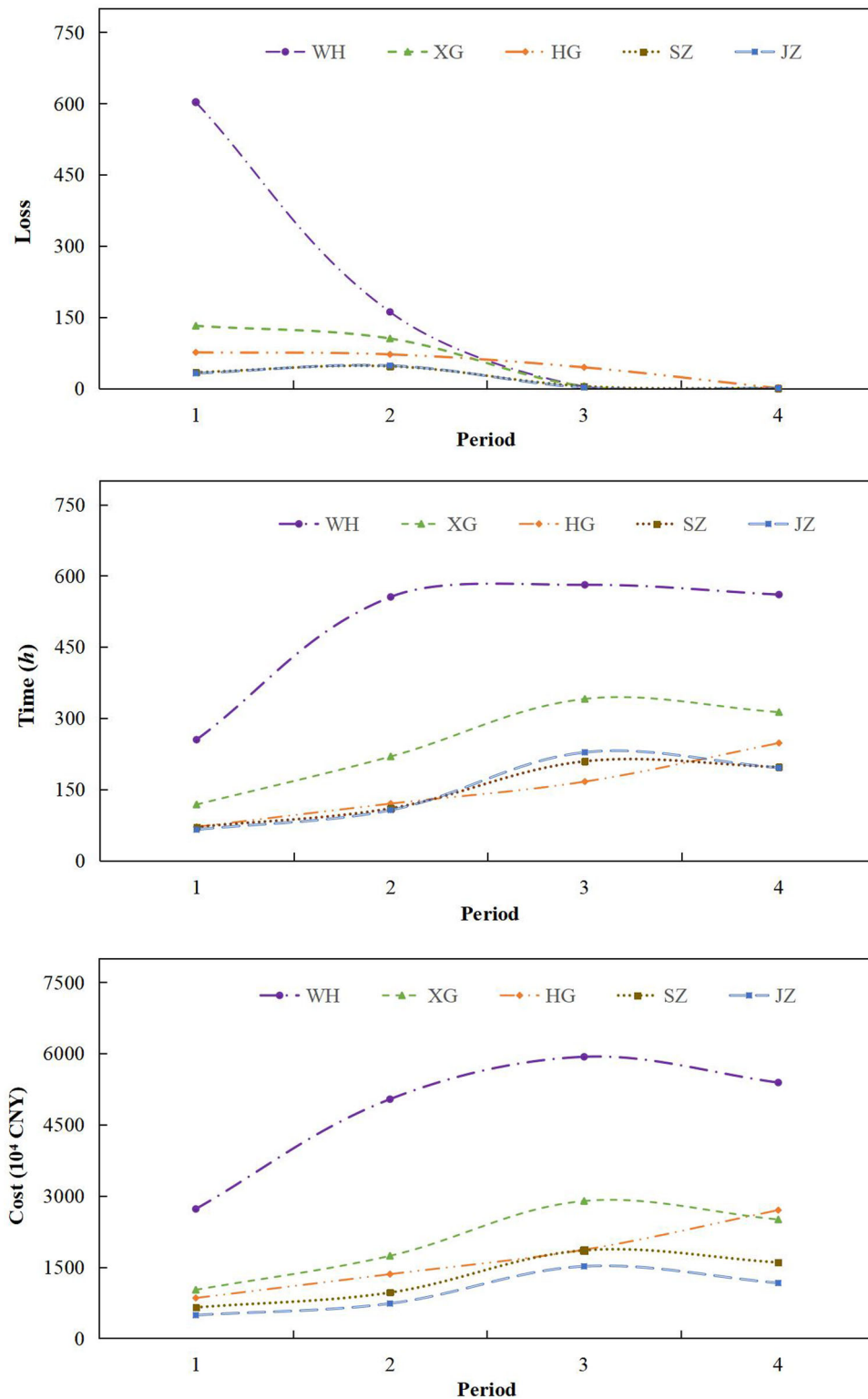


Fig. 7 Loss, time and cost of emergency resource allocation at each affected area in each period under the trade-off criterion. a Loss caused by resource shortfall of each affected area in each period (under trade-off criterion). **b** Time required for each affected area to obtain resources in each period (under trade-off criterion). **c** Cost required for each affected area to obtain resources in each period (under trade-off criterion).

criterion have an increasing influence on the overall resource allocation result.

Thirdly, the balance criterion (balancing the three objectives of loss, time and cost) has advantages in the process of large-scale multiperiod emergency resource allocation during the COVID-19 pandemic. Compared to other decision criteria, the balance criterion

yields better results in terms of total loss, total time, and total cost of resource allocation. This suggests that the decision scheme formed based on this criterion can effectively balance various indicators in the resource allocation process, taking into account specific disaster conditions and rescue information. As a result, it helps to avoid extreme allocation situations as much as possible.

In conclusion, the developed model is applicable not only to the allocation of emergency resources for COVID-19 pandemic, but also to the multi-period optimal allocation of emergency resources for other large-scale public health emergencies, and can provide implications for the government and relevant management departments to formulate emergency resource allocation policies and plans.

Discussion

Implications for management. This study can provide enlightenment on the emergency resource allocation decisions for emergency decisionmakers:

Firstly, it is necessary and important to consider the heterogeneity of affected areas in emergency resource allocation decisions. In the future, attention should be paid to the heterogeneity of different affected areas in the allocation of emergency resources for major public health emergencies, so that victims in the most severely affected areas and the most urgent need for resources can obtain emergency resources in a timely manner.

Secondly, in emergency resource allocation decisions, efficiency, economy, and fairness are important goals for disaster relief. Decision makers must achieve a balance between these three criteria in emergency rescue operations to meet the resource needs of all affected areas as soon as possible with the shortest delivery time and lowest cost, thereby minimizing losses caused by resource shortfalls.

Thirdly, in the early stages of emergency relief, decision-makers should prioritize equity criterion to prevent significant system losses caused by resource scarcity in affected areas during peak demand periods. If the rescue task is urgent and time is tight, decision-makers should prioritize efficiency criterion and allocate limited resources to the affected areas that can be served most effectively. With sufficient supplies in the middle and later stages of a rescue operations, decision-makers can gradually turn their attention to economic criterion to complete resource allocation tasks at the lowest possible cost.

Limitations. This study also has some limitations. First of all, how to consider more heterogeneous factors besides disaster coefficient and demand urgency in model construction, and how to obtain real-time dynamic data information such as cost and supply to avoid the potential impact of estimated data on results, are directions worth considering and studying in the future. In addition, emergency resource allocation is a complex and systematic multi-period process, and as the scale and complexity of research problems increase, it is necessary to design more effective model solving methods. Therefore, the consideration of more heterogeneous factors, the acquisition of real-time dynamic data sets and the design of efficient solution methods still need to be further discussed and explored in future studies.

Data availability

The research data (Tables 2–10) used in this article has been included in the article.

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Author contributions

YW: Conceptualization, methodology, data analysis, investigation, validation, resources, writing-original draft preparation, writing-review and editing, project administration, and funding acquisition. ML: investigation, and visualization. BS: conceptualization, and supervision. All authors have read and agreed to the published version of the manuscript.

Competing interests

The authors declare no competing interests.

Ethical approval

Not applicable as this study did not involve human participants.

Informed consent

This article does not contain any studies with human participants performed by any of the authors.

Additional information

Correspondence and requests for materials should be addressed to Yanyan Wang, Mingshu Lyu or Baiqing Sun.

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