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Research article

A cross-regional emergency supply pre-positioning with partial collaboration cost-sharing strategy

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Abstract: Collaborative pre-positioning of emergency supplies enhances the efficiency of emergency response. A partial collaboration cost-sharing strategy is proposed for cross-regional emergency supply pre-positioning. In the proposed strategy, demand-based costs and risk-based costs are incorporated while considering both the benefits of collaboration and the principle of territoriality. To encourage regional involvement, regional relevance is incorporated into the proposed cost-sharing strategy, reflecting the interdependence among regions. A distributionally robust chance-constrained optimization model is developed to address the uncertainties in emergency supply pre-positioning. Numerical results demonstrate that the proposed partial collaboration strategy achieves a more practically feasible trade-off between fairness and efficiency than the independent and centralized strategies. Sensitivity analyses are performed on the parameters of the proposed model. The findings yield practical managerial insights for implementing collaborative emergency supply pre-positioning. This study provides valuable implications for designing a cross-regional emergency supply pre-positioning system.

Keywords: cross-regional collaboration; cost sharing; emergency supply pre-positioning; distributionally robust chance-constrained optimization
Mathematics Subject Classification: 90B90, 90C17, 90C15

1. Introduction

Humanitarian logistics accounts for 80% of total disaster relief funding [1]. Among warehousing, procurement, and transportation, procurement constitutes up to 65% of total expenditures. This makes procurement the most costly activity in humanitarian operations [2]. Therefore, reducing the cost of emergency supply procurement has become a crucial pathway to improve the efficiency of relief funding. Current practices adopted by emergency management agencies include establishing pre-positioning agreements with suppliers and collaborating with non-governmental organizations. In addition, the cross-regional pre-positioning of emergency supplies has been recognized as an effective strategy to reduce procurement costs [3,4]. In recent years, major disasters, such as the 2021 Zhengzhou floods and the 2023 Beijing-Tianjin-Hebei floods, have highlighted the importance of cross-regional pre-positioning of emergency supplies. These events exposed the limitations of independent pre-positioning, including insufficient supplies, delayed allocation, and resource mismatches. They also demonstrated the necessity of cross-regional collaboration in pre-positioning strategies. Therefore, this paper aims to address the critical issue of designing an effective cross-regional collaborative pre-positioning mechanism for emergency supplies.

Currently, cross-regional collaboration for emergency supplies is largely reactive, being typically initiated only after a disaster occurs. In this ad hoc approach, supplies are allocated based on immediate post-disaster needs, which introduces significant shortcomings. First, post-disaster logistics are often delayed by complex cross-regional procedures and vulnerable supply chains. Such delays severely affect rescue efficiency, especially during the golden 72-hour window. Second, due to a lack of routine collaboration mechanisms, regions tend to plan their emergency supply pre-positioning systems independently before disasters. This fragmented planning may result in redundancy of commonly used supplies while leading to shortages of specialized ones. Consequently, there is an urgent need to shift from this reactive strategy to a proactive one. This should center on establishing a collaborative pre-disaster emergency supply pre-positioning agreement.

There are two challenges in the cross-regional collaborative pre-positioning of emergency supplies. The first is the absence of an effective cost-sharing strategy. Pre-positioning emergency supplies requires substantial capital investment, yet reaching a consensus on cost allocation is complicated by disparities in regional fiscal capacity. This often leads to a “free-rider” problem: less affluent regions may be unable to contribute equitably, while wealthier regions are reluctant to bear a disproportionate share of the financial burden. Therefore, designing a fair and efficient cost-sharing mechanism becomes a critical research challenge. The second is the demand uncertainty. The unpredictability of emergency supplies makes it difficult for regions to agree on unified pre-positioning and allocation strategies. Each region fears that its local demands may not be prioritized during a disaster. This fear incentivizes autonomous pre-positioning over regional collaboration. As a result, the model for cross-regional collaborative pre-positioning must not only incorporate a fair cost-sharing strategy but also ensure that the emergency demands of all participating regions are adequately addressed.

This paper proposes a partial collaboration cost-sharing strategy for emergency supply pre-positioning. While a fully centralized collaboration strategy offers economies of scale and risk pooling benefits, it conflicts with the territorial principle of emergency management. Conversely, purely independent pre-positioning leads to redundant costs and leaves regions vulnerable to supply shortages during extreme disasters. The proposed strategy enables regions to collaborate selectively rather than adopting the average cost allocation of a fully centralized strategy. It preserves the territorial principle while capturing the benefits of cross-regional collaboration.

To encourage regional participation in pre-positioning collaboration, regional relevance is integrated into the cost-sharing strategy. Existing studies on cost-sharing strategies for emergency supplies relied on the amount of allocated supplies. Several studies further incorporated disaster risk and regional economic disparities in the cost-sharing strategy [4–6]. However, these allocation strategies neglect the influence of inter-regional dependence. In reality, disaster events not only cause losses in directly affected regions; they may also generate cross-regional ripple effects through economic, social, or supply chain channels. These effects impact interconnected regions [7,8]. Therefore, regional relevance should be regarded as a critical factor in designing the cost-sharing strategy.

Demand uncertainty further compounds the challenge of cost sharing in collaborative pre-positioning. When future needs are highly unpredictable, regions become reluctant to commit financial resources to shared supplies. They fear that their contributions may not benefit their own constituencies when disasters strike. Traditional deterministic optimization methods fail to capture such uncertainty. Stochastic programming approaches require precise probability distributions, but these are rarely available in disaster contexts. Distributionally robust optimization (DRO) offers a middle ground. It constructs an ambiguity set that characterizes distributional uncertainty. This yields robust solutions that perform well even under worst-case demand realizations. Thus, DRO is particularly suited to risk-averse emergency management. Although DRO has been preliminarily applied to emergency supply distribution [6,9], its integration with chance constraints remains underexplored in the context of pre-positioning [10,11]. Chance constraints are particularly valuable here, as they allow decision-makers to explicitly specify acceptable levels of shortage risk. This paper bridges that gap by incorporating chance constraints to address demand risk. It further extends the model to support multi-period, cross-regional collaborative pre-positioning for reusable emergency supplies.

This paper makes three main contributions to cross-regional collaborative emergency supply pre-positioning. First, a partial collaboration cost-sharing strategy is proposed. The hybrid strategy modulates the degree of collaboration to balance the territorial principle of emergency management with the efficiency gains of cross-regional collaboration. Second, regional relevance is incorporated into the cost-sharing strategy. In addition to demand and disaster risk, the proposed cost-sharing model explicitly accounts for inter-regional interdependence, thereby enhancing both fairness and collaboration incentives. Third, to address demand uncertainty, a multi-period chance-constrained distributionally robust optimization model is established. This model captures distributional ambiguity while allowing decision-makers to specify acceptable shortage risk levels. These contributions provide an integrated framework for cross-regional collaborative emergency supply pre-positioning.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature. Section 3 details the model construction and its reformulation. Section 4 presents the case study, and Section 5 provides the concluding remarks.

2. Literature review

This literature review synthesizes current research across three key themes: emergency supply pre-positioning and cross-regional collaboration, cost-sharing strategies in emergency pre-positioning, and optimization methods under demand uncertainty.

2.1. Emergency supply pre-positioning and cross-regional collaboration

Research on emergency supply pre-positioning has evolved from independent regional stockpile decisions to multi-organizational collaboration within jurisdictions, and further to cross-regional coordination across administrative boundaries. This evolution has been driven by the inadequacy of localized approaches under extreme disasters and the persistent spatial mismatch of resources.

In emergency supply pre-positioning research, the primary focus has been on the pre-positioning quantities and locations for individual regions. Chang et al. [12] developed a scenario-based model for flood emergency logistics in a specific region of Taiwan, representing an early attempt to optimize localized response. Rawls and Turnquist [13] formulated a two-stage stochastic programming model for pre-positioning supplies. It focused on location and quantity decisions for a centralized planner managing a self-contained network. Similarly, Mete and Zabinsky [14] addressed medical supply location and allocation from the perspective of a municipal health authority making independent decisions for its jurisdiction. Extending this line of research, Döyen et al. [15] proposed a two-echelon stochastic facility location model that optimized central warehouses and local distribution points within a defined region. Practical applications were demonstrated by Duran et al. [16], who optimized the pre-positioning network for CARE International, a global humanitarian organization operating its own independent warehouses. As noted in the comprehensive review by Sabbaghtorkan et al. [17], these early location models predominantly assumed a single decision-maker planning for a fixed set of demand points. It reflects the dominant paradigm of independent regional pre-positioning decisions in the formative years of disaster operations management research.

Preparing for low-probability, high-impact disasters requires regions to stockpile large quantities of supplies. This leads to waste during normal times. Yet, when local capacity is exceeded, these stockpiles prove insufficient. Incorporating enterprises and social organizations addresses the limitations of relying solely on government capacity in terms of both efficiency and scale. Balcik et al. [3] provided a foundational framework for understanding coordination practices and challenges in humanitarian relief chains. These include issues of communication, resource sharing, and role clarification among diverse organizations. Ergun et al. [18] examined how technology-enabled collaboration can improve humanitarian operations through enhanced coordination among multiple actors. Aghajani et al. [19] introduced an option contract integrated with supplier selection and inventory pre-positioning that addresses compensation and incentive problems in government-enterprise collaboration. Wang et al. [20] proposed a bi-level multi-phase emergency planning model involving government–enterprise coordination for procurement, pre-positioning, and allocation. It demonstrates that coordinated location strategies yield optimal relief benefits. Liu et al. [21] developed a disaster insurance model with capacity reservation functionality that integrates financial and operational elements to facilitate public–private collaboration, and found that zero-deductible contracts can serve as optimal mechanisms in localized disasters.

When extreme disasters exceed local carrying capacity or destroy local storage facilities, resources become depleted even with full local integration. Under such circumstances, cross-regional collaboration becomes imperative. Jiang et al. [22] demonstrated that coordinated pre-positioning across regions significantly improves response efficiency under demand uncertainty. Lei et al. [23] identified three path models for cross-regional emergency cooperation, finding autonomous regulation most effective. Wang et al. [24] showed the benefits of coalition-based integrated management in regional healthcare systems. Chen et al. [25] established a cross-regional emergency supply pre-positioning model considering regional priorities. They demonstrated that regional collaboration can significantly reduce expected costs across regions. These studies suggest that cross-regional collaboration addresses the spatial mismatch problem. It enables resource sharing across administrative boundaries and provides access to external reserves when local capacity is overwhelmed.

2.2. Cost-sharing strategies in emergency pre-positioning

Pre-positioning incurs high fixed costs that often surpass the financial capacity of any single government, particularly for low-probability extreme events. This has made fair and efficient cost-sharing among multiple participants a central issue.

Research on government-enterprise collaboration has proposed various cost-sharing mechanisms. A substantial body of literature has focused on option contracts as a primary mechanism for government-enterprise cost sharing. Liang et al. [26] developed an option contract pricing model, demonstrating that such contracts effectively share inventory risks between governments and suppliers. Wang et al. [27] extended this work, showing that option contracts can achieve supply chain coordination under symmetric information. Torabi et al. [28] integrated relief pre-positioning with procurement planning, combining option contracts with direct purchasing to balance cost and responsiveness. Ghavamifar et al. [29] proposed a hybrid contract combining options with buyback and revenue-sharing mechanisms, demonstrating superior performance under dual uncertainties. Chen et al. [30] developed a bi-objective model for contract design considering extreme disaster scenarios. Guo and Zhu [31] addressed capacity reservation through an efficient decomposition method for large-scale problems. Taghvaei et al. [32] extended this line by considering hybrid contracts alongside public donations and item perishability. Beyond option contracts, other contractual forms have been explored. Kord and Samouei [33] investigated quantity flexibility contracts combined with spot market purchasing under demand uncertainty. Aghajani et al. [19] examined integrated procurement-warehousing decisions under supply disruption. Behavioral and game-theoretic perspectives have also enriched this literature. Yao et al. [34] analyzed evolutionary dynamics of supervision-compliance games, revealing how supervision intensity influences enterprise compliance. Shao et al. [35] examined incentive contracts under multiplayer competition and cooperation, showing how inter-firm relationships affect optimal contract design.

The cost-sharing problem becomes more complex in cross-regional collaborative pre-positioning. When multiple administrative regions jointly invest in shared pre-positioning facilities, questions arise regarding how to allocate costs based on regional risk profiles, expected benefits, and economic capacity. Balcik et al. [4] laid the groundwork by developing a collaborative pre-positioning network design for hurricane-prone Caribbean regions, demonstrating the potential benefits of regional cooperation in disaster preparedness. Building on this foundation, Rodríguez-Pereira et al. [5] proposed a formal cost-sharing mechanism for multi-country partnerships, explicitly incorporating both demand uncertainty and national income levels into their model. Their approach allocates costs by ensuring each region pays no more than its individual stand-alone cost while achieving cross-subsidy-free allocations. Its effectiveness was validated through comparisons with established cooperative game theory methods. These include the Shapley value, the alternative cost avoided method, and the equal profit method. More recently, Li and Liu [6] examined collaborative emergency response network design at the national level using a distributionally robust optimization approach. Extending the cost-sharing framework established by Rodríguez-Pereira et al. [5], they adopted GDP as a proxy for regional economic capacity and further refined the allocation mechanism to account for ambiguous probability distributions of demand.

2.3. Optimization methods under demand uncertainty

Demand uncertainty is a fundamental challenge in emergency supply pre-positioning, and the choice of optimization method determines how effectively this uncertainty is addressed. Stochastic programming has been the most widely adopted approach in the early literature, representing uncertainty through discrete scenarios with known probability distributions. Rawls and Turnquist [13] formulated a two-stage stochastic programming model for pre-positioning emergency supplies. In their model, first-stage decisions determine stockpile locations and quantities, and second-stage decisions allocate supplies after disaster occurrence based on realized demand scenarios. Similar stochastic programming frameworks were subsequently developed by Mete and Zabinsky [14] for medical supply location and distribution, Döyen et al. [15] for two-echelon facility location, and Torabi et al. [28] for integrated pre-positioning and procurement planning combining option contracts with direct purchasing. These stochastic programming models provide a solid foundation for decision-making under uncertainty, but require precise knowledge of demand distributions.

When historical data are insufficient to estimate accurate probability distributions, DRO has emerged as a powerful approach that bridges stochastic programming and traditional robust optimization. DRO seeks the optimal solution under the worst-case distribution within an ambiguity set characterized by partial distribution information. A growing body of research has integrated chance constraints with DRO to address reliability requirements in disaster management. Liu et al. [36] developed a distributionally robust optimization model for emergency medical service station location and sizing problems with joint chance constraints. They demonstrated that their DRO approach outperforms both stochastic programming and traditional robust optimization when distributional information is limited. Jiang et al. [11] proposed a two-stage distributionally robust joint chance-constrained model for humanitarian relief network design, considering uncertainties in both demand and unit allocation costs. They investigated moment-based and Wasserstein ambiguity sets. Through a Gulf Coast case study, they demonstrated that the Wasserstein-based DRJCC model achieves a better trade-off between cost and network reliability than both moment-based DRO and classical stochastic programming. Wang et al. [37] established a distributionally robust chance-constrained model for resource allocation and vehicle routing problems during the post-disaster response phase. They implemented a safe approximation for the chance constraint. Sarmadi and Amiri-Aref [38] examined a location-routing problem for urban search and rescue operations using a distributionally robust optimization approach with joint chance constraints. They enhanced computational tractability by reformulating the chance constraints using approximation techniques.

2.4. Gap analysis

The literature review reveals three research gaps. First, existing models typically assume unconditional collaboration. Existing models assume unconditional collaboration, but the territorial management system makes local governments accountable for their own jurisdictions. This paper addresses this issue by proposing a partial collaboration cost-sharing strategy. The strategy is controlled by a tunable parameter that bridges independent and centralized strategies. Second, existing mechanisms neglect inter-regional interdependence. Current cost-sharing mechanisms treat regions as independent, ignoring geographic, economic, and infrastructural linkages. We fill this gap by incorporating regional relevance into the cost allocation framework. Third, DRO has not been applied to cross-regional pre-positioning with reusable supplies. Distributionally robust optimization has been applied only to single-region settings, and most models assume supplies are consumed. This paper develops a multi-period distributionally robust joint chance-constrained model for reusable supplies, reformulated as a mixed-integer linear program.

3. Problem description and formulation

The parameters and decision variables are shown in Table 1.

Table 1. Notation.

		Explanation
Sets	N	Set of regions, $i,\ j \in N,\ \|N\| = n$.
	T	Set of periods, $t \in T,\ \|T\| = T$.
	K	Set of historical demand samples, $k \in K$, $\|K\|$ is the sample size.
Parameters	t	Period $t \in T$.
	$i,\ j$	Region $i,\ j \in N$.
	k	Sample $k \in K$.
	$\tilde{d}_{it}$	Demand in region i during period t, uncertain parameter.
	$\hat{d}_{it}^{k}$	Sample of historical demand, $\hat{d}_{it}^{k} \in \hat{\boldsymbol{d}}$, μ_{it} and σ_{it} are its mean and standard deviation, respectively.
	c_{ij}	Dispatching cost from region i to region j for unit emergency supply.
	p	Pre-positioning cost for unit emergency supply.
	r_{ij}	Regional relevance between region i and region j.
	R_i	Relevance of region i, $R_i = \sum_{j \in N \setminus \{i\}} r_{ij}$.
	ϑ, φ	Weights for the risk-based cost, ϑ is the weight of disaster risk, φ is the weight of regional relevance.
	α	The degree of regional collaboration. The larger the value of the parameter, the higher the degree of regional participation in collaboration.
	ϵ	The maximum allowable violation probability.
	δ	Wasserstein radius.
Decision variables	x_i^t	Quantity of emergency supplies available for local use in region i during period t.
	y_{ij}^t	Quantity of emergency supplies dispatched from region i to region j at the beginning of period t.
	z_i	Cost shared by region i.
	γ, v_k, s_k, u_k	Auxiliary variables that are used in chance constraint reformulation.

3.1. Problem description and assumptions

This paper investigates a cross-regional collaborative pre-positioning problem for reusable emergency supplies (e.g., large-scale rescue equipment). Such supplies incur high procurement costs but are reusable, making it financially inefficient for any single region to maintain sufficient inventories independently. To address this, we consider a coalition of multiple regions that agree to establish a shared resource pool and coordinate inventory management over a multi-period planning horizon $t \in T$.

In the preparedness phase, regions collectively procure supplies based on a pre-established agreement. During the warning phase, supplies are dispatched to potential disaster regions to ensure timely availability. In the response phase, affected regions utilize both pre-positioned reserves and supplies allocated during the warning phase. Figure 1 illustrates the overall framework, highlighting the three phases and the interactions among regions.

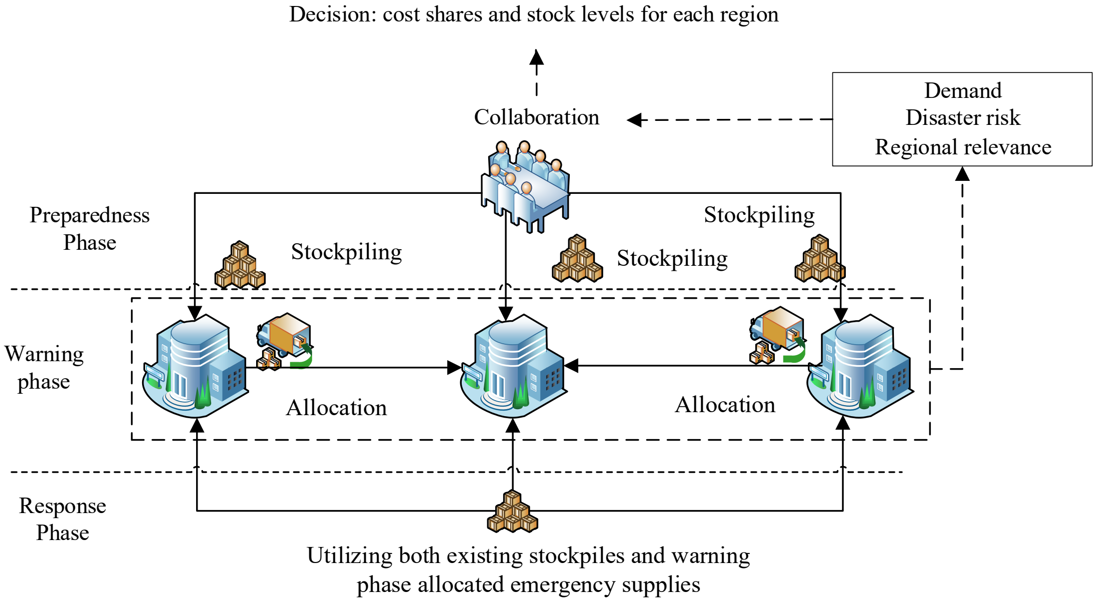

Figure 1. Cross-regional collaborative pre-positioning problem.

At the beginning of the first period, each region i determines its initial stock level x_i^1 by procuring reusable supplies at a unit cost p. These procurement costs are shared among all participating regions through a cost-sharing mechanism, where each region bears a portion z_i. During each period t, regional demand $\tilde{d}_{it}$ is realized. To meet demand, regions can dispatch supplies to each other. However, due to logistical delays, any shipment dispatched from region i to region j at the beginning of period t (denoted as y_{ij}^t) will only arrive and become available in region j at the beginning of period $t+1$. This one-period lead time distinguishes our model from instantaneous transshipment models. Figure 2 depicts the inventory evolution process, showing how dispatched supplies arrive one period later.

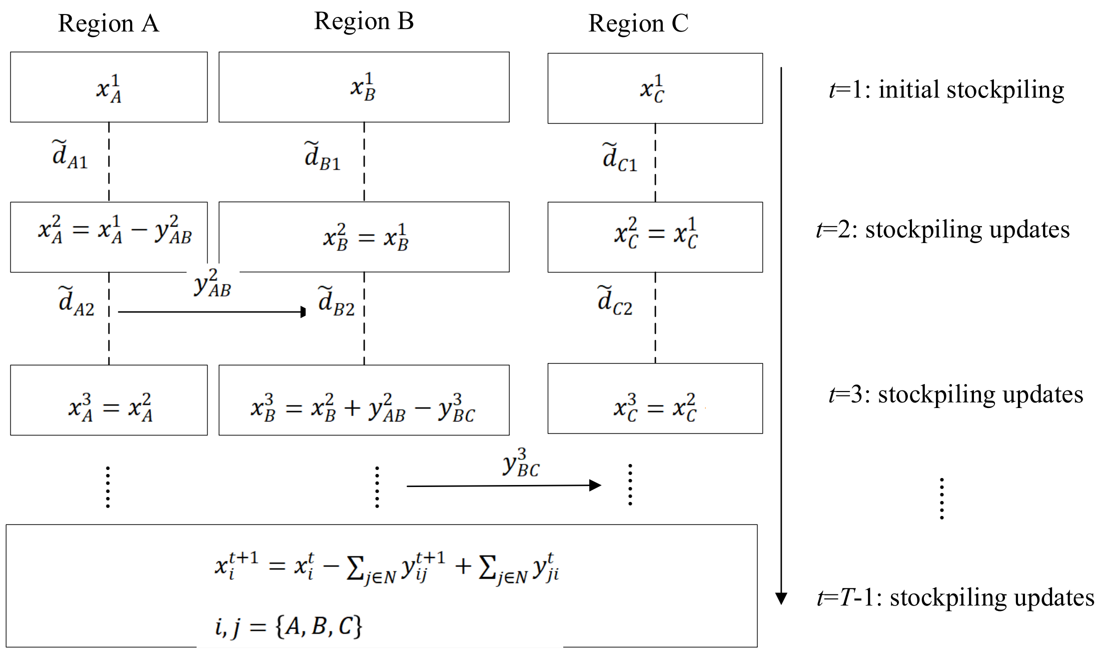

Figure 2. Stockpiling updates process.

Based on the above description, we introduce the following assumptions to formalize the problem.

Assumption 1: The emergency supplies considered in this study are high-value and reusable (e.g., large-scale rescue equipment, mobile medical units, generator sets). Due to their high procurement costs, it is inefficient for any single region to maintain sufficient inventories independently. Moreover, their reusable nature enables sustainable scheduling and circular utilization across multiple periods.

Assumption 2: Emergency supplies should be allocated during the early warning phase. Specifically, any shipment dispatched from region i to region j at the beginning of period t arrives at the beginning of period $t+1$. Consequently, supplies dispatched in period t are not available for allocation until period $t+1$.

Assumption 3: Pre-positioning costs are shared among all participating regions, whereas dispatch costs are solely borne by the receiving region. This follows prevailing emergency management practices, where transportation costs during the response phase are covered by the receiving agency. Accordingly, the total cost incurred by each region consists of its shared pre-positioning cost and its incurred dispatch costs.

3.2. Cost-sharing model

The cost-sharing strategy is a critical factor influencing the effectiveness of cross-regional collaboration in emergency management. Most existing studies on cost sharing of emergency supplies have incorporated historical demand, while some have further integrated disaster risk factors. Several approaches have also introduced economic indicators (such as GDP), suggesting that economically developed regions should share more costs. However, a GDP-based cost-sharing strategy primarily reflects unilateral assistance from affluent regions to less developed ones, ignoring the bidirectional interdependencies. This study further analyzes mutual dependencies among regions and develops a cost-sharing strategy that incorporates regional relevance.

The incorporation of regional relevance into the cost-sharing strategy is primarily driven by the ripple effects of disasters. He et al. [7], in their study of flood disasters in the Yangtze River Economic Belt, revealed that such disasters not only impact the directly affected areas but also generate ripple effects transmitted through regional interconnections. Similarly, Ding and Wu [8] analyzed the impact on the economic system using the Shanghai rainstorm event as a case study. Their research revealed that flooding and the ensuing traffic disruptions not only harm local economic activity but also generate significant ripple effects transmitted through economic linkages to other connected regions. Therefore, collaborative pre-positioning of emergency supplies among connected regions is not merely an act of mutual assistance but also a strategy to enhance their own resilience. This dual benefit provides a compelling rationale for regions to engage in collaboration. Building on existing research, this paper identifies historical demand, disaster risk, and regional relevance as the three primary factors influencing emergency supply cost sharing.

A partial collaboration cost-sharing strategy is proposed. In this model, the total cost for each region consists of two components: demand-based costs and risk-based costs. The demand-based component reflects the principle of territorial responsibility, as it allocates costs according to the demand of each region. In contrast, the risk-based component reflects the principle of risk sharing, as it allocates costs based on potential future threats that affect all regions, thereby encouraging collective preparedness. The risk-based component is determined by combining disaster risk with regional relevance.

The degree of collaboration is controlled by the parameter $\alpha \in [0,1]$. When $\alpha = 0$, constraint (1) forces every region to pay exactly its demand-proportional share. Since τ is an endogenous variable determined by the optimization, the model sets $\tau = 0$ at optimality, and the upper bound collapses to the lower bound, which corresponds to the independent strategy (no cross-subsidization). When $\alpha = 1$, the lower bound vanishes, and the upper bound is determined purely by risk and relevance, which approximates a centralized strategy. For $0 < \alpha < 1$, the cost share z_i is allowed to vary between the demand-based lower bound and the risk-based upper bound, giving each region flexibility to negotiate its contribution. Thus, the partial collaboration strategy is not represented by a fixed allocation rule but by a feasible region together with an optimization objective. The final cost shares are determined endogenously, which captures the idea that regions negotiate their contributions within the boundaries set by demand, risk, and relevance. Based on this framework, the following cost-sharing model is constructed.

$$z_i \geq (1-\alpha)\sum_{i\in N} z_i \frac{\sum_{t\in T}\mu_{it}}{\sum_{i\in N}\sum_{t\in T}\mu_{it}}, i \in N \tag{1}$$

$$z_i \leq (1-\alpha)\sum_{i\in N} z_i \frac{\sum_{t\in T}\mu_{it}}{\sum_{i\in N}\sum_{t\in T}\mu_{it}} + \left(\vartheta\sqrt{\sum_{t\in T}{\sigma_{it}}^2} + \varphi R_i\right)\tau, i \in N \tag{2}$$

Formula (1) defines the lower bound of costs allocated to each region, which corresponds to the demand-based cost component. This component is calculated primarily based on the average historical demand of each region. Formula (2) specifies the upper limit of costs and relies on the risk-based cost component. This component is primarily determined by the disaster risk (measured by, e.g., historical demand variance and disaster probability) and regional relevance (measured by, e.g., trade flow, industrial synergy index, and network density).

The cost-sharing bounds (1)–(2) are designed to balance territorial responsibility with risk sharing. The lower bound (1) is demand-based and reflects the territorial principle: each region should contribute at least a baseline amount proportional to its expected demand, because it is primarily responsible for preparing for its own potential disasters. This ensures that no region can free-ride on others' contributions. The upper bound (2) is risk-based and reflects the mutual-benefit principle: regions that are more exposed to disaster risk or more centrally connected in the inter-regional network are permitted to contribute more, but this is an upper limit rather than a mandatory payment. The actual cost share z_i is determined endogenously by the optimization within these bounds, meaning that high-risk regions are not forced to pay the maximum unless the overall cost structure requires it.

We recognize that high-risk regions may also have weaker fiscal capacity, and that requiring them to pay more could reduce fairness and participation incentives. This is a valid and important point. The proposed model offers two features to mitigate this concern. First, the partial collaboration parameter α is a global parameter negotiated among all participating regions. A smaller α shifts the allocation closer to the demand-based lower bound. This is particularly beneficial for regions with limited fiscal capacity, as it reduces their financial exposure. Second, the model does not prescribe a fixed allocation. The bounds define a feasible range, and the actual distribution is determined by the optimization, which balances across all regions. Nonetheless, we agree that incorporating fiscal capacity or GDP into the cost-sharing mechanism would further enhance fairness. We identify this as a valuable extension for future research.

3.3. Optimization model for collaborative emergency supply pre-positioning

This paper investigates the cross-regional collaborative pre-positioning of emergency supplies, considering cost sharing. Given the rigid demand for emergency supplies, the consequences of shortages are difficult to reasonably quantify using monetary penalty costs. Moreover, introducing excessively high penalty coefficients may distort the cost structure and obscure the fairness of cost sharing in collaborative pre-positioning. Therefore, this paper formulates the reliability requirement for demand satisfaction as a distributionally robust chance constraint (DRCC). The objective function includes only the directly quantifiable pre-positioning and transportation costs, without incorporating revenue or shortage penalty terms. In the context of cross-regional collaboration, the optimization must balance two potentially conflicting objectives. These are minimizing the total system cost (efficiency) and ensuring that no single region bears a disproportionately high financial burden (fairness). This paper adopts a minimax objective to minimize the maximum regional cost. Rather than enforcing equal monetary burdens, which would be inappropriate given regional disparities in economic capacity, the minimax criterion ensures that no region is forced to bear a disproportionately high cost relative to others. This prevents the most extreme form of unfairness in collaborative arrangements. Risk aversion is instead embedded in the distributionally robust chance constraint (7) and the minimax formulation, rather than via a shortage penalty term.

$$min \ \max_{i \in N} \{ z_i + \sum_{t \in T} \sum_{j \in N} c_{ji} y_{ji}^t \} \tag{3}$$

s. t.

$$\sum_{j \in N} y_{ij}^t \leq x_i^{t-1}, i \in N, t \in T \backslash \{1\} \tag{4}$$

$$y_{ij}^1 = 0, i, j \in N \tag{5}$$

$$x_i^{t+1} = x_i^t - \sum_{j \in N} y_{ij}^{t+1} + \sum_{j \in N} y_{ji}^t, i \in N, t \in T \backslash \{T\} \tag{6}$$

$$\inf_{\mathbb{P}\in\mathcal{P}} \mathbb{P}\{\tilde{d}_{it}: \tilde{d}_{it} \le x_i^t, \forall i \in N, \forall t \in T\} \ge 1-\epsilon \tag{7}$$

$$\sum_{i\in N} z_i = p\sum_{i\in N} x_i^1 \tag{8}$$

(1), (2)

$$x_i^t, y_{ij}^t, z_i, \tau \ge 0, i, j \in N, t \in T \tag{9}$$

In the proposed model, Formula (3) is the objective function. The total cost for each region contains both pre-positioning costs and dispatch costs. To ensure fairness in collaboration, the objective is to minimize the maximum cost across all regions. Equation (4) is a capacity constraint, ensuring that the quantity of emergency supplies dispatched from region i at the end of period $t-1$ (equivalently, at the beginning of period t) does not exceed the inventory that was available for local use in the previous period, x_i^{t-1}. This timing reflects the fact that dispatches are made from the previous period's stock, while x_i^t is reserved for local demand satisfaction in period t. Formula (5) indicates that no supplies are dispatched between any two regions in the first period. This is because supplies dispatched in the first period would not arrive until the second period, rendering them unavailable for immediate response. Such a delayed dispatch would incur transportation costs without contributing to first-period relief efforts, making it inefficient and thus excluded from the model. Moreover, any dispatch from region i to j in period 1 can be equivalently represented by transferring the corresponding initial inventory from x_i^1 to x_j^1 without changing the total procurement cost or feasibility. Therefore, imposing $y_{ij}^1 = 0$ does not restrict the optimal solution. Equation (6) describes the inventory dynamics for subsequent periods. In addition to outgoing shipments, it also accounts for incoming shipments from other regions that were dispatched in the previous period. This captures the delayed effect of transportation, ensuring that supplies sent from region j to region i in the previous period become available at the beginning of the current period. Because the supplies are reusable, satisfying demand does not consume them. The inventory level decreases only when supplies are dispatched to other regions. Hence, the inventory update equation (6) does not include a deduction for demand fulfillment. Equation (7) is a joint DRCC that requires the probability of simultaneously satisfying demand in all regions and all periods to be at least $1-\epsilon$. Equivalently, the probability that any shortage occurs in any region-period pair does not exceed ϵ. This formulation handles demand uncertainty for any distribution within the Wasserstein ambiguity set $\mathcal{P}$. Constraint (8) requires that the total regional contributions cover exactly the one-time procurement cost. We formulate it as an equality to ensure strict budget balance across all participating regions. Equation (9) enforces non-negativity constraints on all decision variables.

3.4. Reformulation of the distributionally robust chance constraint

In the proposed model, the distributionally robust chance constraint (7) is computationally difficult to solve directly. Wang et al. [10] and Jiang et al. [11] have transformed distributionally robust chance constraints to facilitate their solution. This paper employs the method proposed by Xie [39], utilizing the Wasserstein ambiguity set and the large M method, to transform the chance constraint into a set of constraints. Thus, the proposed model is reformulated as a mixed-integer programming model.

Theorem 1: Let $\mathcal{P}$ be the Wasserstein ambiguity set centered at the empirical distribution $\mathbb{P}_{\hat{d}}$ with radius $\delta > 0$, i.e., $\mathcal{P} = \{\mathbb{P}: \mathbb{P}\{\tilde{d} \in \Xi\} = 1, W(\mathbb{P}, \mathbb{P}_{\hat{d}}) \leq \delta\}$, where $\mathbb{P}_{\hat{d}} = \frac{1}{|K|}\sum_{k\in K}\delta_{\hat{d}^k}$ is constructed from i.i.d. samples $\{\hat{d}^k\}_{k\in K}$. Then the feasible set $Z := \left\{x \in \mathbb{R}^n: \inf_{\mathbb{P}\in\mathcal{P}} \mathbb{P}\{\tilde{d}_{it} \leq x_i^t, i \in N, t \in T\} \geq 1-\epsilon\right\}$ is equivalent to the following mixed integer linear system:

$$Z = \left\{ x \in \mathbb{R}^n: \begin{array}{c} \delta - \epsilon\gamma \leq \frac{1}{|K|}\sum_{k\in K} v_k, \\ v_k + \gamma \leq s_k, \forall k \in K, \\ s_k \leq x_i^t - \hat{d}_{it}^k + M(1-u_k), \forall k \in K, i \in N, t \in T, \\ s_k \leq M u_k, \forall k \in K, \\ v_k \geq s_k - \gamma - M(1-b_k), \forall k \in K, \\ v_k \geq -M b_k, \forall k \in K, \\ s_k \geq 0, \gamma \geq 0, v_k \leq 0, u_k \in \{0,1\}, b_k \in \{0,1\}, \forall k \in K. \end{array} \right\} \tag{10}$$

where M is a sufficiently large constant satisfying $M \geq max_{i\in N, t\in T, k\in K}\{|x_i^t - \hat{d}_{it}^k|\}$ for all feasible x. The binary variables u_k and b_k are purely mathematical auxiliary variables introduced for linearization and carry no operational interpretation, and γ, v_k, s_k are continuous.

Proof:

We begin by transforming the original chance constraint into a worst expectation form and applying the Wasserstein strong duality [40,41]. Following the steps detailed in Appendix A, the condition reduces to the linear inequality

$$\delta - \epsilon\gamma \leq \frac{1}{|K|}\sum_{k\in K} v_k \tag{11}$$

with $v_k = min\{\Phi_k(x) - \gamma, 0\}$ and $\Phi_k(x) = min_{i,t} max\{x_i^t - \hat{d}_{it}^k, 0\}$.

To obtain a tractable mixed-integer linear formulation, we linearize $\Phi_k(x)$ using the big-M method and a binary variable u_k:

$$s_k \leq x_i^t - \hat{d}_{it}^k + M(1-u_k), \forall i \in N, t \in T \tag{12}$$

$$s_k \leq M u_k, \forall k \in K \tag{13}$$

$$s_k \geq 0, \forall k \in K \tag{14}$$

which enforces $s_k = \Phi_k(x)$ at optimality (see Appendix A for verification).

The relation $v_k = min\{s_k - \gamma, 0\}$ is linearized by introducing an additional binary variable b_k and the following constraints:

$$v_k + \gamma \leq s_k, \forall k \in K \tag{15}$$

$$v_k \geq s_k - \gamma - M(1-b_k), \forall k \in K \tag{16}$$

$$v_k \geq -M b_k, \forall k \in K \tag{17}$$

$$v_k \leq 0, b_k \in \{0,1\}, \forall k \in K \tag{18}$$

The upper bounds alone would only give $v_k \leq min\{s_k - \gamma, 0\}$; the lower bounds with b_k force equality for any feasible solution, independent of the optimization direction. A complete derivation is provided in Appendix A.

Collecting the above constraints yields exactly the mixed-integer linear system stated in the theorem. □

The detailed proof process is provided in Appendix A.

3.5. Complexity analysis of the reformulated model

The reformulated model in Theorem 1 is a mixed-integer linear program (MILP). For a problem instance with $|N|$ regions, $|T|$ time periods, and $|K|$ historical demand samples, the numbers of variables and constraints are as follows:

Continuous variables include $|N| \cdot |T|$ inventory variables x_i^t, $|N|^2 \cdot |T|$ dispatch variables y_{ij}^t, $|N|$ cost-share variables z_i plus auxiliary variables s_k (one per sample) and γ. Binary variables include $|K|$ variables u_k and $|K|$ variables b_k. The constraint structure consists of one inequality from the Wasserstein robust constraint, $2|K|$ constraints from the linearization of the $\min\{\cdot, 0\}$ function, $|N| \cdot |T| \cdot |K|$ constraints from the big-M bounds, and additional constraints from the cost-sharing mechanism [constraints (1)–(2)], inventory dynamics [constraints (4)–(6)], and non-negativity. In total, the MILP contains approximately $O(|N||T||K| + |N|^2|T|)$ constraints.

For the numerical study in Section 4 ($|N| = 6, |T| = 18, |K| = 90$), the MILP contains approximately 1200 continuous variables, 180 binary variables, and about 10,000 constraints. The model is solved using Gurobi 12.0.1 with default settings on a workstation with a 1.8 GHz CPU and 16 GB RAM. The relative MIP gap tolerance is set to 0.0001, and a time limit of 1 h is imposed for each instance. All reported solutions are optimal with a verified optimality gap of 0%. Across the extended sensitivity analysis runs (7 instances with $\delta \in [0.0001, 0.1]$), the solution times range from 1.5 to 1.7 seconds, with a mean of 1.5 seconds and a median of 1.5 seconds. This computational performance is highly efficient for offline pre-positioning planning, where solution time is not a binding constraint. For larger-scale problems, decomposition methods such as Benders decomposition could be employed to improve scalability, which we leave for future research.

Compared to alternative solution methods in the literature, such as sample average approximation (SAA) with scenario reduction or Benders decomposition, our reformulation is solved directly as an MILP. This approach avoids the complexity of implementing decomposition algorithms while maintaining tractability for the problem sizes considered. For larger-scale problems, one could integrate the proposed linearization with cutting-plane methods or use the indicator constraint to further reduce the binary variable count. However, such extensions are beyond the scope of this paper and are left for future research.

4. Case study

This study conducts a real-world case study based on the six provinces covered by the "Rise of Central China" national strategy: Shanxi (SX), Anhui (AH), Jiangxi (JX), Henan (HA), Hubei (HB), and Hunan (HN). These provinces are frequently affected by severe flooding during the summer monsoon season. Historical flood disaster data for the period 2015–2019, including affected population, economic losses, and emergency material requisition records, were collected from the National Disaster Reduction Center of China, as well as the China Water Resources Bulletin and provincial emergency management yearbooks. The dataset consists of 5 years of flood season records, with each flood season discretized into 18 ten-day periods, yielding 90 historical demand samples. Each of the 90 samples corresponds to a complete flood season (one year) consisting of 18 consecutive ten-day periods, covering the six months from April to September when flood risk is most concentrated in the study region based on historical records. For each sample k, the demand vector $\hat{d}_{it}^{k}$ provides demand realizations for all regions $i \in N$ and all periods $t \in T$ simultaneously. Thus, each sample is a complete 18-period demand scenario for a single year. The model treats the 90 samples as independent observations of the 18-period flood season. The chance constraint (7) requires that the pre-positioning decisions are feasible across all samples simultaneously. This structure captures the temporal correlation of demand within each flood season, while treating different years as independent draws from the underlying demand distribution. The demand for lifeboats in each flood season period was estimated using the guidelines of the International Federation of Red Cross and Red Crescent Societies (IFRC) and the International Organization for Migration (IOM), as detailed below. This real-world dataset ensures that the numerical experiments reflect actual disaster characteristics and regional interdependencies.

This study focuses on reusable, high-value emergency supplies, such as lifeboats, which are used as a representative example in the subsequent numerical experiments. Accordingly, the following section details the methodology for estimating lifeboat demand. Assuming a capacity of 8 persons per boat and 2 trips per hour (including return time), a single boat working 12 h per day can transport approximately $12 \times 8 \times 2 = 192$ persons. Consequently, approximately 5 boats are required per thousand people. Additionally, the IFRC's guidelines for flood emergency response 2021 and the IOM's manual on emergency operations recommend one lifeboat per 200 people. Therefore, this study assumes a requirement of 5 lifeboats per thousand people. Based on tender data from emergency management agencies, the price of a lifeboat typically ranges from ¥10,000 to ¥100,000. Therefore, a unit procurement cost of ¥50,000 is assumed. To ensure the economic incentive for regional collaboration, the dispatch cost per unit is set significantly lower, at ¥1,000–¥9,000.

The remaining parameters are set as follows. The study period spans the annual flood season from April 1 to September 30, which is discretized into 18 operational periods of 10 days each. Regional relevance is estimated by the actual railway freight flow between regions, with data derived from the OD table in the China Statistical Yearbook 2023. Railway freight flows are used as a proxy for regional relevance because they reflect the intensity of economic and logistical interdependence between regions. Higher freight exchange indicates a greater likelihood of experiencing ripple effects from disasters occurring in each other's territories. The values of the key parameters are set as follows: The maximum allowable violation probability ϵ for the chance constraint typically ranges from 0.01 to 0.2 and is set to 0.1 in this study. The regional collaboration coefficient α lies in the interval $[0,1]$ and is assigned a value of 0.3. The weights ϑ and φ represent the relative importance assigned to disaster risk and regional relevance, respectively, in the cost-sharing mechanism. For normalization, we impose $\vartheta + \varphi = 1$, which is a standard practice in multi-criteria weighting to express relative importance. The sensitivity analysis in Section 4.3.3 examines a wide range of ϑ values from 0.1 to 1 (with $\varphi = 1 - \vartheta$), confirming that the main conclusions are not sensitive to the exact choice within a broad range. The Wasserstein radius δ is selected through a data-driven procedure [42]. We solve the model over a range of δ values and choose $\delta = 0.002$ as the baseline, as it achieves zero shortage against the historical samples while maintaining a reasonable cost level. The big-M constant used in the reformulation (Theorem 1) is chosen as $M =$

1.5×10^5, obtained by the tight bounding procedure described in Appendix A.4. This value ensures numerical stability while preserving feasibility.

The numerical experiments in this study are structured into three parts. The first part compares the pre-positioning costs associated with the other two pre-positioning strategies. The second part investigates how the selection of collaborative regions influences costs. The third part presents a sensitivity analysis of the key parameters.

4.1. Analysis of emergency supply pre-positioning strategies

Three emergency supply pre-positioning strategies are compared: the independent strategy (IS), the partial-collaboration strategy (PCS), and the centralized strategy (CS). These strategies differ in their approaches to cost sharing. In the independent strategy, there is no cost sharing, as each region bears its own pre-positioning costs. In the centralized strategy, costs are shared equally among regions. In contrast, the partial-collaboration strategy proposed in this paper allocates costs based on demand, disaster risk, and regional relevance. The emergency supply pre-positioning costs for each region under the three strategies are shown in Table 2.

Table 2. Impact of emergency supply pre-positioning strategies on costs.

	Cost			Increase in costs		
Region	IS	PCS	CS	IS Trans. PCS	IS Trans. CS	PCS Trans. CS
AH	1.36E+05	1.36E+05	1.13E+05	0.33%	-16.80%	-17.07%
HA	4.18E+04	1.36E+05	1.13E+05	226.04%	170.39%	-17.07%
HB	2.14E+05	1.36E+05	1.13E+05	-36.46%	-47.31%	-17.07%
HN	1.57E+05	1.36E+05	1.13E+05	-13.43%	-28.21%	-17.07%
JX	1.31E+05	1.36E+05	1.13E+05	3.97%	-13.78%	-17.07%
SX	2.53E+04	1.58E+04	1.13E+05	-37.68%	346.56%	616.60%
Total	7.05E+05	6.97E+05	6.78E+05	-1.24%	-3.94%	-2.73%

As shown in Table 2, the centralized strategy achieves the fairest cost allocation among regions and the lowest total cost. The partial-collaboration strategy results in a slightly higher total cost and unequal regional costs. In contrast, the independent strategy leads to the greatest regional cost disparities and the highest total cost. Therefore, from a cost perspective, the centralized strategy demonstrates a slight advantage over the partial-collaboration strategy, which in turn holds a substantial advantage over the independent strategy.

Table 2 further reveals distinct regional preferences regarding strategy transitions. Transitioning from the independent strategy to the partial-collaboration strategy reduces costs for three regions, while costs for AH remain stable. However, HA experiences a drastic cost increase of 226.04%, and JX faces a modest cost increase of 3.97%. Transitioning from the independent to the centralized strategy results in lower costs for four regions but leads to cost increases for HA and SX by factors of approximately 1.7 and 3.5, respectively. Finally, transitioning from the partial collaboration to the centralized strategy lowers costs for all regions except SX by 17.07%, while SX faces an enormous cost increase of 616.60%.

Consequently, SX strongly opposes the centralized strategy due to its substantially higher costs relative to both IS and PCS. HA also strongly opposes the centralized strategy, as its costs under CS are more than double those under either alternative. When comparing the independent and partial-collaboration strategies, SX, HB, and HN all show a clear preference for PCS due to significant cost reductions. AH remains neutral, as its costs are nearly unchanged. JX, facing a modest cost increase, may be mildly opposed to PCS, while HA, facing a drastic cost increase, is strongly opposed. Therefore, to enhance overall participation under the partial-collaboration strategy, the beneficiary regions (HB, HN, SX) would need to provide appropriate compensation to the disadvantaged regions, particularly HA and, to a lesser extent, JX.

The analysis of total costs shows that the independent strategy is the most expensive. Although the centralized strategy is slightly more cost-effective than the partial-collaboration strategy, its implementation faces significant feasibility challenges, as both HA and SX experience dramatic cost increases compared to the other strategies. The partial-collaboration strategy, while not the absolute lowest in total cost, achieves meaningful cost reductions for a majority of regions and requires compensation only for a limited number of disadvantaged regions. Thus, when considering both efficiency and feasibility, the partial-collaboration strategy emerges as a more practical compromise.

To further demonstrate the value of the distributionally robust formulation, we compare three model variants under the partial-collaboration strategy: a deterministic benchmark, a sample average approximation (SAA) model, and the proposed DRO model. The deterministic model replaces all uncertain demands with their historical means μ_{it} and removes the chance constraint (7). The SAA model is obtained by setting the Wasserstein radius to a negligible value ($\delta \approx 0$), which corresponds to optimizing under the empirical distribution without distributional robustness. The DRO model uses $\delta = 0.002$ as in the main experiment. The cost-sharing mechanism and all other constraints remain identical across all three models. Each model is solved, and its optimal pre-positioning decisions are then evaluated under the same set of historical demand samples.

Table 3. Comparison of different models under the partial-collaboration strategy.

	Deterministic model	SAA model	DRO model
Objective value (minimax)	36,812.54	136,143.77	136,156.81
Shortage quantity	157,329	0	0
Shortage ratio (% of total demand)	35.50%	0%	0%

As shown in Table 3, the deterministic model achieves the lowest objective value but incurs a severe shortage of 157,329 units (35.50% of total demand) when evaluated against actual historical demand patterns. By contrast, both the SAA model and the DRO model eliminate shortages entirely. The SAA model achieves an objective value of 136,143.77, slightly lower than the DRO model's 136,156.81. However, the SAA solution is only guaranteed for the empirical distribution, whereas the DRO solution guarantees feasibility for all distributions within the Wasserstein ball. The negligible cost difference between SAA and DRO (0.01%) reflects the price of distributional robustness, a modest premium for a guarantee that SAA cannot offer. For emergency managers who cannot rely on historical samples perfectly representing future disasters, the DRO solution provides essential protection at negligible additional cost. This comparison confirms that the proposed DRO model effectively addresses demand uncertainty and justifies the additional pre-positioning expenditure.

4.2. Analysis of the selection of collaborative regions

This section investigates the cost implications when a single region opts for an independent pre-positioning strategy while the remaining regions continue to collaborate. We consider six deviation scenarios, each corresponding to one region (AH, HA, HB, HN, JX, or SX) acting independently. Table 4 shows the resulting cost variation rates for each focal region under each defection scenario, with negative values indicating cost savings and positive values indicating cost increases, both relative to the baseline of partial collaboration.

Table 4. Cost variation rates for each region under different defection scenarios (%).

Focal region	Defector					
	AH	HA	HB	HN	JX	SX
AH	-0.33%	-10.73%	-6.60%	-11.71%	-9.36%	-9.53%
HA	-8.86%	-69.33%	-6.60%	-25.58%	-39.88%	-39.60%
HB	-8.86%	-29.89%	57.38%	-11.71%	-10.31%	-9.53%
HN	-8.86%	-1.87%	-38.89%	65.13%	-24.88%	-0.17%
JX	-8.86%	-10.73%	-6.60%	-11.71%	-3.82%	-9.53%
SX	234.19%	484.93%	701.73%	662.92%	683.19%	60.47%

The data in Table 4 show that AH and JX consistently benefit from defection under all scenarios. AH experiences cost savings ranging from 0.33% when it defects to 11.71% when HN defects. JX similarly enjoys savings between 3.82% when it defects and 11.71% when HN defects. Both regions thus have no incentive to oppose any defection and would support independent pre-positioning by any member.

HB and HN exhibit a pattern of benefiting from others' defections while opposing their own. HB's costs decrease by 8.86% to 29.89% when other regions defect, with the largest saving occurring when HA defects, but increase by 57.38% when HB itself defects. HN similarly enjoys savings of up to 38.89% when HB defects, yet incurs a 65.13% cost increase when it defects. Therefore, both regions support defection by any region except themselves.

HA and SX present contrasting incentives. HA achieves substantial cost savings under all defection scenarios, ranging from 6.60% when HB defects to 69.33% when it defects, making it the strongest advocate for independent pre-positioning. SX, by contrast, faces cost increases under all defection scenarios, ranging from 60.47% when it defects to 701.73% when HB defects. Hence, SX strongly opposes any defection by any other region.

These results reveal heterogeneous incentives for collaboration across regions. HA is the most inclined to leave the coalition, as it benefits from every defection scenario, especially its own. HB and HN oppose their own defection but benefit from others' defections, making them potential supporters of defection by other regions. AH and JX have mild incentives to defect and also benefit from others' defections, so they are generally cooperative but not strongly opposed to deviations. SX, however, suffers severely from any defection and therefore strongly resists any change to the collaborative arrangement. These divergent interests highlight the challenge of sustaining stable collaboration without appropriate compensation mechanisms, particularly to protect SX from the extreme cost increases caused by other regions' defections.

The following analysis examines the impact on total cost when a region opts out of collaboration. The total costs for each defection scenario are presented in Figure 3. Data are provided in Appendix B.

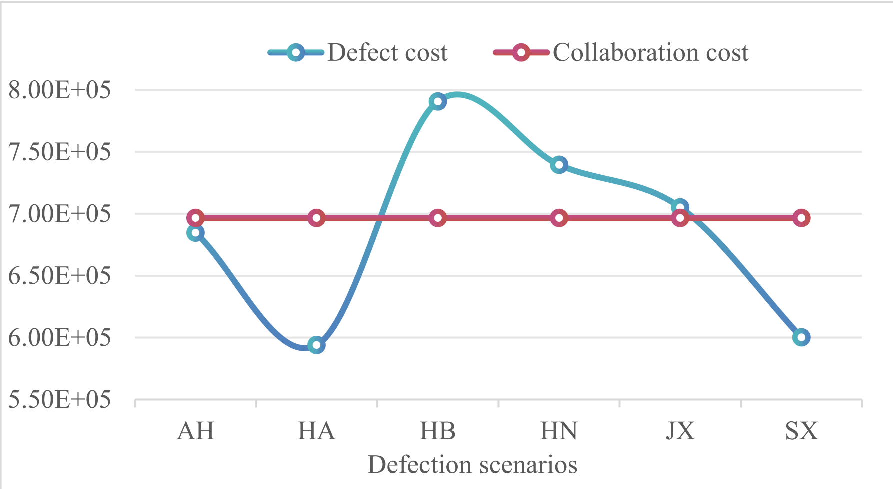

Figure 3. Total cost under different defection scenarios versus partial collaboration.

Figure 3 compares the total cost of the coalition under each defection scenario with the baseline of partial collaboration. The total cost is reduced substantially when HA or SX defect. Defection by AH or JX has a minor impact, while defection by HB or HN increases total cost considerably. Thus, from a system efficiency perspective, the most attractive defection candidates are HA and SX.

Combining the regional incentives derived from Table 4 with the system efficiency perspective reveals a tension between individual rationality and collective efficiency. From a system efficiency standpoint, HA and SX are the most attractive defection candidates, as both yield substantial total cost reductions. However, their individual incentives diverge sharply. As shown in Table 4, HA achieves a dramatic cost reduction of 69.33% when it defects, giving it a strong unilateral incentive to leave the coalition. In contrast, SX suffers a cost increase of 60.47% when it defects, meaning SX would resist its own independent pre-positioning despite its positive effect on total cost. Moreover, when HA defects, SX's cost increases sharply by 484.93%, which makes SX even more opposed to HA's defection. Conversely, when SX defects, HA enjoys a cost saving of 39.60%, and other regions (AH, HB, HN, JX) also benefit moderately.

Therefore, the optimal arrangement must account for both efficiency and feasibility. While HA's defection yields the lowest total cost, it imposes an unbearable burden on SX. SX's defection also reduces total cost but is against SX's own interest. Given that SX is severely harmed by any defection (especially HA's), a stable coalition requires keeping SX inside while perhaps allowing HA to leave, provided that the other benefiting regions (AH, HB, HN, JX) compensate SX for the losses it suffers under HA's defection. Alternatively, if SX stays and HA stays, the partial-collaboration baseline remains.

Consequently, the most feasible arrangement among the six regions is to maintain the partial-collaboration coalition, but with a compensation mechanism that transfers part of the gains from HA to SX when HA defects. Since HA has a strong incentive to defect and SX a strong incentive to stay, any sustainable agreement must include side payments to keep both regions satisfied. This highlights the critical role of compensation in cross-regional collaborative pre-positioning.

4.3. Sensitivity analysis

This section conducts a sensitivity analysis on key parameters within the model, including the maximum allowable violation probability (ϵ) in chance constraints, regional collaborative degree (α), and cost-sharing factors (weight ϑ and weights φ). Since the sum of regional relevance weight φ and disaster risk weight ϑ equals 1, this section only designs a sensitivity analysis for ϑ.

4.3.1. Sensitivity analysis of the probability ϵ in the DRCC

In the preceding numerical experiments, the probability ϵ was set to 0.1. Typically, the $1-\epsilon$ in chance constraints falls within the range of $[0.8, 0.99]$. This section analyzes the change in the objective value as ϵ increases from 0.01 to 0.20 in increments of 0.01. The results are shown in Figure 4.

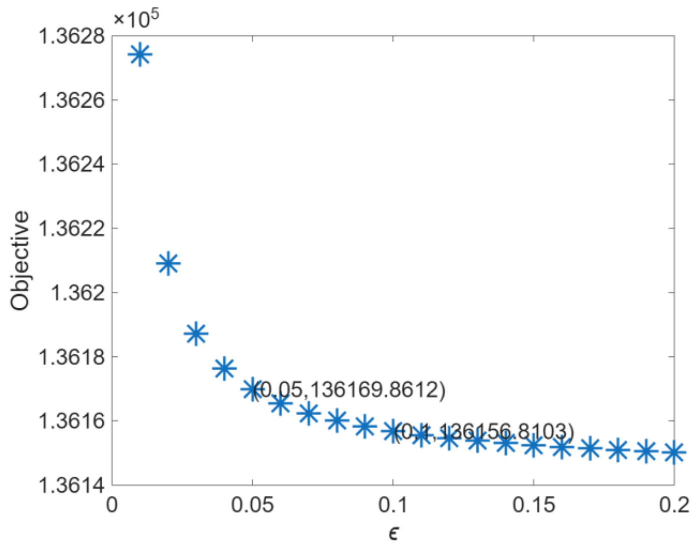

Figure 4. Results of the sensitivity analysis on the probability ϵ.

The objective value exhibits a pronounced decline as ϵ increases from 0.01 to 0.05, reflecting high marginal returns. The rate of decrease is moderate in the interval $[0.05, 0.1]$, indicating sharply diminishing returns. For $\epsilon > 0.1$, the objective value shows minimal sensitivity to further increases. Consequently, $\epsilon = 0.1$ is identified as the economically optimal value. For critical emergency supplies, a more conservative value of $\epsilon = 0.05$ is recommended.

4.3.2. Sensitivity analysis of the regional collaborative degree

In this section, the regional collaboration coefficient α is analyzed. A larger value of parameter α indicates a higher degree of regional collaboration. In the preceding numerical experiments, the initial value of this parameter α was set to 0.3. This section examines the impact on the objective value and total cost as parameter α increases from 0 to 0.9 in increments of 0.1.

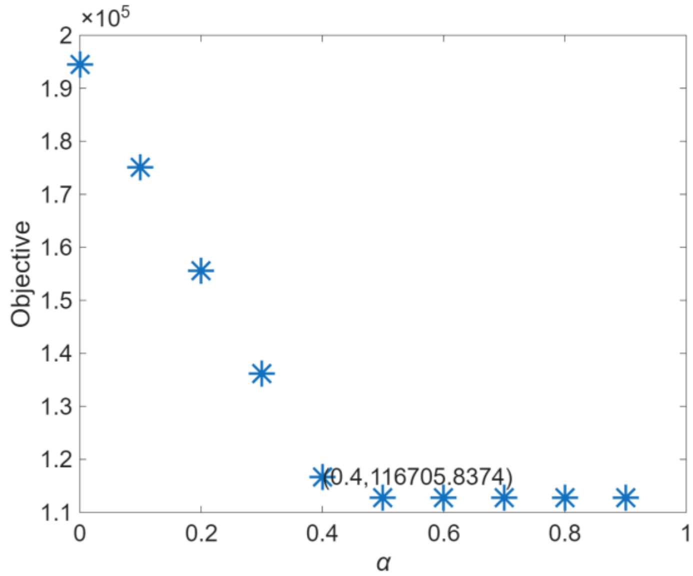

Figure 5. Effect of α on objective.

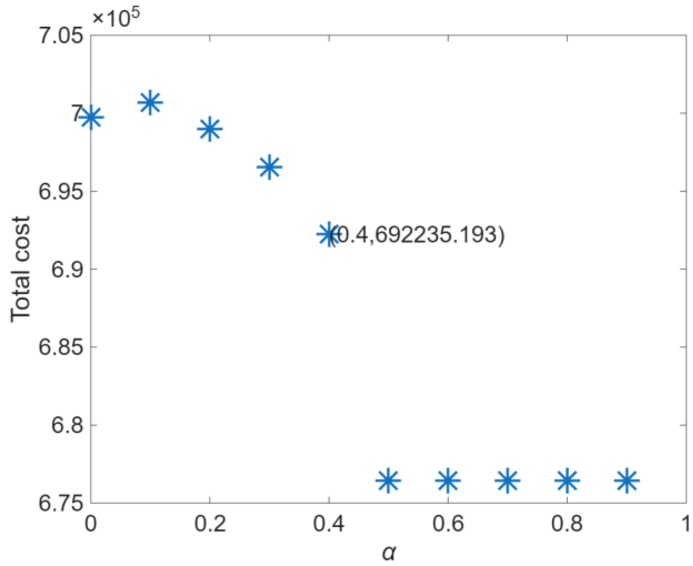

Figure 6. Effect of α on total cost.

Figures 5 and 6 show that as the parameter α increases from 0 to 0.4, both the objective value and the total cost decrease rapidly. However, when α increases from 0.4 to 1, these values exhibit only marginal changes. A higher value of α indicates a higher degree of regional collaboration. Thus, regional coordination contributes to reducing both individual regional costs and the total cost. However, once the coordination degree exceeds a certain threshold (e.g., $\alpha = 0.4$ in this study), further improvement yields diminishing returns on cost reduction. Therefore, it is advisable to set the collaboration degree at an appropriate threshold, such as 0.4, as identified in this paper.

4.3.3. Sensitivity analysis of the risk-based cost weight

This section analyzes the impact of the disaster risk weight ϑ on the risk-based cost allocated to each region. In the preceding numerical experiments, the weight ϑ was fixed at 0.5. We now examine a range of values from 0.1 to 1 in increments of 0.1. This corresponds to a simultaneous decrease in the regional relevance weight from 0.9 to 0. The results are presented in Figure 7. Detailed data are provided in Appendix B.

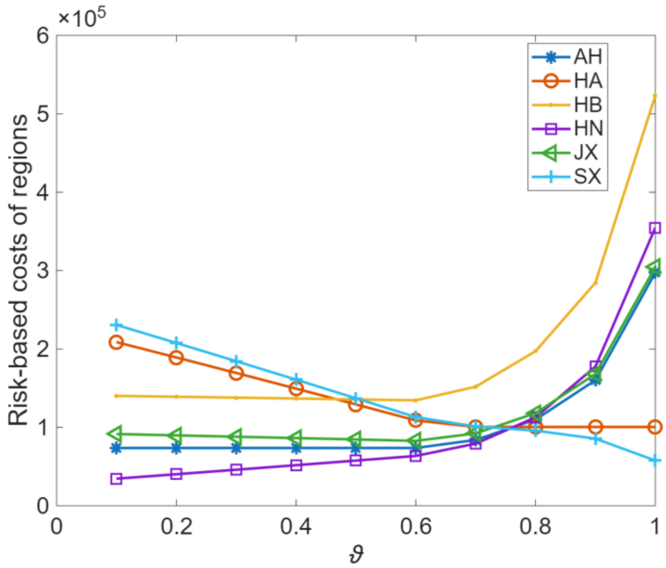

Figure 7. Regional risk-based costs under varying disaster risk weights.

In Figure 7, the horizontal axis represents the disaster risk weight (ϑ), while the vertical axis shows the risk-based cost allocated to each region. As the disaster risk weight increases from 0 to 0.6, the allocated costs for most regions remain relatively stable. The notable exceptions are cost reductions in SX and HA, and a moderate increase in HN. In contrast, when the weight exceeds 0.7, a sharp cost increase is observed for four regions, while SX and HA continue their gradual decline. Therefore, an optimal balance is achieved when the disaster risk weight is set between 0.6 and 0.7 (equivalent to a regional relevance weight between 0.3 and 0.4). Within this range, the risk-based cost allocation is not only reasonable overall but also exhibits minimal disparity among regions, indicating a more equitable distribution. Therefore, when the disaster risk weight is set within the interval [0.6, 0.7] and the regional relevance weight within [0.3, 0.4], the resulting risk-based cost allocation strikes an effective balance between efficiency and equity.

4.3.4. Sensitivity to the Wasserstein radius

In the preceding numerical experiments, the Wasserstein radius δ was set to 0.002. To examine the robustness of the model to the choice of the ambiguity set, this section analyzes the impact of varying δ from 0.001 to 0.02 in increments of 0.001. The results are shown in Figure 8.

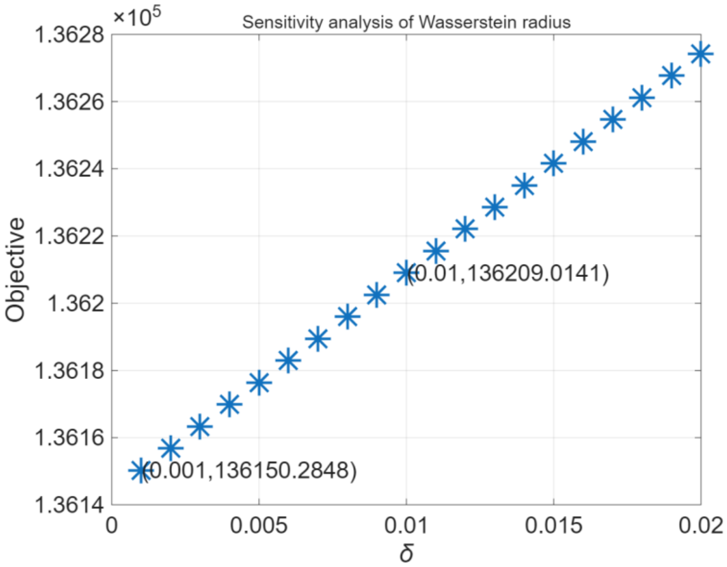

Figure 8. Effect of Wasserstein radius on objective.

As shown in Figure 8, the objective value increases almost linearly with δ. The value at $\delta = 0.02$ is approximately 0.09% higher than at $\delta = 0.001$ (from about 1.3615×10^5 to about 1.3627×10^5). This indicates that the model is quite robust to the choice of δ. Even a tenfold increase in the radius leads to only a negligible cost increase.

To further examine the impact of δ on the optimal decisions, we analyze the optimal cost shares z_i, which directly reflect the allocation of financial burdens among regions. Table B3 in Appendix B reports z_i under different Wasserstein radii. The results show that z_i remains nearly constant across $\delta \in [0.001, 0.02]$. This stability is attributable to two factors. First, the values of δ examined are consistent with the magnitudes used in the numerical experiments of related DRO studies. For instance, Tonbari et al. [42] tested Wasserstein radii of 0.001 and 0.01 in their synthetic experiments. At this scale, the Wasserstein ambiguity set contains only distributions that are very close to the empirical distribution, yielding essentially indistinguishable optimal decisions. Second, constraints (1)–(2) impose structural bounds on the feasible range of z_i, which further limit its sensitivity to δ. Thus, the optimal cost-sharing decisions are robust within the examined range of δ, confirming that the model does not produce overly conservative solutions. For datasets with greater demand variability, the influence of δ may be more pronounced, which we leave for future research.

We further extended the sensitivity analysis to cover δ values from 0.0001 to 0.1 to examine the model's behavior across a wider range. The results, reported in Table B.4 in Appendix B, show that the objective value increases from 136144.41 at $\delta = 0.0001$ to 136796.31 at $\delta = 0.1$, a modest increase of only 0.48%, while the shortage ratio remains at zero throughout the entire range. This indicates that the model is highly robust to the choice of δ. Even a three-order-of-magnitude increase in the radius leads to negligible cost deterioration. Therefore, $\delta = 0.002$ is a suitable choice for the numerical study, and the model's performance is not highly sensitive to the exact value of δ.

4.4. Managerial implications

The numerical experiments yield several valuable managerial insights, which may be useful for emergency management agencies in pre-positioning emergency supplies.

(1) A partial-collaboration cost-sharing model is proposed for cross-regional emergency supply pre-positioning. This model integrates the principle of territorial management with the benefits of regional collaboration. Additionally, the partial-collaboration strategy offers the flexibility to adjust the degree of collaboration among regions. Numerical experiments demonstrate that, compared to the independent strategy and the centralized strategy, the partial-collaboration strategy achieves a superior balance between equity and efficiency. Therefore, it is recommended that emergency management agencies adopt the partial-collaboration strategy for pre-positioning emergency supplies.

(2) Partner selection should be regarded as a strategic decision in organizing collaborative emergency supply pre-positioning. Optimal outcomes are not guaranteed by merely including all members in an agreement, as regions exhibit heterogeneous incentives and cost implications under collaboration. A selective partnership enhances both cost-effectiveness and feasibility by accommodating regional preferences and avoiding arrangements that impose unsustainable cost burdens on individual participants. Therefore, emergency management agencies are advised to prioritize identifying suitable partners over pursuing universal collaboration, with attention to compensation mechanisms that can stabilize cooperative arrangements when necessary.

(3) A cost-sharing model is developed for collaborative emergency supply pre-positioning. Building upon traditional factors of demand quantity and disaster risk, the regional relevance is introduced in the cost-sharing model. This model not only ensures fairness in cost allocation but also incentivizes regional collaboration in emergency supply pre-positioning. Numerical results demonstrate that assigning an excessive or insufficient weight to regional relevance leads to suboptimal cost-sharing performance. Therefore, it is recommended that emergency management agencies incorporate regional relevance as a key variable in the design of collaborative mechanisms and maintain its weight within a reasonable range to achieve an optimal balance between cost efficiency and equity.

(4) This study applies a distributionally robust optimization model with chance constraints to the problem of collaborative emergency supply pre-positioning. Numerical experiments reveal that the confidence level within the chance constraints significantly influences the cost allocation among regions. Therefore, it is recommended that emergency management agencies set different confidence levels for different categories of emergency supplies. For instance, a higher confidence level should be adopted for critical and scarce supplies to mitigate potential disaster losses, whereas a lower level may be suitable for readily available daily supplies to reduce pre-positioning costs.

(5) The trade-off between robustness and conservativeness in parameter selection should be explicitly considered in implementing the proposed model. The confidence level ϵ and the Wasserstein radius δ jointly determine the robustness of the pre-positioning decisions. A smaller ϵ imposes a stricter reliability requirement, leading to higher pre-positioning costs but lower shortage risk. A larger ϵ reduces costs at the expense of increased risk exposure. The sensitivity analysis in Section 4.3.1 shows that the marginal benefit of decreasing ϵ diminishes beyond $\epsilon = 0.1$, suggesting this value offers a cost-effective balance. For the Wasserstein radius, the sensitivity analysis in Section 4.3.4 indicates that the optimal decisions remain stable for $\delta \in [0.001, 0.02]$, meaning that, within this range, the model provides robust decisions without inducing excessive conservativeness. In practice,

it is recommended that emergency management agencies select these parameters based on supply criticality and risk appetite. More conservative settings (smaller ϵ) are justified for critical life-saving supplies, while less conservative settings are suitable for non-critical items.

5. Conclusion

This study addresses the challenge of cross-regional emergency supply collaboration by introducing a partial collaboration strategy. To address the critical issue of cost sharing, a novel strategy accounting for regional relevance is proposed. Then, a distributionally robust chance-constrained optimization model incorporating the cost-sharing strategy is proposed.

To solve the proposed model, the Wasserstein ambiguity set and the big M method are employed to reformulate it into a mixed-integer programming model. Numerical experiments yield the following conclusions: 1) When considering both economic efficiency and institutional feasibility, the partial-collaboration strategy provides a more implementable solution than the centralized strategy, although it does not strictly dominate it in terms of cost or fairness alone. 2) Regional relevance is a critical factor in cost sharing. Assigning an excessively high or low weight to it can adversely affect the outcome. Therefore, its weight must be set within an appropriate range. 3) The confidence level of the DRCC should be set individually for each category of emergency supplies, thereby achieving an optimal balance between meeting demand requirements and minimizing pre-positioning costs. 4) Partner selection significantly influences the cost efficiency of collaboration. Therefore, the strategic selection of partners is recommended to lower costs and promote consensus in cross-regional emergency supply collaboration.

Subsequent research will advance the study of cross-regional emergency supply collaboration through three key avenues. First, the critical issue of transportation time uncertainty caused by road damage and traffic congestion will be incorporated into optimization models to enhance system resilience by balancing cost and timeliness. Second, we will develop more adaptive cost-sharing strategies that consider the unique attributes of cooperating regions, ensuring adherence to the beneficiary-pays and capacity-pays principles for greater alliance stability. Third, the integration of unmanned aerial vehicles will be investigated from a pre-positioning perspective, focusing on the collaboration of emergency supply and auxiliary equipment to improve rescue efficiency and cost-effectiveness. Finally, a systematic comparison between the proposed distributionally robust optimization approach and the sample average approximation (SAA) method will be conducted. This will include out-of-sample performance evaluation, which we leave for future research.

Author contributions

Jingke Zhou contributed to the methodology, investigation, data curation, validation, and writing of the original draft. Yingzhen Chen contributed to conceptualization, supervision, and the review and editing of the manuscript. All authors have read and agreed to the published version of the manuscript.

Use of Generative-AI tools declaration

During the preparation of this manuscript, the authors used ChatGPT for language polishing and expression improvement.

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Conflict of interest

The authors declare that there is no conflict of interest.

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