Annals of Operations Research
https://doi.org/10.1007/s10479-025-06909-w

ORIGINAL RESEARCH

A cooperative covering model for optimizing critical supply networks under disruption risks

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Received: 19 December 2024 / Accepted: 15 October 2025

Abstract

In disaster preparedness, strategically placing relief supplies is crucial to guarantee timely and adequate relief efforts. Important decisions in this process include determining optimal warehouse locations, assessing logistical resources, and strategically allocating critical supplies to distribution points. The inherent uncertainty surrounding a potential disaster amplifies the complexity of these decisions. We formulate a scenario-based multi-objective optimization model that integrates the advanced placement and allocation of relief supplies, extending the general form of a cooperative covering location problem. The proposed model maximizes demand coverage while minimizing underlying storage and logistics costs. Furthermore, the model accounts for diverse disruption scenarios using stochastic programming, treating the disaster impact of individual factors as random variables. Given large-scale disaster situations, our model evaluates the effect of potential disruptions, enabling the assessment of optimal network solutions. Based on an empirical case study focusing on the German national food stockpiling system, we demonstrate the feasibility of the introduced methodology in developing efficient stockpiling and preparedness strategies while facilitating the identification of vulnerabilities to enhance overall resilience. Our results show that incorporating stochastic factors, such as warehouse availability and operability, route failure, coverage radius limitations, and demand volatility, can significantly impact the optimal network configuration and influence demand coverage and total costs. Furthermore, the methodology proves to be both scalable and feasible when applied to a large-scale scenario.

Keywords Network analysis · Disaster preparedness · Location problem · Supply chain resilience · Uncertainty

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Published online: 28 October 2025

1 Introduction

The efficient management of supply chains is a critical component of logistics affecting various industries, governments, and stakeholders. However, the importance of resilient supply chains becomes even more pronounced in the face of potential disasters. Every year, extreme weather events, earthquakes, droughts, diseases, and other disasters disrupt various regions worldwide, resulting in significant economic and social impacts. In addition, climate change, coupled with factors like population growth, urbanization, and deficient infrastructure planning and management, not only heightens the likelihood of disasters but also accentuates the growing vulnerability of developed countries to such events (WMO, 2021). For example, the COVID-19 pandemic exposed weaknesses in global supply chains, leading to widespread disruptions due to border closures, lockdown measures, and changes in consumer behavior (Sharma et al., 2021; Kumar et al., 2022). A closer examination of the disruptions caused by the COVID-19 pandemic reveals that even more severe disasters can significantly disrupt commercial supply chains, highlighting the need for resilient strategies and adaptive approaches (Seuring et al., 2022).

As a result, disaster preparedness has become more prominent than ever, driving government agencies to actively enhance their preparedness measures to ensure the continuous flow of critical goods and services during disasters. These efforts include proactively prepositioning essential relief supplies in predetermined locations to improve overall disaster response capabilities. For instance, within the United States, notable research focuses on optimizing the placement of strategic national stockpiles and analyzing critical hubs for food delivery (Shaheen et al., 2023). According to Verma and Gaukler (2015), the national stockpile contains substantial quantities of medicine and medical equipment, protecting the American public in a severe disaster that exhausts local supplies. Likewise, German authorities are engaged in maintaining emergency stocks of food supplies to address large-scale disasters that may result in dysfunctional commercial supply chains (BMEL, 2024). Consequently, authorities are responsible for identifying the most efficient storage sites, determining distribution points, and formulating resource allocation strategies to mitigate potential shortages. This task becomes complicated when pre-positioning occurs well before a disaster, due to the significant uncertainty surrounding the affected areas, available resources, and the potential severity.

A comprehensive understanding of supply chain network performance is essential, particularly when evaluating design alternatives under disruption scenarios. As noted by Roshani et al. (2024), a significant gap remains in thoroughly assessing network strategies and their relative performance. Furthermore, Pires Ribeiro and Barbosa-Povoa (2018) emphasize that traditional risk management approaches often overlook high-impact, low-probability disruptions. They highlight the importance of drawing insights from existing strategies to address such events. Failing to anticipate or accurately evaluate the effects of specific disruptions can severely impair operational efficiency. Consequently, further research is needed to develop robust quantitative models that evaluate existing networks and potential alternatives. These models offer critical insights to aid decision-makers in identifying requirements, setting objectives, and mitigating the adverse impacts of disruptions.

In light of these challenges and research gaps, this study seeks to examine the issues in greater depth, providing valuable insights into the analysis of disruptions and the strategic location and allocation of critical goods. The main contributions of this study can be summarized as follows:

1. We introduce a multi-objective capacitated cooperative covering location model designed to assist decision-makers in formulating strategic preparedness plans tailored for large-scale disaster scenarios, considering diverse disruption factors and inherent uncertainties.
2. Our model addresses crucial decisions related to the strategic placement of facilities for critical supplies and the allocation and distribution of these supplies to various demand locations in the aftermath of a disaster.
3. The model specifically addresses uncertainties surrounding the availability and operability of pre-positioned warehouses, route failure, coverage radius limitations, and demand variations. By incorporating multiple objectives, the model facilitates a comprehensive analysis of potential trade-offs between cost considerations and the extent of supply coverage, providing decision-makers with a tool for optimizing resource allocation.
4. To validate the practical applicability and assess managerial implications, we conduct a detailed case study of Germany's national food stockpiling system, covering 150 potential storage locations and 431 distribution points. We evaluate the system's performance through six scenarios, providing valuable insights for optimizing network strategies that ensure resilience and adaptability in disaster preparedness.

The paper is structured as follows. Section 2 reviews the state-of-the-art literature on disaster preparedness, strategic pre-positioning, and covering models. Section 3 outlines the methodology developed to address the identified research gaps. In Sect. 4, we apply the proposed model to a case study focused on optimizing Germany's national food stockpiling strategy. Sections 5 and 6 present the results, provide a detailed analysis of the findings, and include a sensitivity analysis to assess the model's robustness. Finally, Sect. 7 summarizes the key findings, discusses theoretical and managerial implications, and suggests directions for future research.

2 Theoretical background and related work

2.1 Disaster preparedness and strategic pre-positioning

The unpredictable nature of disasters, including their timing, location, and intensity, highlights the importance of thorough preparation, which significantly impacts disaster response. The pre-positioning of supplies plays a vital role in disaster preparedness and can accelerate response activities by proactively siting essential resources, such as food, water, medication, and technical equipment, in strategic locations before a disaster occurs (Rawls & Turnquist, 2011; Akbarpour et al., 2020; Lei et al., 2016). However, maintaining excessive stocks can lead to financial losses if supplies go unused, while insufficient stockpiling may result in human suffering and loss of life during disasters. Striking the optimal balance is imperative for an effective and responsive preparedness system. The literature addresses various issues related to pre-positioning relief supplies.

For instance, Aslan and Çelik (2019) examine the design of a multi-echelon humanitarian response network. They address pre-disaster decisions regarding warehouse locations and item pre-positioning, considering uncertainties in demand and the vulnerability of roads and facilities after a disaster. Additionally, they conduct computational experiments on a potential earthquake scenario in Istanbul, Turkey, employing a sample average approximation for heuristic solutions. Rothkopf et al. (2023) analyze the impact of transportation capacity in pre-positioning humanitarian supplies. Therefore, they develop a stochastic linear program that optimizes the delivery of essential relief items using a scenario approach. Contributing to pre-disaster relief network design, Erbeyoğlu and Bilge (2020) present a two-echelon model that selects facility locations and stockpiles to ensure the right mix of supplies for various disaster scenarios. Their approach aims to balance adequacy and fairness of services while minimizing costs. The model accounts for potential damages to cities and facilities by incorporating a random variable correlated with the disaster's location through a distance-damage function. Likewise, Verma and Gaukler (2015) incorporate distance-dependent damages to disaster response facilities and population centers, providing a deterministic and stochastic approach. In addition to addressing transport and network disruptions, several studies, such as those by Paul and Batta (2008), Campbell and Jones (2011), and Shehadeh and Tucker (2022), specifically address supply uncertainties. These studies assume that a disaster results in the capacity reduction of a facility or the destruction or isolation of a supply point, incorporating variability in the usable post-disaster fraction of pre-positioned relief items.

While extensive literature on pre-positioning problems exists, a notable gap remains in adopting a macro-focused perspective that integrates multiple disruption factors while incorporating long-term strategic decisions. Sabbaghtorkan et al. (2020) underscore the limited availability of papers that explore uncertainty in asset and supply quantities, along with challenges related to infrastructure disruptions.

2.2 Facility location and covering models

Strategic pre-positioning and facility location models are closely linked in disaster management contexts (Boonmee et al., 2017). Location models aim to determine optimal facility placements to minimize the cost of meeting demand under specific constraints (Hale & Moberg, 2003). Depending on the application, various types exist, such as static, deterministic, covering, and center problems, each with distinct objectives and assumptions (Owen & Daskin, 1998).

In general, covering problems focuses on determining the optimal placement of facilities to provide coverage or service to a set of demand points or regions (Laporte et al., 2015). Farahani et al. (2012) classify the works concerning the traditional Location Set Covering Problem (LSCP) and the Maximum Covering Location Problem (MCLP), considering specific extension-related characteristics, solution methods, and applications. Berman et al. (2010) further expand on covering objectives, discussing classic, gradual, cooperative, and variable models. Table 1 reviews essential models related to our study comprising the model objective, type, considered uncertainty parameters, coverage approach, and their application in disaster scenarios.

Using a deterministic approach, Alizadeh and Nishi (2020) propose a hybrid model combining set covering and maximal covering formulations to locate first aid centers in Japan.

Table 1 Overview of key characteristics and relevant studies on covering models

Reference	Objective		Model		Uncertain Parameters					Coverage	Application	
	Type	Function	Problem	Method	Demand	Supply	Costs	Network	Cov radius		Disaster case	Geo-graphical Extension
Alizadeh and Nishi (2020)	Multi	max Cov min TC	HCLP	Det						Gradual	Threat scenarios	Japan (N)
Bagherinejad et al. (2018)	Single	max Cov	CGMCLP	Det						Gradual & Cooperative	N/D	Numerical example
Bakker et al. (2023)	Single	min TC	MMPoDSuP	Det						Binary	Slow-onset	Berlin, Germany (L,R)
Balcik and Beamon (2008)	Single	max Cov	MCLP	Sce	✓					Gradual	Earthquake	Numerical example
Barzinpour and Esmaeili (2014)	Multi	max Cov min TC	L-A	Det						Gradual & Cooperative	Sudden-onset	Tehran, Iran (L)
Eligüzel et al. (2023)	Multi	max Cov min TD	MCLP LSCP	Det						Binary	N/D	Global
Jia et al. (2007)	Single	max Cov	MCLP	Prob	✓					Gradual & Cooperative	Large-scale	Los Ange-les, USA (R)
Liu et al. (2021)	Single	min TC	DRCC-FLP	OA	✓	✓		✓		Binary	Hurricane	Southeast US (R)
Murali et al. (2012)	Single	max Cov	MCLP	CCP	✓					Gradual & Cooperative	Bio-terror attack	Los Ange-les, USA (R)
Park et al. (2022)	Single	min TC	ULAP	Rob, USets	✓					Variable & Gradual	Medical	Numerical example
Rancourt et al. (2015)	Single	min TC	UFLP LCP	Det						Cooperative	Extreme weather	Garissa, Kenya (L)
Razavi et al. (2021)	Multi	min TC min D max Cov	L-A-R	Rob, Sce	✓	✓	✓			Cooperative	Sudden-onset	Mazanda-ran, Iran (R)

Table 1 (continued)

Reference	Objective		Model		Uncertain Parameters					Coverage	Application	
	Type	Function	Problem	Method	Demand	Supply	Costs	Network	Cov radius		Disaster case	Geographical Extension
Salman and Yücel (2015)	Single	max ECov	MCLP	Sce				✓		Binary	Sudden-onset	Istanbul, Turkey (L)
Shaw et al. (2022)	Multi	min TC min TT max Cov	MOSLAP	FuzzL	✓	✓				Binary	Sudden-onset	Numerical example
Sheikholeslami and Zarrinpoor (2023)	Multi	min TC max Cov	HLN	FuzzL	✓		✓		✓	Binary	N/D	Fars province, Iran (R)
Li et al. (2018)	Single	max ACov	MCLP	Sce	✓					Binary Cooperative	N/D	Numerical example
Zhang et al. (2017)	Single	min NF max Cov	LSCP MCLP	FuzzyL	✓			✓		Binary	Earthquake	Sichuan, China (R)
This work	Multi	max Cov min TC	MCLP	Sce, Prob	✓	✓		✓	✓	Cooperative	Large-scale	Germany (N)

ACov, Appeal coverage; CCP, Chance-constrained programming; CGMCLP, Cooperative gradual maximal covering location problem; Cov, Coverage; D, Discontent; Det, Deterministic; DRCC-FLP, Distributionally robust chance-constrained facility location problem; ECov, Expected coverage; FuzzL, Fuzzy logic; HCLP, Hybrid covering location problem; HLN, Humanitarian logistics network; L, Local; L-A, Location allocation; L-A-R, Location allocation routing; LCP, Location covering problem; LSCP, Location Set Covering Problem; MCLP, Maximum Covering Location Problem; MMPoDSuP, Mixed Mode PoD Set-Up Problem; MOSLAP, Multi-objective solid location-allocation problem; N, National; N/D, Not defined; NF, Number of Facilities; OA, Outer-approximation; Prob, Probabilistic; R, Regional; Rob, Robust; Sce, Scenario; TC, Total cost; TD, Travel distance; TT, Travel time; ULAP, Unmanned aerial vehicle for the emergency medical service location-allocation problem; UFLP, Uncapacitated facility location problem; US, United States; USets, Uncertainty sets

Bakker et al. (2023) address public food supply through a mixed-mode capacitated set covering model, allowing distribution via public centers and mobile trucks. Barzinpour and Esmaeili (2014) develop a location-allocation model for earthquake response, integrating humanitarian and cost objectives using goal programming. Eligüzel et al. (2023) analyze the UN's distribution plan, optimizing depot placement and travel distances using MCLP and LSCP formulations. Lastly, Rancourt et al. (2015) examine food aid distribution under weather-induced shocks, proposing a stakeholder-inclusive model that minimizes social welfare costs.

Due to the inherent variability of disaster scenarios, deterministic models often fall short of capturing uncertainties such as population demand and network functionality. As a result, many covering models incorporate stochastic elements. For instance, Balcik and Beamon (2008) extend the MCLP by modeling disaster location and demand uncertainties through scenario-based disaster-impact pairs. Similarly, Salman and Yücel (2015) and Li et al. (2018) use scenario-based approaches to address uncertain parameters. Salman and Yücel (2015) model random link failures and their dependencies using a distance-based failure model. Li et al. (2018) capture demand uncertainty across varying disaster severities within a maximum covering framework. Robust optimization is another technique to handle uncertainty, ensuring solution feasibility across various conditions. Park et al. (2022) apply this method to emergency medical logistics using UAVs, modeling demand uncertainty with a cardinality-constrained set. Razavi et al. (2021) also uses robust optimization to manage uncertain demand, return rates, and cost parameters in disaster settings. Other approaches include fuzzy logic (Shaw et al., 2022; Sheikholeslami & Zarrinpoor, 2023), outer-approximation (Liu et al., 2021), chance-constrained programming (Murali et al., 2012), and probabilistic modeling (Jia et al., 2007), each offering alternative ways to incorporate uncertainty into covering models.

Moreover, the models in Table 1 incorporate various coverage objectives, including binary, cooperative, gradual, and variable methods. Binary coverage, the most common, assumes each demand point is either fully covered or not at all, as seen in Bakker et al. (2023), Liu et al. (2021), Salman and Yücel (2015), Shaw et al. (2022), Sheikholeslami and Zarrinpoor (2023), and Zhang et al. (2017). Cooperative models, by contrast, allow multiple facilities to jointly cover a demand point, as in Rancourt et al. (2015), Razavi et al. (2021), and Li et al. (2011). Gradual models, often linked to cooperative ones, relax the binary constraint by considering partial coverage based on distance (Alizadeh & Nishi, 2020; Bagherinejad et al., 2018; Balcik & Beamon, 2008; Barzinpour & Esmaeili, 2014; Jia et al., 2007; Murali et al., 2012). Less common are variable coverage models, which adjust the coverage radius based on conditions such as demand intensity or resource availability (Park et al., 2022).

In summary, the review of the literature reveals several gaps in current research regarding pre-positioning strategies and covering models. For instance, cooperative covering models are still scarce, particularly those considering the possibility of varying coverage radii. Specifically, of the reviewed works, only Sheikholeslami and Zarrinpoor (2023) adopt varying coverage radii depending on the operability of facilities. Additionally, many models focus on deterministic approaches, such as those by Alizadeh and Nishi (2020) and Eligüzel et al. (2023), rather than incorporating stochastic considerations. Studies addressing disruptions, such as those by Balcik and Beamon (2008) and Park et al. (2022), often focus on single types of disruptions, such as demand fluctuations, overlooking the complex interactions among multiple disruption factors. This gap underscores the need for models incorporating probabilistic parameters and leveraging stochastic programming techniques. Moreover, Roshani et al. (2024) advocate for network strategies that balance monetary and non-monetary objectives within multi-objective frameworks. According to our research, only a limited number of studies, such as those by Razavi et al. (2021), Shaw et al. (2022), and Sheikholeslami and Zarrinpoor (2023), consider these objectives in combination with disruptions.

Regarding real-world case studies, there remains a significant gap in applying developed models to practical scenarios, particularly within humanitarian logistics and the national level. Among the reviewed literature, only Jia et al. (2007) and Murali et al. (2012) present comprehensive large-scale case studies, though their focus is limited to the effects of demand disruptions. Additionally, most existing case studies in covering models concentrate on sudden-onset disasters, such as hurricanes or earthquakes, that typically affect local or regional areas, as demonstrated in the works of Barzinpour and Esmaeili (2014), Salman and Yücel (2015), and Liu et al. (2021). These findings are in line with the results of Pires Ribeiro and Barbosa-Povoa (2018) and Katsaliaki et al. (2022), stating that research on supply chain resilience has yet to thoroughly assess performance across various disruptive scenarios, particularly in real-world cases involving high-impact, low-probability events. This aspect represents a critical area for further research, as a deeper understanding of such scenarios is vital for effective decision-making and advancing knowledge of overall supply chain dynamics.

Our work aims to bridge the identified gaps in covering and multi-objective models by explicitly addressing the impact of diverse disruption factors and failure probabilities on various resources. Unlike the reviewed literature, our model integrates multiple objectives and various uncertainty factors, individually and in combination. These factors include supply disruptions due to warehouse failures and operational losses, route failures, varying coverage radii, and demand variability. Additionally, we incorporate a cooperative approach to facilitate joint coverage. Furthermore, our study introduces a novel and comprehensive case study with a national scope, specifically addressing high-impact disruptions. It leverages the country's network infrastructure, incorporating decisions related to facility openings and allocations while accounting for resource constraints under uncertain conditions. This broader perspective yields valuable insights, especially given Germany's diverse logistical complexities. In this context, our work contributes to a deeper understanding of supply chain network performance and significantly enhances the practical relevance of the proposed model.

3 Methodology

3.1 Problem setting

When preparing for a disaster and strategically placing relief supplies, decision-makers such as authorities or companies must consider several critical factors. These include identifying optimal warehouse locations to maximize demand coverage, assessing logistical resources, and strategically allocating relief supplies to demand points. In addition, they should balance the overall cost of stockpiling with the need to meet demand effectively while accounting for the inherent uncertainty of disasters that may impact the planned network. With thorough analysis and well-established contingency plans, decision-makers can sustain the supply system's efficiency during disasters, ensuring that investments in pre-positioned stocks yield the intended benefits.

We formulate the described setting in a multi-objective capacitated cooperative covering location model under disruption risks to support decision-makers in strategically placing warehouses for critical supplies. Subsequently, these supplies are allocated and distributed to various demand points called Points of Distribution (PoDs) following a disaster. Our model incorporates cooperative delivery options within the operational radii of warehouses, enabling multiple warehouses to supply a PoD, as illustrated in Fig. 1. In addition, a PoD can be fully, partially, or not covered, depending on the capacities of the warehouses.

Besides incorporating cooperative supply options and capacity constraints, we specify the coverage formulation by addressing transportation considerations and various disruption factors. Furthermore, the model incorporates two primary objectives: (1) maximizing demand coverage and (2) minimizing operational costs. Within this work, we make the following assumptions:

1. *Warehouse pre-positioning:* All supply nodes are potential candidates for locating warehouses. However, pre-positioning numerous facilities until a disaster occurs may be impractical due to budget constraints. Hence, the total number of potential warehouse locations is restricted. Additionally, all warehouses maintain a consistent coverage radius unless operational disruptions such as limited fuel supply or technical defects constrain the coverage range.
2. *Node demand coverage:* PoDs within a warehouse's coverage radius are served based on the facility's capacity level. If a warehouse reaches its capacity limit or disruptions occur, constraints may affect the complete coverage of a node's demand, resulting in either partial or no coverage. In cases where a PoD falls within the overlapping range of multiple radii, cooperation between warehouses allows for joint coverage.
3. *Demand fulfillment and prioritization:* A service level is implemented, which denotes the minimum percentage of demand that must be fulfilled at a given PoD. The service level compels the model to extend its supply network to distant locations irrespective of costs, promoting a more equitable distribution of resources. In aiming to meet the

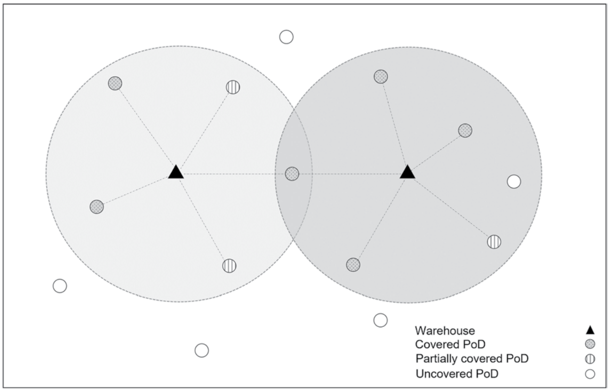


Fig. 1 Schematic representation of a capacitated cooperative covering approach

required service level at PoDs, the model acknowledges and penalizes any shortfalls arising from potential limitations in warehouse availability and capacity.

4. *Constraints on operations and vehicles:* The number of available vehicles is limited at the individual warehouse level. This restriction considers the operational capacity of each warehouse and vehicle availability. In addition, there are also explicit limitations on the transport capacity of each vehicle.
5. *Scenario analysis and disaster impact:* We assume the system can encounter various disruption scenarios, including warehouse failures, operability losses, route failures, coverage radius limitations, and demand volatility. To address these, we define a set of discrete scenarios with probabilistic parameters and employ a Monte Carlo Simulation approach. Additionally, the system may face different disaster durations, which we analyze by aggregating daily demand over multiple time horizons.
6. *Multiple objectives:* As we are looking at a setting in humanitarian logistics, the primary objective is alleviating the population's suffering. Although costs are less critical, they cannot be disregarded entirely. Therefore, using a lexicographic approach, we prioritize providing sufficient supplies over financial costs. Consequently, the optimization process adheres to this hierarchy, addressing the highest priority objective before proceeding to the next.

3.2 Notation and model formulation

The mathematical formulation of the model includes the sets *I*, representing potential warehouse locations, and *J* denoting the PoDs. Each PoD *j* requires a supply of d_j goods, ensured by a service level ζ, and can be assigned to one or more warehouses based on the maximum coverage radius *R* and supply capacity s of warehouse *i*. Supplies are transported from warehouse *i* to PoD *j* under the constraint of a limited number of processable truckloads per warehouse during working hours, described by M_{max}. Each loaded truck has a capacity of *Q* units and operating costs of c_{ij}. Additional parameters include the disaster duration *T*, warehousing costs c^w, travel time τ_{ij}, and a large coefficient *M*. The primary objective is to maximize demand coverage while minimizing costs, though unmet demand quantities denoted by μ_{ij} are possible. The binary parameter r_{ij} indicates if a PoD is within the radius of a warehouse.

Moreover, various probabilistic factors are integrated into the model to account for potential disruptions. Thus, scenario parameters include binary matrices φ_i^w, φ_m^o, φ_{ij}^r, φ_i^c, and φ_j^d, which indicate the functionality of individual warehouses, the ability to process a certain amount of truckloads, route allocation possibility of PoDs, disrupted coverage radius, and demand variations, respectively. The value for the limited coverage radius of each warehouse *i* is defined by R_i^c, and ζ^h comprises the increase in demand level at certain hotspots.

Decision variables include the binary variable y_i, indicating if a warehouse is located, v_{ij}, determining as binary variable if a PoD can be supplied, x_{ij}, the amount of transported relief items from warehouse *i* to *j*, n_{ij}, the number of required truckloads, μ_j, the amount of unmet demand, and h_{ij}, an auxiliary variable for linearization. An overview of the implemented sets, parameters, and decision variables is provided in Table 2.

$$\mathcal{L}: \quad \text{lexmin} \quad (-f_1, f_2) \tag{1}$$

Table 2 Notation of sets, parameters, and decision variables

Sets	
I	Set of candidate locations for warehouses ($i \in I$)
J	Set of PoDs ($j \in J$)
M_{max}	Maximum truckloads *m* processed per warehouse during working hours ($m \in M_{max}$)
Parameters	
T	Disaster duration
d_j	Demand of PoD *j*
s_i	Supply capacity of warehouse location *i*
c^w	Warehousing costs
c_{ij}	Operating costs from *i* to *j*
τ_{ij}	Travel time from *i* to *j*
Q	Capacity limit of truck
ζ	Service level
r_{ij}	$\begin{cases} 1, \text{ if PoD } j \text{ is in radius } R \text{ of warehouse } i \\ 0, \text{ otherwise} \end{cases}$
M	Large coefficient *M*
Scenario parameters	
φ_i^w	$\begin{cases} 1, \text{ if warehouse } i \text{ is functional} \\ 0, \text{ otherwise} \end{cases}$
φ_m^o	$\begin{cases} 1, \text{ if truckload } m \text{ is processed} \\ 0, \text{ otherwise} \end{cases}$
φ_{ij}^r	$\begin{cases} 1, \text{ if PoD } j \text{ can be allocated to warehouse } i \\ 0, \text{ otherwise} \end{cases}$
φ_i^c	$\begin{cases} 1, \text{ if coverage radius } R_i \text{ of warehouse } i \text{ is unrestricted} \\ 0, \text{ otherwise} \end{cases}$
φ_j^d	$\begin{cases} 1, \text{ if demand of PoD } j \text{ is stable} \\ 0, \text{ otherwise} \end{cases}$
R_i^c	Limited coverage radius of warehouse *i*
ζ^h	Increase in demand level at certain hotspots
Decision variables	
y_i	$\begin{cases} 1, \text{ if warehouse } i \text{ is located} \\ 0, \text{ otherwise} \end{cases}$
v_{ij}	$\begin{cases} 1, \text{ if warehouse } i \text{ can supply PoD } j \\ 0, \text{ otherwise} \end{cases}$
x_{ij}	Relief items transported from warehouses *i* to PoD *j*
n_{ij}	Number of truckloads being transported from warehouse *i* to PoD *j*
μ_j	Quantity of unmet demand at PoD *j*
h_{ij}	Auxiliary variable

$$f_1 = \sum_{i \in I} \sum_{j \in J} x_{ij} - \mu_j$$

$$f_2 = \sum_{i \in I} s_i \cdot y_i \cdot c^w + \sum_{i \in I} \sum_{j \in J} c_{ij} \cdot h_{ij} \tag{2}$$

$$\text{s.t.} \quad \sum_{j \in J} Q \cdot h_{ij} \leq s_i \cdot \varphi_i^w \qquad \forall i \in I$$

$$\sum_{i \in I} Q \cdot h_{ij} = ((\zeta + \zeta^h) \cdot (1 - \varphi_j^d)) \cdot d_j \cdot T - \mu_j \quad \forall j \in J \tag{3}$$

$$\sum_{j \in J} n_{ij} \leq \sum_{m \in M_{max}} \varphi_m^o \quad \forall i \in I \tag{4}$$

$$v_{ij} \leq r_{ij} \cdot \varphi_{ij}^r \cdot y_i \quad \forall i \in I, j \in J \tag{5}$$

$$Q \cdot h_{ij} = x_{ij} \quad \forall i \in I, j \in J \tag{6}$$

$$h_{ij} \leq v_{ij} \cdot M \quad \forall i \in I, j \in J \tag{7}$$

$$h_{ij} \geq -v_{ij} \cdot M \quad \forall i \in I, j \in J \tag{8}$$

$$h_{ij} \leq n_{ij} + (1 - v_{ij}) \cdot M \quad \forall i \in I, j \in J \tag{9}$$

$$h_{ij} \geq n_{ij} - (1 - v_{ij}) \cdot M \quad \forall i \in I, j \in J \tag{10}$$

$$x_{ij}, h_{ij}, n_{ij}, \mu_j \geq 0 \quad \forall i \in I, j \in J \tag{11}$$

$$y_i, v_{ij} \in \{0, 1\} \quad \forall i \in I, j \in J \tag{12}$$

Objective (1) aims to maximize the demand coverage in f_1 while minimizing total costs in f_2 employing a lexicographic approach. This method prioritizes objectives by first addressing the highest priority objective of maximizing coverage and maintaining its optimal value while optimizing the subsequent objective of costs. Although more complex and time-consuming than single-objective optimization, the lexicographic approach is widely used to prioritize competing goals. In our model, this approach ensures that the humanitarian objective of maintaining an adequate supply takes precedence, while cost considerations, though secondary, are still incorporated. Constraint (2) limits the deliveries from a warehouse to its capacity s_i and its operational efficiency φ_i^w. If the probability of disruption is zero, all warehouses remain fully operational. Constraint (3) ensures demand fulfillment at every PoD, given that sufficient resources are available. Otherwise, unmet demand μ_j occurs. In case of demand disruptions, specific locations undergo spikes in demand denoted by an increase in the service level ζ by ζ^h. Constraint (4) restricts the processable number of truckloads to the parameter M_{max}. In case of a disruption in operability, the number of trucks departing from the warehouse is limited, constraining the supply. Hence, the summation of binary values from the parameter φ_m^o places a constraint on the number of trucks. Constraint (5) specifies that a warehouse can supply a PoD only if it is within the designated coverage radius, as defined in Equation 13.

$$r_{ij} = \begin{cases} 0 & \text{if } \tau_{ij} > R_i, R_i^c \text{ depending on } \varphi_i^c \\ 1 & \text{otherwise} \end{cases} \tag{13}$$

In cases where the radius is disrupted, denoted by φ_i^c, the radius R_i is reduced to R_i^c based on a specific probability affecting the value of r_{ij} as described in more detail in Sect. 4.3.

Additionally, the route must be functional, meaning the allocation is not restricted by φ_{ij}^{r} due to disruptions in allocation routes. Constraint (6) ensures that the delivered quantity x_{ij} from a warehouse to a PoD equals the available capacity Q of a truckload. Constraints (7)-(10) linearize the product of the decision variables n_{ij}, which represents the number of truckloads, and v_{ij}, which indicates the ability of warehouse i supplying PoD j. This linearization, achieved using an auxiliary variable and the big M method, is a common optimization technique to handle nonlinearities, providing simplification and increased computational efficiency (Asghari et al., 2022). Finally, constraints (11) and (12) restrict the decision variables to their respective domains.

3.3 Incorporation of scenario parameters

The model addresses uncertainty by developing specific disruption scenarios that impact crucial supply chain components, such as warehouse availability and operability, route failure, coverage radius limitations, and demand variations. We employ the Monte Carlo approach to model the probability of failures in these instances. As outlined by Klibi and Martel (2012), this computational technique thoroughly explores potential outcomes by introducing random variations in input parameters, fostering a nuanced understanding of the model's behavior in diverse settings. Specifically, we define disruption probabilities in 10% increments, ranging from no disruption (0%) to complete disruption (100%). This discrete probabilistic framework captures varying levels of disaster severity and provides a robust basis for scenario analysis. Furthermore, this method ensures high flexibility and applicability, particularly in national-level disaster preparedness planning by avoiding reliance on sparse or unrepresentative historical data for low-frequency, high-impact events. Additional details on the implemented disruption scenarios are provided in Sect. 4.3.

4 Case study

4.1 Background

We apply the model to a case study examining a large-scale disaster in Germany, resulting in a complete collapse of the commercial food supply chain. This scenario necessitates a strategic response to ensure the provision of essential food supplies from the national stockpile to the population. The national stockpiling system in Germany maintains approximately 150 warehouses distributed across the country, storing diverse food supplies such as wheat, rice, lentils, and peas (Eberhardt et al., 2024). These reserves aim to alleviate supply shortages for several weeks during large-scale disasters, including widespread and prolonged power outages, pandemics, extensive radioactive releases, or defense scenarios (BMEL, 2024). However, the strategic process during a disaster has yet to be comprehensively examined, necessitating detailed specifications regarding the supply network, logistical processes, and the allocation of warehouses to distribution points. Our detailed analysis will shed light on the system's performance, enabling the identification of vulnerabilities and offering practical recommendations for decision-makers to optimize the current network strategy, ensuring resilience and responsiveness to diverse disruptions.

4.2 Parameter settings

The required data input and the different scenario settings are detailed in the following subsections. The descriptions provide information on data sources, calculations, and the parameters for simulating diverse disruption scenarios.

4.2.1 Warehouse parameters

Warehouse locations: Information regarding storage locations in Germany is not publicly accessible in order to prevent looting during disasters. Therefore, we incorporate and model the geographical and boundary conditions set by the German Government using ArcGIS Pro to simulate a realistic system (Esri, 2021). According to BRH (2019) guidelines, the restrictions for storage locations involve:

1. Proximity to urban areas while remaining outside city centers,
2. ensuring geographical dispersion,
3. avoiding proximity to military facilities, and
4. avoiding proximity to large-scale industrial installations.

We generate feasible locations according to the specified criteria, utilizing the pre-established number of approximately 150 storage locations. Figure 2 provides a comprehensive illustration of the process flow.

The initial step involves mapping the population density in Germany (Fig. 2a) based on a dataset from Statista (2023b). To adhere to the requirement of situating warehouses on the outskirts of metropolitan areas but not within city centers, we excluded areas with a population density exceeding 1250 per km^2 from the dataset based on a definition by Haas (2024). We also exclude areas near nuclear plants, military or power facilities, and fuel stations (Fig. 2b), using data from OpenStreetMap (OSM, 2024). Next, we perform a multivariate cluster analysis, focusing on population density within adjacent areas. This analysis generates 150 clusters, representing the estimated number of storage locations in Germany while ensuring geographical dispersion (Fig. 2c). Finally, we align the identified cluster centers with nearby industry warehouse locations from OpenStreetMap using the Overpass API

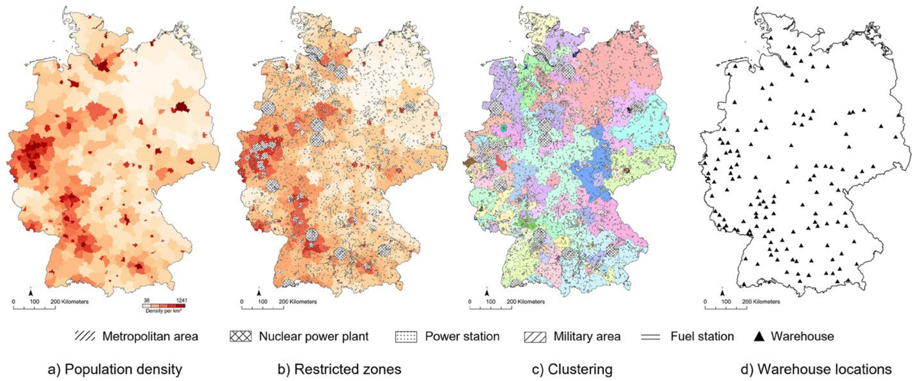


Fig. 2 Process steps for identifying potential warehouse locations

(OSM, 2024). According to the specifications, this process results in 150 warehouse locations fitting the requirements (Fig. 2d).

Warehouse capacities: According to BRg (2022), the total quantity stored ranges from a minimum of 618,000 tons to a maximum of 823,000 tons. To ensure that the total storage quantity in the case study falls within this specified range, discussions with experts established maximum and minimum storage quantities ranging from 1,500 to 9,500 tons per warehouse. The actual storage quantity for each warehouse is then randomly selected within this capacity range. As a result, the 150 locations can store an amount of goods totaling 820,069 tons.

4.2.2 Points of distribution

Location of PoDs: Public buildings such as schools and parking lots are widely recognized as effective supply distribution points, as demonstrated by Bakker et al. (2023). Taking advantage of the strategic establishment of vaccination centers during the COVID-19 pandemic, we selected these sites based on their status as public buildings, central geographical location, and accessibility. Consequently, we incorporated the centers into our case study, assuming their suitability for food distribution. Therefore, data from 431 district-level centers (NUTS 3 level) was collected from various health authorities and processed for representation.

Demand of PoDs: When assessing the demand at each PoD, we assume that residents within a district consistently visit their designated distribution point. In cases where multiple PoDs are within a district, we evenly distribute the population among these centers, facilitating the computation of residents per PoD. We subsequently determine the demand per resident by establishing the fundamental survival-calorie requirement based on Müller (2021). This assumption aligns with the Federal Government's objective of covering essential needs (BMEL, 2024). Next, we identify the number of residents per age group and federal state and compute an average calorie requirement per federal state based on the distribution (Statista, 2023a). On average, this value amounts to 1395 kcal per person. Subsequently, we calculate the calorie content per gram of the products stored in the food reserves, resulting in the average quantity of goods required per person to meet the demand according to Equation 14. In the last step, we multiply the calculated demand per person by the number of beneficiaries n assigned to the corresponding PoD and the considered disaster duration T, resulting in the overall demand d_j in tons at PoD j over the given period.

$$d_j = \frac{1,395 kcal^1}{3,507 \frac{kcal}{1g} \cdot 1,000,000} \cdot n \cdot T \tag{14}$$

1

4.2.3 Transport parameters

Vehicle type and capacity: Given that the PoDs are exclusively accessible by trucks, the distribution of relief supplies depends on this mode of transportation. The daily number of

[1] Sample value for the respective calorie requirements of the federal states, determined by age structure and gender.

trucks departing from each warehouse is contingent upon vehicle availability and the efficiency of the loading process. Based on consultations with experts, we estimate each truck's capacity to be 27 tons, with the entire process–from arrival and loading to departure–taking approximately one hour per vehicle. With warehouses operating for 16 h a day and assuming workers operate in two shifts, we anticipate that up to 16 trucks can depart from a warehouse daily, provided there are no disruptions.

Distance calculation and coverage radius: The distances and travel times calculation for trucks driving from warehouses to designated PoDs is based on Openrouteservice using a Python API (ORS, 2022). Regarding the coverage radius, we assume the presence of truck drivers during the loading and unloading processes, with a maximum daily working time of ten hours (BKat, 2024). Allocating two hours specifically for loading and unloading, we assume the coverage radius is constrained to a maximum of eight hours in the baseline scenario and an average travel speed of a vehicle of 60 km/h.

4.2.4 Cost parameters

Warehouse and storage costs: The model's warehouse costs are tailored to conform to the specifications outlined in the federal budget. As per the 2023 budget, the allocated storage costs for food reserves in Germany amount to €27 million (BMF, 2024). Consequently, a total storage quantity of 820,069 tonnes generates an annual cost of €32.92 per tonne.

Transport costs: Data from a logistics service provider indicates that the expenses for a 27-tonne truck are approximately €2.05 per kilometer (Sommer & Elso, 2024), aligning with the average industry data reported by BMEnet (2023). These costs are then used with the calculated distance matrix to determine route expenses.

4.2.5 Summary of data

Table 3 provides a detailed summary of the case study's relevant input parameters, assumptions, and data sources, forming the basis for scenario development and subsequent result analysis.

4.3 Scenario analysis

4.3.1 Simulation of scenario parameters

This study examines various disruption scenarios, each affecting critical components of the supply chain, such as warehouse failures, operability losses, route failures, coverage radius limitations, and demand uncertainties. We employ a Monte Carlo approach to model the probability of these failures using a simulation with 10,000 iterations. Each iteration randomly assigns a binary operational status based on a predefined disruption probability, simulating whether the considered component remains functional. A fixed random seed ensures the reproducibility of results across all simulations. Preliminary tests indicated that output metrics, such as average operational availability per warehouse, stabilized after approximately 5,000 iterations. Therefore, 10,000 iterations were deemed sufficient to ensure representative outcomes.

Table 3 Data summary of relevant case study parameters

Parameters		Description	Value	Data source
Warehouse	Locations	Fictitious storage locations are modeled to match governmental criteria and distribution patterns	150 Locations	ArcGIS Pro based on: BRH (2019), Statista (2023b), Haas (2024), OSM (2024)
	Capacities	Capacities are randomly assigned within the expert range to match the system total	1,500 to 9,500 tons per warehouse	BRg (2022), experts from BLE and BMEL
PoDs	Locations	Public buildings are selected based on COVID-19 vaccination sites	431 Locations	Bakker et al. (2023), district health authorities
	Demand	Demand is based on caloric needs, scaled by beneficiaries and disaster duration	Equation 14	Müller (2021), BMEL (2024), Statista (2023a)
Transport	Vehicle type and capacity	PoDs are exclusively accessible by trucks	Type: Truck Capacity: 27 tons Processing time: 1 h Work shift: 16 h Max. truckloads/day per warehouse: 16	Expert opinions from BLE and BMEL
	Distance calculation	Truck distances and times to PoDs were calculated via ORS using road network data	Distance and travel time matrices	ORS (2022), python API
	Coverage radius	Radius is determined assuming a 10-hour workday with 2 h for handling	8 h	BKat (2024)
Cost	Warehouse and storage	Warehouse costs are aligned with the specifications set forth in the federal budget	Annual cost: €32.92	BMF (2024)
	Transport	Transport costs are based on logistics provider rates and industry data	€2.05 per km	Sommer and Elso (2024), BMEnet (2023)

4.3.2 Scenario implementation

The following section briefly describes the analyzed disruption scenarios, as outlined in Table 4. The baseline scenario, denoted as S_0, provides a comparative baseline without disruptions. Scenarios S_1 through S_5 introduce targeted disruptions to critical components of the supply network, namely warehouses, transportation, and demand. Table 4 specifies, for each scenario and component, whether the network operates without restrictions (as in the baseline scenario), is subject to probabilistic disruptions, or, regarding demand, follows a deterministic pattern (as in S_0) or exhibits stochastic behavior. In addition, scenario S_6 considers multiple simultaneous disruptions affecting the supply network.

The analysis focuses on scenarios that reflect realistic and policy-relevant disruptions, streamlining the assessment and avoiding redundancy. Although additional combinations are theoretically possible, the chosen set provides a structured comparative framework, with each scenario evaluated against the defined baseline S_0. This approach enables the isolation of specific disruption effects, supports the identification of targeted mitigation strate-

Table 4 Summary of the analyzed disruption scenarios (S_0 to S_6) and the affected parameters

Scenario		Affected processes in the network		
Name	Code	Warehouse	Transport	Demand
Baseline	S_0	Unrestricted	Unrestricted	Deterministic
Warehouse failure	S_1	Disrupted	Unrestricted	Deterministic
Operability loss	S_2	Unrestricted	Disrupted	Deterministic
Route failure	S_3	Unrestricted	Disrupted	Deterministic
Coverage radius limitation	S_4	Unrestricted	Disrupted	Deterministic
Demand uncertainty	S_5	Unrestricted	Unrestricted	Stochastic
Combined disruptions	S_6	Disrupted	Disrupted	Stochastic

gies, reduces computational complexity, and enhances the clarity and interpretability of the results.

Baseline scenario (S_0):

In the *Baseline Scenario*, all critical elements of the supply chain, including warehouses, transport, and demand, operate under unrestricted conditions. Hence, the scenario assumes a relief chain under optimal conditions, where all critical parameters are known. The purpose is to establish a foundational context for evaluating the impact of disruptions in contrast to a standard operational state.

Warehouse failure (S_1):

In the *Warehouse Failure Scenario*, the analysis focuses on situations where disruptions specifically target warehouse locations within the supply chain. Employing a Monte Carlo approach, particular warehouses may encounter functional failures resulting from attacks, power outages, or natural disasters affecting designated locations. The result of the simulation process is a binary matrix, where the disruption probability ρ^w signifies the likelihood of failure. In this context, the binary matrix φ^w represents the operational status of each warehouse *i*, defined as:

$$\varphi_i^w = \begin{cases} 1, & \text{if warehouse } i \text{ is operational} \\ 0, & \text{if warehouse } i \text{ experiences a failure} \end{cases}$$

Operability loss (S_2):

The *Operability Loss Scenario* involves disruptions affecting operational efficiency, particularly within the loading process at warehouses. These disruptions, triggered by personnel shortages or power outages, necessitate manual truck loading and limit the number of trucks departing from the warehouse, constraining the supply. Like in the warehouse failure scenario, the likelihood of experiencing operability loss during the loading process is labeled as ρ^o. Hence, the summation of binary values $\sum_{m \in M_{max}} \varphi_m^o$ places a constraint on the number of trucks that can be loaded at a warehouse during labor shifts.

Route failure (S_3):

In the *Route Failure Scenario*, specific routes connecting warehouses and PoDs experience disruptions, such as road blockages. The disruption probability ρ^r is introduced, creating a binary matrices φ^r:

$$\varphi^r_{ij} = \begin{bmatrix} \varphi_{11} & \varphi_{12} & \cdots & \varphi_{1j} \\ \varphi_{21} & \varphi_{22} & \cdots & \varphi_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ \varphi_{i1} & \varphi_{i2} & \cdots & \varphi_{ij} \end{bmatrix}$$

where

$$\varphi^r_{ij} = \begin{cases} 1, & \text{if PoD j can be allocated to warehouse i} \\ 0, & \text{otherwise} \end{cases}$$

This matrix is designed to model allocation failures between warehouses *i* and demand locations *j*, explicitly limiting the solution to available routes.

Coverage radius limitation (S_4):

In the *Coverage Radius Limitation Scenario*, specific warehouses may face constraints on their coverage radius due to potential vehicle limitations, such as fuel supply issues, based on the disruption probability ρ^c. If a warehouse's coverage radius is affected, it reduces the coverage range. Equation 15 defines the adjusted coverage range R^c_i for a specific warehouse *i*. This adjustment depends on the binary matrix value φ^c_i, which indicates the operational status of the warehouse. If the warehouse is affected ($\varphi^c_i = 0$), a random factor between zero and one drawn from a uniform distribution, denoted as δ, is introduced to add variability and simulate the dynamic nature of the coverage radius adjustment:

$$R^c_i = \varphi^c_i \cdot R_i + ((1 - \varphi^c_i) \cdot \delta) \tag{15}$$

Furthermore, we integrate the assumption that a significant disruption reduces the coverage radius of a specific warehouse to less than one hour. This modeling approach is intended to reflect the severe operational impacts of critical bottlenecks. We justify this assumption by acknowledging that specific constraints, such as fuel shortages, driver unavailability, or scenario-specific limitations (e.g., during pandemics), can severely restrict the operational reach of distribution networks, even when physical infrastructure remains intact. Insights from expert consultations further reinforce this assumption, as practitioners recommended focusing on short-distance scenarios (i.e., under one hour) to capture the most critical and disruptive conditions realistically.

Demand uncertainty (S_5):

The *Demand Uncertainty Scenario* comprises specific locations that undergo spikes in demand, referred to as demand hotspots. These hotspots extend beyond the essential survival-calorie requirements, encompassing the necessity to fulfill nutritional needs for prolonged physical exertion based on the PAL (Physical Activity Level) 2.0 index (Brooks et al., 2004). The probability ρ^d is introduced to factor in the occurrence of probabilistic hotspots at PoDs, addressing uncertainties in demand patterns. Based on Equation 16, the demand value d_j is adjusted based on the disruption status at a PoD *j*. In instances where φ^d_j is equal to zero at particular locations, the service level ζ experiences an increase of ζ^h.

$$(\zeta + \zeta^h) \cdot (1 - \varphi_j^d) \cdot d_j \tag{16}$$

Combined disruptions (S_6): In the case of the *Combined Disruption Scenario*, we evaluate the simultaneous occurrence of multiple disruptions, encompassing warehouse failures, operational losses, route failures, coverage limitations, and demand uncertainty. This scenario represents a worst-case assessment, providing a comprehensive perspective on the potential challenges that may arise when the selected disruptions converge.

5 Results

5.1 Baseline scenario

The model is implemented in Python and solved using the Gurobi solver on a 3.8 GHz computer with 64 GB memory. Table 5 provides a comprehensive overview of the solved instances for the scenario S_0 within our case study, spanning disaster durations ranging from a time of 7 (T7) to 56 (T56) days.

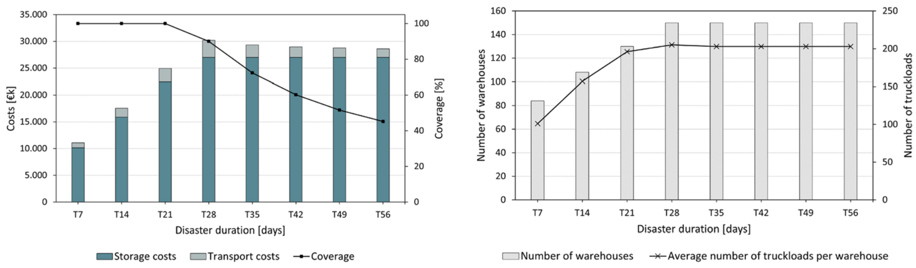
Initially, the system's inventory meets demand for at least 21 days, maintaining a coverage level of 100%. However, as the disaster duration extends, demand coverage decreases, resulting in shortages of nearly 55% after 56 days. This trend is also reflected in the rising warehouse costs, which continue to increase until week four (T28) when the system reaches the maximum capacity of 150 locations and utilizes all available warehouse locations. Consequently, with prolonged duration, only transport costs fluctuate due to altered allocations, slightly decreasing after T28. Further analysis shows that this shift towards larger transport volumes over shorter distances occurs because not all demands can be met. Hence, the system preferentially delivers to closer PoDs when resources are insufficient, as evident in Fig. 4d.

Furthermore, Fig. 3 visually represents the required costs and resources. Total costs, including storage and transport, rise steadily over longer durations as new warehouses are opened and additional stock is required, reaching the capacity limit at T28 (Fig. 3a). At this point, coverage begins to fall below 100%, indicating that despite increasing costs, the system struggles to maintain supply levels during prolonged disasters.

Figure 3b illustrates the relationship with the required resources. The number of warehouses used increases until T28, after which it plateaus at the maximum capacity of 150. The required average number of truckloads per warehouse rises with the duration of the

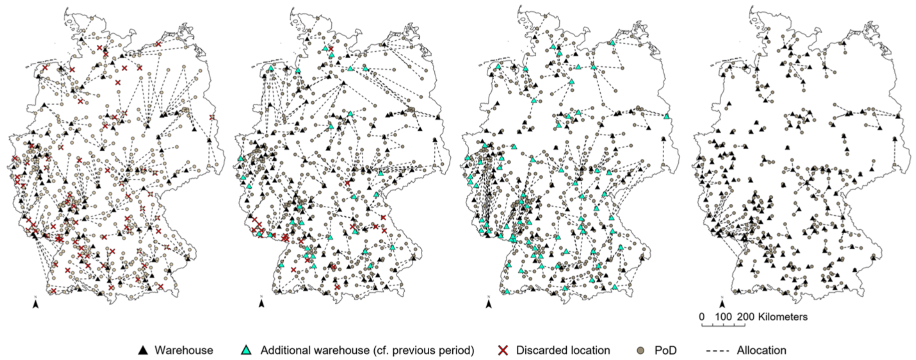
Table 5 Overview of baseline scenario results depending on the disaster duration

Disaster duration	T7	T14	T21	T28	T35	T42	T49	T56
Coverage [Mt]	0.03	0.45	0.68	−12.35	−46.39	−80.44	−114.49	−148.53
Demand covered [%]	100	100	100	90.33	72.26	60.22	51.62	45.26
Shortage value [Mt]	0	0	0	0.09	0.32	0.54	0.77	0.99
Shortage value [%]	0	0	0	9.67	27.74	39.78	48.38	54.84
Total costs [m€]	11.09	17.53	24.94	30.21	29.32	28.99	28.76	28.59
Warehouse costs [m€]	10.13	15.88	22.45	27.00	27.00	27.00	27.00	27.00
Transport costs [m€]	0.96	1.65	2.49	3.21	2.32	1.99	1.76	1.59
Number of warehouses	84	108	130	150	150	150	150	150
Number of truckloads	8,406	16,812	25,218	30,373	30,372	30,371	30,371	30,369



(a) Coverage and costs (b) Required warehouses and truckloads

Fig. 3 Objective values and required resources depending on the disaster duration



a) T7 b) T21 c) T28 d) T56

Fig. 4 Decisions on warehouse locations and their allocation to PoDs

disaster as more truckloads are needed. Interestingly, this number slightly decreases after T28 due to trucks' higher transport capacity utilization.

5.1.1 Warehouse location and allocation

Figure 4 illustrates the spatial distribution of warehouses, PoDs, and their allocation across different disaster durations of 7, 21, 28, and 56 days in Germany.

The figure shows that the existing network evolves and adapts to the increasing demand throughout the disaster. The network remains relatively sparse at the shortest duration, requiring only a limited number of warehouses to meet the existing demand. Additionally, the system prefers longer transport distances over implementing more warehouses due to lower costs. As the disaster duration extends, the system introduces additional warehouses (colored triangles) to address growing demand and geographical coverage needs. The network becomes denser, with more allocation routes established until the logistics system reaches its capacity limit at T28. At this point, shortages occur, and the system serves fewer PoDs with higher demand quantities, resulting in fewer and shorter allocation routes.

5.1.2 Occurrence and spatial distribution of shortages

Figure 5 depicts the spatial distribution and density of PoDs experiencing shortages, highlighting their proximity.

The disaster duration expands progressively, from 7 to 28, 42, and 56 days. At a disaster duration of seven days (T7), shortages are non-existent, according to the values in Table 5. During this period, the distribution network is sufficient to meet demand, with warehouses having adequate capacity to handle requests. However, shortages begin to cluster between 21 and 28 days in certain regions, particularly in areas distant from warehouse locations or where warehouse capacities are strained due to high population density, as shown in Fig. 2a. By 56 days, shortages become widespread and densely clustered in regions with high population density, particularly in cities like Berlin, Cologne, Frankfurt, Stuttgart, and Munich. This progression highlights a systemic failure due to the prolonged strain on warehouse capacities.

5.2 Disruption scenarios

The heat maps in Fig. 6 reveal the results of the impact analysis of the six disruption scenarios (S_1 to S_6) described in Sect. 4.3.2. These results show the level of coverage under different failure probabilities ρ for various disaster durations, ranging from 7 days (T7) to 56 days (T56). The demand coverage rate [%] represents the percentage of the population's demand that the logistics network successfully fulfills. The baseline scenario, with a failure probability of 0%, serves as a reference point for performance without additional disruptions.

5.2.1 Results of warehouse failure scenario

Scenario S_1 examines the failures of individual warehouse locations becoming non-functional according to a certain probability ρ. The heatmap for S_1 in Fig. 6a shows that demand coverage declines rapidly as the failure probability ρ increases, even with short disaster durations (T7–T28). With a failure rate of 50%, shortages occur after just seven days due to the reduced number of available warehouses. As the failure probability rises, a corresponding proportion of warehouses becomes non-operational. Hence, the failure of warehouses

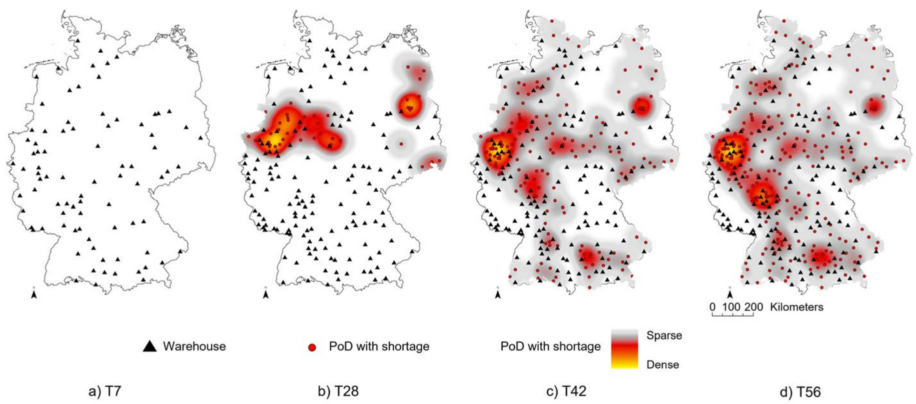


Fig. 5 Development and spatial distribution of PoDs with shortages

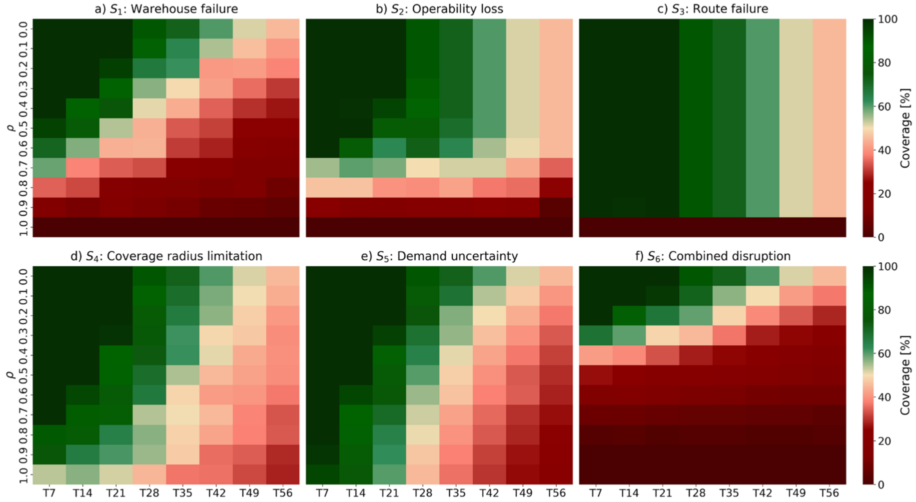


Fig. 6 Heat maps illustrating the scenario-dependent coverage rate of population demand as a function of disaster duration T and failure probability ρ

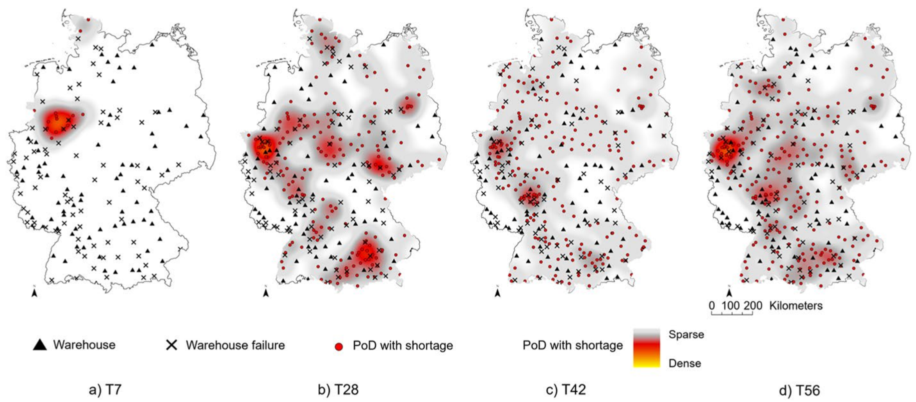


Fig. 7 Warehouse failure and spatial distribution of PoDs with shortages in S_1 and $\rho = 0.5$

leads to a steady decline in the network's capacity to meet demand, resulting in an evenly distributed decrease in coverage. In addition, Fig. 7 emphasizes that the failure probability impacts all warehouses uniformly, eliminating any region-specific bias in the failure pattern.

Compared to Fig. 5, shortages are more severe and widespread, even at earlier stages (e.g., T28). Additionally, the effects over extended disaster durations are more pronounced, disrupting previously well-supplied areas. Shortages become more dispersed and less predictable, with hotspots emerging near regions with scarce operational warehouses. The clustering now depends on the random failure of warehouses rather than solely on geographic distance, population density, and demand. Consequently, the network's ability to serve PoDs deteriorates rapidly and unpredictably.

5.2.2 Results of operability loss scenario

Scenario S_2 addresses transportation failures by assuming fewer trucks can be loaded daily due to personnel bottlenecks. The impact on supply efficiency is less severe than in S_1, as the heatmap in Fig. 6b illustrates, but additional shortages still occur at higher failure probabilities and within the first few weeks. As an example, Table 6 indicates the effect of a 70% disruption probability of operability on the coverage level, total costs, number of warehouses, and average number of truckloads in S_2 compared to the baseline scenario S_0.

The restrictions are particularly noticeable in the first few weeks. Warehouses can process significantly fewer truckloads compared to the baseline scenario. For instance, in T7, the limit is approximately 34 truckloads per warehouse instead of 112, with a 70% failure probability and some fluctuations due to the Monte Carlo simulation. Hence, the average of 31 loads indicates full utilization of all warehouses. Different from the baseline scenario, the restricted number of truckloads cannot supply all PoDs, leading to shortages after seven days. From T28 onward, the coverage levels and the number of truckloads begin to converge as the issue shifts from truckload availability to the availability of goods and the limited capacity of the warehouses.

However, another challenge is that some warehouses can only dispatch a limited daily amount of supplies with the available truckloads, resulting in lower demand coverage. Furthermore, overall costs increase significantly because all 150 warehouses must be operational from T7 onward (compared to 84 in the baseline scenario) to compensate for the reduced operability per warehouse. However, in S_2, the total cost remains lower between T28 and T56, as no additional warehouses are available and the number of feasible transports is reduced, thereby lowering transportation costs. The results show that reduced operability can significantly impact the supply level once a certain failure probability is exceeded. While additional warehouses can partially compensate for reduced operability, there is a threshold beyond which coverage significantly decreases since the warehouses reach their capacity limits.

5.2.3 Results of route failure scenario

Scenario S_3 considers the failure of individual routes, affecting the assignment options of warehouses to PoDs. Given the numerous assignment options and short distances in Germany, this disruption has no measurable effect on the coverage level compared to the baseline scenario, as evidenced by the similar pattern in the corresponding heatmap Fig. 6c.

Table 6 Comparison of baseline and operability loss results with $\rho = 0.7$

Baseline scenario S_0	T7	T14	T21	T28	T35	T42	T49	T56
Demand covered [%]	100	100	100	90.33	72.26	60.22	51.62	45.26
Total costs [m€]	11.09	17.53	24.94	30.21	29.32	28.99	28.76	28.59
Number of warehouses	84	108	130	150	150	150	150	150
∅ Truckloads per warehouse	101	157	196	205	203	203	203	203
Operability loss S_2	**T7**	**T14**	**T21**	**T28**	**T35**	**T42**	**T49**	**T56**
Demand covered [%]	55.30	59.50	57.6	49.83	52.10	52.04	43.24	34.42
Total costs [m€]	27.25	27.57	27.83	27.86	28.20	28.47	28.24	28.41
Number of warehouses	150	150	150	150	150	150	150	150
∅ Truckloads per warehouse	31	67	97	112	146	175	170	192

However, total costs, particularly transportation costs, increase as the network must adapt to the altered allocation. For instance, in T7, with a failure probability of 0.9 and approximately 90% of the allocation routes restricted, costs rise by 18.61%.

5.2.4 Results of coverage radius limitation scenario

The effects of limited and varying coverage ranges, such as those caused by fuel supply shortages, are analyzed in scenario S_4. Significant impacts are observed depending on the duration of the disaster, as goods can only be transported within a restricted radius. The heatmap Fig. 6d shows a relatively even decrease in the coverage level over the period considered, with minor fluctuations between the failure probability values. Furthermore, Fig. 8 illustrates the impact of coverage limitations for a disaster duration of 21 days, considering failure probability values ρ of 20%, 50%, 80%, and 100%. The black triangles indicate unaffected warehouses with an 8-hour delivery radius, ensuring coverage across all regions of Germany. In contrast, black-and-white triangles represent warehouses constrained by the coverage limitation.

The figure demonstrates that variations in the coverage radius of specific warehouses significantly impact allocation and delivery capabilities. This effect is particularly noticeable compared to the baseline scenario for T21, where warehouse capacities are sufficient. In S_4, with lower failure probabilities such as 20%, changes in coverage radius can be compensated by other warehouses whose radii remain unaffected, as Fig. 8a illustrates. However, the baseline scenario shows that the allocation of PoDs to warehouses differs, as illustrated in Fig. 4b. The difference highlights that even minor changes in radius necessitate adjustments to the allocation. Interestingly, the model utilizes fewer warehouses, 128 compared to 130 in the baseline scenario, but overall costs increase by 4.60%. This increase occurs because the model selects warehouses with higher storage capacities, and transportation costs rise by 40.84% due to the modified allocation.

At higher failure probabilities, such as 50%, some warehouses may become nonfunctional due to their severely constrained service range, reflecting the conditions of scenario S_1. Specifically, Fig. 8b shows that 17 affected warehouses cannot serve PoDs. Additionally, despite having PoDs within their range, three warehouses remain unused because nearby warehouses can cover the same points. However, while this redundancy saves warehouse

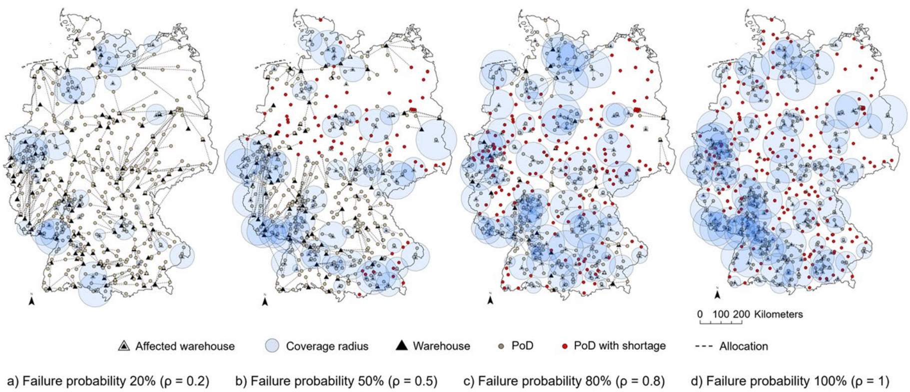


Fig. 8 Impact of coverage radius variations on allocation and supply of PoDs

costs, it results in supply shortages, as these unused warehouses would be necessary to meet overall demand.

Furthermore, specific warehouses are restricted to transporting goods over short distances, which limits their ability to address capacity shortages at other locations. Consequently, even PoDs within a warehouse's radius may experience unmet demand due to the capacity constraints of individual warehouses, as indicated by the red dots representing PoDs with demand shortages. Therefore, areas with a low density of warehouses are particularly vulnerable, leading to shortages that tend to occur first in the northern and eastern regions of the country. In contrast, the southern and western regions are relatively better served.

In addition, the random impact on radius size can result in varying numbers of PoDs being covered. Consequently, the heatmap shows low fluctuations across instances. For example, coverage levels slightly increase at T28 with a failure probability of 80% compared to the previous 70%, even though more warehouses are affected by the coverage limitation. If 100% of the warehouses are affected by radius modifications, only points within the respective radii can be supplied, as depicted in Fig. 8d. This restriction significantly limits delivery options and results in over 50% shortages. However, these effects are relatively minor compared to scenario S_1 and manifest, as in scenario S_2, at higher failure probabilities or during extended disaster durations.

5.2.5 Results of demand uncertainty scenario

Scenario S_5 examines the impact of higher demand at PoDs compared to the baseline scenario, revealing that shortages occur earlier, exacerbating the supply situation (Fig. 6e). Further analysis of the distribution of shortages indicates that the concentration shifts with the emergence of hotspots, leading to a reallocation of PoDs to different warehouses. Additionally, the occurrence of these hotspots necessitates opening more warehouses to compensate for the increase in demand. For instance, at T7, with a failure probability of 70%, 138 warehouses are required compared to 84 in the baseline scenario. This significant increase underscores the strain on the supply chain infrastructure. At higher values of ρ, the solution reaches the limit of 150 warehouses as early as T7, resulting in shortages despite the increased capacity. Furthermore, the rise in the number of warehouses leads to higher overall costs, emphasizing the need to balance preparedness for potential demand surges with maintaining cost efficiency.

5.2.6 Results of combined disruptions scenario

Scenario S_6 simulates the extreme case where all disruptions from S_1 to S_5 co-occur, significantly impacting the coverage rate, as demonstrated by the heatmap in Fig. 6f. When the disruption probability exceeds 40%, maintaining supply to the population becomes nearly impossible. The results clearly illustrate the severe consequences of not preparing for these disruptions, rendering the system ineffective and negating the investment in pre-positioning stocks.

6 Sensitivity analysis

6.1 Trade-offs between cost and coverage

The study's methodology is grounded in a multi-objective optimization model comprising two objective functions based on a lexicographic approach. Since this approach solves multi-objective problems by strictly prioritizing objectives, it does not explore the Pareto Front or provide a spectrum of trade-off solutions. To facilitate a more nuanced analysis of the trade-offs between cost and coverage objectives, we employ the ε-constrained method, which is widely used for problems involving conflicting objectives (Mesquita-Cunha et al., 2023). This scalarization technique optimizes one objective while converting the others into constraints bounded by ε-values (Ehrgott & Ruzika, 2008). Specifically, we incorporate f_1, the maximization of coverage, as a constraint and minimize the cost objective f_2 as defined in Equation 17. We then evaluate the outcomes across varying ε-values, progressively increasing the required coverage to the maximum achievable value Cov_{max}.

$$\min_{x \in X} \quad f_2(x) \quad \text{s.t.} \quad f_1(x) \geq (1 - \varepsilon) \cdot Cov_{max} \tag{17}$$

Figure 9 presents the resulting trade-off curve, which shows a monotonic trend where slight decreases in coverage lead to consistent cost reductions. Each point reflects a Pareto-optimal solution, where improving one objective requires compromising the other.

The analysis indicates that full coverage (100%) can be achieved for €24.938 million with a disaster duration of T21. Allowing up to a 10% reduction in coverage leads to only marginal cost savings, less than 1% of the total cost. This curve offers practical insights for decision-makers comparing full and partial coverage. In the case study, especially in humanitarian logistics, full coverage is often essential and may justify the additional cost. If small reductions in coverage are acceptable, the potential savings in this case remain limited. These findings support using a lexicographic approach, especially when coverage is considered a non-negotiable priority, providing a clear and policy-consistent basis for strategic decisions.

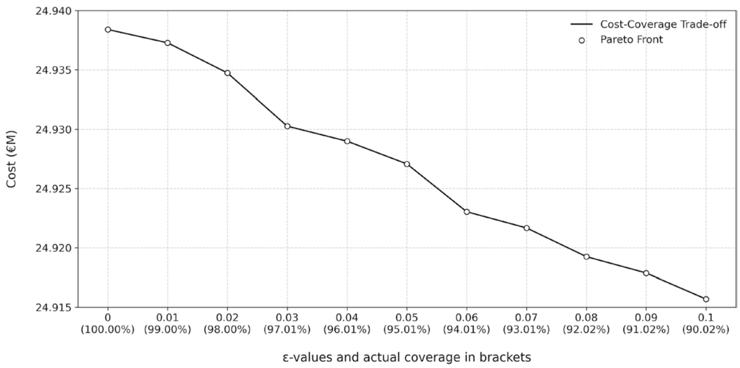


Fig. 9 Trade-off curve between objective functions f_1 (coverage) and f_2 (cost) using the ε-constraint method

6.2 Impact of variations in storage capacity

The case study results highlight storage capacity as a frequent bottleneck in system performance. To assess its impact, warehouse capacities were incrementally increased by 5% to 25% to evaluate potential gains in coverage and cost efficiency that could justify additional investments. Table 7 presents the results for both the baseline scenario (S_0) and the warehouse failure scenario (S_1), assuming a 28-day disaster duration (T28).

The results show that increasing warehouse storage capacity significantly improves system performance, particularly regarding coverage. In the baseline scenario, full coverage is achieved with a 15% increase in capacity, after which additional increases yield no further coverage gains. After 15%, costs begin to decline, indicating that the model leverages the extra capacity to optimize the network, serving the same demand with fewer strategically located warehouses. Initially, the system prioritizes coverage but shifts toward cost efficiency once coverage is maximized. A similar trend is observed in the warehouse failure scenario ($\rho = 0.1$), though a 20% increase in storage is needed to achieve full coverage. Because failures are random and can affect any warehouse, the impact of added capacity varies slightly. While both scenarios benefit from increased capacity, the improvements are more pronounced and cost-intensive under failure conditions. The decision to increase storage capacity depends on the decision-maker's risk tolerance, budget priorities, and a careful evaluation of the associated investment costs.

6.3 Computational performance

The multi-objective capacitated cooperative covering location model belongs to the class of NP-hard problems known for their computational complexity. As a result, solving such models can be resource-intensive, especially at larger scales. Table 8 presents key performance indicators across selected scenarios and parameter settings to assess the model's computational efficiency under varying conditions.

In the baseline scenario (S_0) and under low failure probabilities, the model exhibits substantial computational demands, requiring significant CPU time, memory, and solver iterations. However, as failure probability (ρ) increases (e.g., in S_6), the model becomes significantly easier to solve due to reduced feasible solutions.

Despite the inherent computational complexity, the model demonstrates robust performance even when applied to a large-scale setting involving 150 potential storage locations and 431 distribution points. Nevertheless, scaling to even larger instances will depend

Table 7 Impact of increased storage capacity on baseline and warehouse failure scenario (T28)

Increase Storage [%]	Baseline ($S_0, \rho = 0$)				Warehouse failure ($S_1, \rho = 0.1$)			
	Cov. [%]	Δ Cov. [%]	Cost [€M]	Δ Cost [%]	Cov. [%]	Δ Cov. [%]	Cost [€M]	Δ Cost [%]
0	90.33	0	30.21	0	81.46	0	26.85	0
5	94.85	5.00	32.16	6.48	84.87	4.19	28.06	4.53
10	99.37	10.00	34.35	13.70	92.87	14.01	31.72	18.16
15	100	10.71	34.29	13.51	93.87	15.23	31.88	18.76
20	100	10.71	33.87	12.14	100	22.76	34.69	29.23
25	100	10.71	33.55	11.08	100	22.76	34.64	29.02

Table 8 Computational performance across selected scenarios, disaster duration T, and failure probabilities ρ

	T	ρ	Gap [%]	CPU Time [s]	Iterations	Memory [MB]
S_0	T7	0	0	16,727.20	13,194,059	18,976.75
	T21	0	0	13,289.59	9,855,467	15,326.63
	T28	0	0	159.86	69,725	155.15
S_2	T21	0.2	0	15,321.97	11,795,927	17,730.29
	T21	0.5	0	121.50	54,946	119.82
	T21	0.8	0	16.97	40,612	13.10
S_4	T21	0.2	0	11,242.28	10,130,377	12,513.99
	T21	0.5	0	58.96	46,731	63.27
	T21	0.8	0	3.82	8,029	2.66
S_6	T21	0.2	0	16.45	19,043	17.03
	T21	0.5	0	1.37	2,011	0.92
	T21	0.8	0	0.59	51	0.29

on the specific characteristics of the case and may require the integration of algorithmic enhancements or heuristics.

7 Discussion and conclusion

7.1 Findings

In this paper, we introduce a multi-objective capacitated cooperative covering location problem to optimize logistics networks. The model emphasizes the strategic placement of warehouses to enhance the distribution of critical supplies, focusing on preparedness measures and mitigating disaster effects. Furthermore, our work considers multiple disruption scenarios with specific failure probabilities, accounting for stochastic conditions. A case study on the national food stockpiling system in Germany illustrates the effectiveness of the proposed model. Given a large-scale disaster, the model assesses the impact of warehouse failure, operability loss, route failure, coverage limitations, demand uncertainty, and combined disruptions, enabling the evaluation of optimal network solutions.

The baseline scenario results indicate the system is initially robust, maintaining full coverage for the first 21 days. However, as the disaster duration extends, the system's ability to meet demand decreases significantly, leading to substantial shortages at PoDs. This decline in coverage is accompanied by rising costs, particularly in transportation and later in storage, until the system reaches its maximum capacity of 150 warehouses after 28 days. Once this capacity is reached, the model solution prioritizes deliveries to closer PoDs when resources are insufficient. This shift results in increased transport volumes over shorter distances, optimizing the use of available resources and reducing transportation costs, even though shortages cannot be avoided. Despite these adjustments, the system struggles to maintain adequate supply levels during prolonged disasters, as evidenced by the steady rise in costs and a decline in coverage.

In addition to the baseline scenario, the analysis of disruption scenarios clearly shows that disturbances to the network significantly impair supply efficiency. Scenario S_1 underscores the critical impact of warehouse failures on the overall network's performance. Failures across multiple warehouses lead to a more unpredictable and widespread shortage pattern. Scenario S_2 examines operational failures, where fewer trucks can be loaded daily due to staffing shortages or technical issues. Although the impact is less severe than warehouse failures in S_1, transportation bottlenecks still result in significant demand shortages, particularly at higher failure probabilities and during the early stages of a disaster. The findings indicate that while the supply network can partially adapt to reduced operability, there are critical thresholds beyond which supply efficiency is compromised.

Nevertheless, Scenario S_3 demonstrates that disruptions do not invariably result in significant declines in the coverage rate. Due to multiple allocation options and an extensive supply radius, the parameters in this scenario predominantly influence operational costs rather than the extent of demand coverage. In contrast, the analysis of the coverage constraint in Scenario S_4 underscores the substantial influence of limited and variable coverage ranges on supply transportation and warehouse allocation. The results reveal that even minor reductions in warehouse radii can significantly increase costs and lead to shortages, particularly under higher failure probabilities. The variability in coverage range poses an elevated risk to regions with limited warehouse access. The demand uncertainty analysis in Scenario S_5 highlights the critical importance of flexibility and scalability in supply chain systems. When demand surpasses baseline projections, the infrastructure can quickly become overburdened, necessitating rapid adjustments in inventory allocation and driving up overall costs. Similarly, scenario S_6 demonstrates that if disruptions co-occur, their adverse effects can be significantly amplified. This analysis underscores the importance of comprehensive preparedness strategies to mitigate the severe consequences of extreme scenarios. Without adequate contingency planning, the effectiveness of the supply system is likely to deteriorate, and investments in pre-positioned stocks may not deliver the expected benefits. Moreover, the sensitivity analysis reveals that permitting up to a 10% reduction in coverage yields only marginal cost savings, whereas expanding storage capacity can significantly improve both coverage and cost efficiency under specific conditions.

7.2 Implications for theory and practice

Theoretically, the model advances existing approaches by enabling a comprehensive assessment of network design, resource requirements, supply duration, and system performance across various disruption scenarios. Understanding how supply networks behave in such conditions is essential for evaluating design alternatives and formulating effective mitigation strategies. The model offers a quantitative framework to support decision-makers in identifying system requirements, setting priorities, and minimizing the impact of disruptions.

In terms of practical relevance, the model offers actionable insights for decision-makers, emphasizing the need for comprehensive strategic planning that accounts for diverse disruption scenarios while ensuring flexibility and scalability in pre-positioning critical supplies. The baseline scenario highlights the importance of capacity planning and adaptive logistics in maintaining supply levels during prolonged disruptions. Strategically locating facilities and optimizing resource allocation are essential for operational continuity and system efficiency. The analysis advises determining warehouse number and capacity based on clear supply objectives, supported by appropriate safety stock to buffer against uncertainty. The sensitivity analysis further shows that increasing storage capacity can significantly enhance coverage and cost efficiency. Additionally, disruption scenarios S_1 through S_6 provide a robust framework for identifying and mitigating systemic bottlenecks.

In this context, Scenario S_1, characterized by warehouse failure, demonstrates that such disruptions severely impact system performance, often resulting in unpredictable and widespread shortages. This finding highlights the critical need for robust warehouse resilience strategies. Recommended measures include the implementation of backup power systems, integration of solar energy solutions, enhancement of physical security, maintenance of safety stock reserves, and the optimization of warehouse operations to safeguard continuity and responsiveness. Scenario S_2, which involves operability loss at specific warehouses, also significantly impacts supply chain efficiency at certain probability levels. These disruptions underscore the necessity of securing labor, optimizing and automating logistics processes, and maintaining adequate reserves of fuel and electricity to prevent operational setbacks such as the need for manual loading.

Additionally, the analysis of Scenario S_4, which examines constraints on warehouse coverage radii, reveals that reductions in coverage range can lead to increased costs and supply shortages. This finding highlights the importance of accounting for fluctuating transportation distances during crises. Recommended measures include maintaining sufficient fuel reserves, securing transport routes, and strategically distributing warehouses to better absorb localized disruptions and offset potential constraints on other facilities. Moreover, Scenario S_5 demonstrates the relevance of securing high-demand areas. Placing additional warehouses in regions with high population density, planning for a surge in demand, and maintaining excess capacity in resources and safety stocks are essential strategies. These measures enhance the system's ability to respond to demand spikes and ensure the availability of critical supplies in densely populated regions.

Scenario S_6 illustrates how simultaneous disruptions can trigger cascading effects, severely amplifying supply shortages and potentially leading to total system collapse. This aspect underscores the vulnerability of networks with tightly coupled supply processes and the need to address both individual and compound disruptions. While isolated failures may be managed through ad hoc responses, multiple disruptions require proactive, pre-planned strategies. Strengthening systemic resilience involves integrated mitigation measures, such as enhancing redundancy in storage and transport infrastructure, pre-positioning reserves in high-demand areas, and deploying decentralized storage units to improve coverage in remote regions. Adaptive mechanisms, such as dynamic rerouting, flexible resource allocation, and real-time monitoring, might improve responsiveness during evolving crises.

Beyond the scenario-specific findings, several broader implications emerge. Planning for rising operational costs is critical to ensure financial preparedness and to prevent supply shortfalls driven by budgetary constraints. The results also indicate that PoDs in remote or high-demand areas are particularly vulnerable to shortages when demand exceeds supply. This aspect underscores the importance of ethical decision-making in resource allocation, especially when prioritizing critical facilities such as hospitals or retirement homes. Implementing needs-based or vulnerability-oriented allocation frameworks can help ensure timely support for at-risk populations. In addition, while the primary focus of the case study is on public authorities and governmental decision-makers, the model is equally applicable to private-sector contexts. For instance, it can be adapted to global corporate supply chains or tailored to regional networks facing uncertainty. Companies and managers can identify targeted mitigation strategies depending on the use case. Similarly, public authorities may collaborate with key private actors to establish security agreements, address bottlenecks, and strengthen disaster preparedness.

However, decision-makers should consider the practical implementation challenges of the proposed methodology. Key challenges include scalability, availability of technical resources, and financial limitations. Additional barriers, such as limited data availability, legal and regulatory constraints, insufficient coordination between public and private stakeholders, and the need for specialized expertise to operate and interpret the model, may also hinder adoption. Overcoming these challenges calls for investment in data infrastructure and interoperability, strengthened collaboration, and the development of accessible, practitioner-oriented decision-support tools.

7.3 Limitations and future research

While our study offers significant contributions, some limitations warrant further exploration. First, further works can extend the scenarios to incorporate additional constraints, such as varying levels of infrastructure damage, cost uncertainties, stochastic occurrences of disaster locations and affected areas, or other supply chain-related disruptions. Moreover, real-time data, such as population movement, infrastructure conditions, or transport availability, supports more responsive and adaptive planning. Incorporating dynamic adjustment mechanisms based on current network status would further strengthen the model's ability to respond to evolving crisis conditions.

Second, the assumption of uniform coverage radii in the baseline scenario is simplistic, chosen due to Germany's well-maintained and dense infrastructure. However, in other contexts, terrain, infrastructure, and logistical constraints can significantly affect coverage. Addressing these variables enables the model to reflect real-world conditions and enhance its applicability.

Third, in the case study, warehouse capacities are randomly allocated within the predefined minimum and maximum ranges, validated by experts, due to the confidentiality of sensitive data. Future research could refine this approach by incorporating warehouse sizing decisions based on population density, proximity to disaster-prone areas, infrastructure accessibility, and other logistical considerations. Integrating these spatial and demographic criteria enables more targeted, data-driven preparedness planning. Similarly, the underlying demand estimation may not fully capture real-world heterogeneity. While the current method accounts for demographic variation through age-specific calorie requirements at the federal-state level, the assumption of evenly distributed residents among PoDs in one district oversimplifies spatial dynamics. A more accurate approach could allocate residents using high-resolution population data and accessibility metrics, such as proximity or travel time to each PoD. Incorporating district demographic data and socioeconomic indicators further enhances the precision of demand estimates by reflecting geographic and demographic variability.

Fourth, future research should explore algorithmic enhancements, such as decomposition methods or meta-heuristics, to improve scalability as network complexity increases with additional disruption scenarios, commodities, and potential locations. These techniques enable more efficient optimization and support detailed modeling of dynamic factors like daily demand fluctuations and uncertain crisis durations, offering a more realistic and fine-grained analysis. In addition, increased computation efficiency enables the integration of prioritization strategies when demand exceeds supply. Such approaches could comprise a lexicographic minimax approach to enhance fairness while focusing on the distribution of relative shortages across PoDs. The method sequentially minimizes the largest, second-largest, and subsequent relative shortages, with each step proceeding after the larger shortages have been minimized and held constant.

Fifth, future research should implement stochastic scenario generation to capture a wider range of disruption patterns beyond the predefined cases, enabling a more robust assessment of model performance under uncertainty. In addition, evaluating the impact of specific preparedness and post-disaster measures on network performance, cost efficiency, and coverage can support more effective system design and response strategies.

Finally, while our case study specifically focuses on Germany's national food stockpiling system, the proposed model can be adapted to other contexts, such as different countries or other critical supply chains. In conclusion, this work provides valuable insights for decision-makers, enabling them to anticipate and mitigate supply disruptions, enhance the system's adaptability to changing circumstances, sustain operational effectiveness, and optimize resource allocation.

Acknowledgements This manuscript is supported by funds from the Federal Ministry of Food and Agriculture (BMEL) based on a decision made by the Parliament of the Federal Republic of Germany via the Federal Office for Agriculture and Food (BLE), grant number 2821HS012.

Funding Open Access funding enabled and organized by Projekt DEAL.

Data availability Data supporting the findings of this study are available on a reasonable request from the authors.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Akbarpour, M., Ali Torabi, S., & Ghavamifar, A. (2020). Designing an integrated pharmaceutical relief chain network under demand uncertainty. *Transportation Research Part E: Logistics and Transportation Review, 136*, Article 101867. https://doi.org/10.1016/j.tre.2020.101867

Alizadeh, R., & Nishi, T. (2020). Hybrid set covering and dynamic modular covering location problem: Application to an emergency humanitarian logistics problem. *Applied Sciences, 10*(20), 7110. https://doi.org/10.3390/app10207110

Asghari, M., Fathollahi-Fard, A. M., Mirzapour Al-e-hashem, S. M. J., & Dulebenets, M. A. (2022). Transformation and linearization techniques in optimization: A state-of-the-art survey. *Mathematics, 10*(2), 283. https://doi.org/10.3390/math10020283

Aslan, E., & Çelik, M. (2019). Pre-positioning of relief items under road/facility vulnerability with concurrent restoration and relief transportation. *IISE Transactions, 51*(8), 847–868. https://doi.org/10.1080/24725854.2018.1540900

Bagherinejad, J., Bashiri, M., & Nikzad, H. (2018). General form of a cooperative gradual maximal covering location problem. *Journal of Industrial Engineering International, 14*(2), 241–253. https://doi.org/10.1007/s40092-017-0219-5

Bakker, H., Diehlmann, F., Wiens, M., Nickel, S., & Schultmann, F. (2023). School or parking lot? Selecting locations for points of distribution in urban disasters. *Socio-Economic Planning Sciences, 89*, Article 101670. https://doi.org/10.1016/j.seps.2023.101670

Balcik, B., & Beamon, B. M. (2008). Facility location in humanitarian relief. *International Journal of Logistics Research and Applications, 11*(2), 101–121. https://doi.org/10.1080/13675560701561789

Barzinpour, F., & Esmaeili, V. (2014). A multi-objective relief chain location distribution model for urban disaster management. *The International Journal of Advanced Manufacturing Technology, 70*(5), 1291–1302. https://doi.org/10.1007/s00170-013-5379-x

Berman, O., Drezner, Z., & Krass, D. (2010). Generalized coverage: New developments in covering location models. *Computers & Operations Research, 37*(10), 1675–1687. https://doi.org/10.1016/j.cor.2009.11.003

BKat. (2024). Welche Arbeitszeit ist für LKW-Fahrer gesetzlich vorgeschrieben? (Bußgeldkatalog, Ed.). Retrieved December 10, 2024, from https://www.bussgeldkatalog.org/arbeitszeit-lkw-fahrer/#taegliche_und_woechentliche_arbeitszeit_was_lkw-fahrer_duerfen

BMF. (2024). Erstattung der Kosten für die zivile Notfallreserve und die Bundesreserve Getreide an die Bundesanstalt für Landwirtschaft und Ernährung (BLE) (Bundesministerium der Finanzen, Ed.). Retrieved January 22, 2024, from https://www.bundeshaushalt.de/DE/Bundeshaushalt-digital/bundeshaushalt-digital.html

BMEL. (2024). Staatliche Vorsorge (Bundesministerium für Ernährung und Landwirtschaft, Ed.). Retrieved January 15, 2024, from https://www.ernaehrungsvorsorge.de/staatliche-vorsorge

BMEnet. (2023). BME-Marktinformationen Frachten: Straßengüterverkehr national und international (BMEnet GmbH, Ed.). Retrieved April 30, 2024, from https://shop.bme.de/products/bme-preisspiegel-frachten-26782349-7cf0-4524-8811-9609e691fbf8?

Boonmee, C., Arimura, M., & Asada, T. (2017). Facility location optimization model for emergency humanitarian logistics. *International Journal of Disaster Risk Reduction, 24*, 485–498. https://doi.org/10.1016/j.ijdrr.2017.01.017

BRH. (2019). Abschließende Mitteilung an das Bundesministerium für Ernährung und Landwirtschaft über die Prüfung zur Ernährungsnotfallvorsorge des Bundes (Bundesrechnungshof (B, Ed.). Retrieved November 20, 2024, from https://www.bundesrechnungshof.de/SharedDocs/Downloads/DE/Berichte/2019/ernaehrungsnotfallvorsorge-volltext.pdf?__blob=publicationFile&v=1

BRg. (2022). Antwort der Bundesregierung auf die Kleine Anfrage der Abgeordneten René Springer, Peter Felser, Dietmar Friedhoff, weiterer Abgeordneter und der Fraktion der AfD: Drucksache 20/2807 (Bundesregierung, Ed.). Retrieved January 18, 2024, from https://dserver.bundestag.de/btd/20/030/2003009.pdf

Brooks, G. A., Butte, N. F., Rand, W. M., Flatt, J.-P., & Caballero, B. (2004). Chronicle of the institute of medicine physical activity recommendation: How a physical activity recommendation came to be among dietary recommendations. *The American Journal of Clinical Nutrition, 79*(5), 921S-930S. https://doi.org/10.1093/ajcn/79.5.921S

Campbell, A. M., & Jones, P. C. (2011). Prepositioning supplies in preparation for disasters. *European Journal of Operational Research, 209*(2), 156–165. https://doi.org/10.1016/j.ejor.2010.08.029

Eberhardt, K., Stieler, S., Kaiser, F. K., & Schultmann, F. (2024). Comparative analysis of strategies for national food stockpiling: A case study of germany and switzerland. In *Proceedings of the International ISCRAM Conference*. https://doi.org/10.59297/d3kgg415

Ehrgott, M., & Ruzika, S. (2008). Improved ε-constraint method for multiobjective programming. *Journal of Optimization Theory and Applications, 138*(3), 375–396. https://doi.org/10.1007/s10957-008-9394-2

Eligüzel, İM., Özceylan, E., & Weber, G.-W. (2023). Location-allocation analysis of humanitarian distribution plans: A case of united nations humanitarian response depots. *Annals of Operations Research, 324*(1–2), 825–854. https://doi.org/10.1007/s10479-022-04886-y

Erbeyoğlu, G., & Bilge, Ü. (2020). A robust disaster preparedness model for effective and fair disaster response. *European Journal of Operational Research, 280*(2), 479–494. https://doi.org/10.1016/j.ejor.2019.07.029

Esri. (2021). *Arcgis pro* (Version 2.9.8). https://www.esri.com/de-de/arcgis/products/arcgis-pro/overview

Farahani, R. Z., Asgari, N., Heidari, N., Hosseininia, M., & Goh, M. (2012). Covering problems in facility location: A review. *Computers & Industrial Engineering, 62*(1), 368–407. https://doi.org/10.1016/j.cie.2011.08.020

Haas, H.-D. (2024). Verdichtungsraum (L.-M.-U. M. Lehrstuhl für Wirtschaftsgeographie, Ed.). Retrieved January 18, 2024, from https://wirtschaftslexikon.gabler.de/definition/verdichtungsraum-48003

Hale, T. S., & Moberg, C. R. (2003). Location science research: A review. *Annals of Operations Research, 123*(1), 21–35. https://doi.org/10.1023/A:1026110926707

Jia, H., Ordóñez, F., & Dessouky, M. M. (2007). Solution approaches for facility location of medical supplies for large-scale emergencies. *Computers & Industrial Engineering, 52*(2), 257–276. https://doi.org/10.1016/j.cie.2006.12.007

Katsaliaki, K., Galetsi, P., & Kumar, S. (2022). Supply chain disruptions and resilience: A major review and future research agenda. *Annals of Operations Research, 319*(1), 965–1002. https://doi.org/10.1007/s10479-020-03912-1

Klibi, W., & Martel, A. (2012). Scenario-based supply chain network risk modeling. *European Journal of Operational Research, 223*(3), 644–658. https://doi.org/10.1016/j.ejor.2012.06.027

Kumar, M., Raut, R. D., Sharma, M., Choubey, V. K., & Paul, S. K. (2022). Enablers for resilience and pandemic preparedness in food supply chain. *Operations Management Research, 15*(3), 1198–1223. https://doi.org/10.1007/s12063-022-00272-w

Laporte, G., Nickel, S., & Da Saldanha Gama, F. (2015). *Location science*. Springer. https://doi.org/10.1007/978-3-319-13111-5

Lei, S., Wang, J., Chen, C., & Hou, Y. (2016). Mobile emergency generator pre-positioning and real-time allocation for resilient response to natural disasters. *IEEE Transactions on Smart Grid*. https://doi.org/10.1109/TSG.2016.2605692

Li, X., Ramshani, M., & Huang, Y. (2018). Cooperative maximal covering models for humanitarian relief chain management. *Computers & Industrial Engineering, 119*, 301–308. https://doi.org/10.1016/j.cie.2018.04.004

Liu, K., Zhang, H., & Zhang, Z.-H. (2021). The efficiency, equity and effectiveness of location strategies in humanitarian logistics: A robust chance-constrained approach. *Transportation Research Part E: Logistics and Transportation Review, 156*, Article 102521. https://doi.org/10.1016/j.tre.2021.102521

Li, X., Zhao, Z., Zhu, X., & Wyatt, T. (2011). Covering models and optimization techniques for emergency response facility location and planning: A review. *Mathematical Methods of Operations Research, 74*(3), 281–310. https://doi.org/10.1007/s00186-011-0363-4

Mesquita-Cunha, M., Figueira, J. R., & Barbosa-Póvoa, A. P. (2023). New ε-constraint methods for multi-objective integer linear programming: A Pareto front representation approach. *European Journal of Operational Research, 306*(1), 286–307. https://doi.org/10.1016/j.ejor.2022.07.044

Müller, C. (2021). Wie viele Kalorien braucht der Mensch? Retrieved October 14, 2024, from https://landeszentrum-bw.de/,Lde/Startseite/wissen/wie-viele-kalorien-braucht-der-mensch

Murali, P., Ordóñez, F., & Dessouky, M. M. (2012). Facility location under demand uncertainty: Response to a large-scale bio-terror attack. *Socio-Economic Planning Sciences, 46*(1), 78–87. https://doi.org/10.1016/j.seps.2011.09.001

ORS. (2022). Time-distance matrix (openrouteservice, Ed.). Retrieved January 10, 2024, from https://openrouteservice.org/

OSM. (2024). Openstreetmap (osm) (F. e.V., Ed.). https://www.openstreetmap.org/

Owen, S. H., & Daskin, M. S. (1998). Strategic facility location: A review. *European Journal of Operational Research, 111*(3), 423–447. https://doi.org/10.1016/S0377-2217(98)00186-6

Park, Y., Lee, S., Sung, I., Nielsen, P., & Moon, I. (2022). Facility location-allocation problem for emergency medical service with unmanned aerial vehicle. *IEEE Transactions on Intelligent Transportation Systems*. https://doi.org/10.1109/TITS.2022.3223509

Paul, J. A., & Batta, R. (2008). Models for hospital location and capacity allocation for an area prone to natural disasters. *International Journal of Operational Research, 3*(5), 473. https://doi.org/10.1504/IJOR.2008.019170

Pires Ribeiro, J., & Barbosa-Povoa, A. (2018). Supply chain resilience: Definitions and quantitative modelling approaches—A literature review. *Computers & Industrial Engineering, 115*, 109–122. https://doi.org/10.1016/j.cie.2017.11.006

Rancourt, M. È., Cordeau, J.-F., Laporte, G., & Watkins, B. (2015). Tactical network planning for food aid distribution in Kenya. *Computers & Operations Research, 56*, 68–83. https://doi.org/10.1016/j.cor.2014.10.018

Rawls, C. G., & Turnquist, M. A. (2011). Pre-positioning planning for emergency response with service quality constraints. *OR Spectrum, 33*(3), 481–498. https://doi.org/10.1007/s00291-011-0248-1

Razavi, N., Gholizadeh, H., Nayeri, S., & Ashrafi, T. A. (2021). A robust optimization model of the field hospitals in the sustainable blood supply chain in crisis logistics. *Journal of the Operational Research Society, 72*(12), 2804–2828. https://doi.org/10.1080/01605682.2020.1821586

Roshani, A., Walker-Davies, P., & Parry, G. (2024). Designing resilient supply chain networks: A systematic literature review of mitigation strategies. *Annals of Operations Research, 341*(2–3), 1267–1332. https://doi.org/10.1007/s10479-024-06228-6

Rothkopf, A., Acimovic, J., & Goentzel, J. (2023). The impact of transportation capacity in pre-positioning humanitarian supplies. *Decision Sciences*. https://doi.org/10.1111/deci.12610

Sabbaghtorkan, M., Batta, R., & He, Q. (2020). Prepositioning of assets and supplies in disaster operations management: Review and research gap identification. *European Journal of Operational Research, 284*(1), 1–19. https://doi.org/10.1016/j.ejor.2019.06.029

Salman, F. S., & Yücel, E. (2015). Emergency facility location under random network damage: Insights from the Istanbul case. *Computers & Operations Research, 62*, 266–281. https://doi.org/10.1016/j.cor.2014.07.015

Seuring, S., Brandenburg, M., Sauer, P. C., Schünemann, D.-S., Warasthe, R., Aman, S., Qian, C., Petljak, K., Neutzling, D. M., Land, A., & Khalid, R. U. (2022). Comparing regions globally: Impacts of covid-19 on supply chains—A Delphi study. *International Journal of Operations & Production Management, 42*(8), 1077–1108. https://doi.org/10.1108/IJOPM-10-2021-0675

Shaheen, I., Azadegan, A., & Davis, D. (2023). Humanitarian supply chains and innovation: A focus on us food banks. *International Journal of Operations & Production Management, 43*(12), 1920–1942. https://doi.org/10.1108/IJOPM-06-2022-0388

Sharma, J., Tyagi, M., & Bhardwaj, A. (2021). Exploration of covid-19 impact on the dimensions of food safety and security: A perspective of societal issues with relief measures. *Journal of Agribusiness in Developing and Emerging Economies, 11*(5), 452–471. https://doi.org/10.1108/JADEE-09-2020-0194

Shaw, L., Das, S. K., & Roy, S. K. (2022). Location-allocation problem for resource distribution under uncertainty in disaster relief operations. *Socio-Economic Planning Sciences, 82*, Article 101232. https://doi.org/10.1016/j.seps.2022.101232

Shehadeh, K. S., & Tucker, E. L. (2022). Stochastic optimization models for location and inventory prepositioning of disaster relief supplies. *Transportation Research Part C: Emerging Technologies, 144*, Article 103871. https://doi.org/10.1016/j.trc.2022.103871

Sheikholeslami, M., & Zarrinpoor, N. (2023). Designing an integrated humanitarian logistics network for the preparedness and response phases under uncertainty. *Socio-Economic Planning Sciences, 86*, Article 101496. https://doi.org/10.1016/j.seps.2022.101496

Sommer & Elso. (2024). Preisliste 2024 (Sommer & Elso GmbH, Ed.). Retrieved January 22, 2024, from https://www.sommer-elso.com/preisliste.php

Statista. (2023a). Bevölkerung nach Nationalität und Bundesländern. Retrieved April 7, 2024, from https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Bevoelkerung/Bevoelkerungsstand/Tabellen/bevoelkerung-nichtdeutsch-laender.html

Statista. (2023b). Kreisfreie Städte und Landkreise nach Fläche, Bevölkerung und Bevölkerungsdichte am 31.12.2022 (Statistisches Bundesamt, Ed.). Retrieved January 23, 2024, from https://www.destatis.de/DE/Themen/Laender-Regionen/Regionales/Gemeindeverzeichnis/Administrativ/04-kreise.html

Verma, A., & Gaukler, G. M. (2015). Pre-positioning disaster response facilities at safe locations: An evaluation of deterministic and stochastic modeling approaches. *Computers & Operations Research, 62*, 197–209. https://doi.org/10.1016/j.cor.2014.10.006

WMO. (2021). Wmo atlas of mortality and economic losses from weather, climate and water extremes (1970–2019) (World Meteorological Organization, Ed.). Retrieved October 6, 2022, from https://library.wmo.int/doc_num.php?explnum_id=10989

Zhang, B., Peng, J., & Li, S. (2017). Covering location problem of emergency service facilities in an uncertain environment. *Applied Mathematical Modelling, 51*, 429–447. https://doi.org/10.1016/j.apm.2017.06.043