Humanitarian Relief Network Design: Responsiveness Maximization and a Case Study of Typhoon Rammasun

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Abstract

In this paper, we study a humanitarian relief network design problem, where the demand for relief supplies in each affected area is uncertain and can be met by more than one relief facility. Given a certain cost budget, we simultaneously optimize the decisions of relief facility location, inventory pre-positioning, and relief facility to affected area assignment so as to maximize the responsiveness. The problem is formulated as a chance-constrained stochastic programming model in which a joint chance constraint is utilized to measure the responsiveness of the humanitarian relief network. We approximate the proposed model by another model with chance constraints, which can be solved based on two settings of the demand information in each affected area: (1) the demand distribution is given; and (2) the partial demand information, e.g., the mean, the variance, and the support, is given. We use a case study of the 2014 Typhoon Rammasun to illustrate the application of the model. Computational results demonstrate the effectiveness of the solution approaches and show that the chance-constrained stochastic programming models are superior to the deterministic model for humanitarian relief network design.

Keywords: Responsiveness maximization; Humanitarian relief network design; Chance-constrained stochastic programming

1 Introduction

Disasters such as earthquakes, floods, or typhoons result in huge property damages and human injuries. According to a report of International Federation of Red Cross and Red Crescent Societies (IFRC) in 2018, 3,751 natural disasters, occurred in 198 countries during 2008-2017, led to 2 billion people affected and the total direct economic losses caused by these disasters were estimated at

US$1,658 billion.[1] The severe influence caused by disasters has attracted extensive attention of relief organizations and researchers in improving the effectiveness of humanitarian relief operations and motivated a growing number of studies related to disaster relief management (see Gupta et al., 2016).

Disaster operations management is composed of four stages (i.e., mitigation, preparedness, response, and recovery), in which the mitigation and preparedness phases are related to pre-disaster relief actions, and the response and recovery phases involve post-disaster relief activities (see Anaya-Arenas et al., 2014). Among these disaster relief efforts, the post-disaster relief operations may produce poor-performance outcomes without the pre-disaster relief commitments (see Salmerón and Apte, 2010). For instance, even if relief organizations obtain adequate relief resources from suppliers like local private enterprises through making contractual agreements (see Wang et al., 2019), as long as they do not pre-position these relief resources in the right relief facilities in the pre-disaster stage, the relief resources may not be delivered to the affected areas timely and sufficiently after a disaster. Since the timely availability of adequate relief supplies has an important effect on the survival rate of the affected people, pre-positioning sufficient relief supplies in the right relief facilities allows relief organizations to provide sufficient relief supplies to the affected areas in time, and thus guarantees the basic life of the affected people. Hong et al. (2015) also discuss the importance of long-term pre-disaster planning, one critical component of which is the design of humanitarian relief network (see Hasanzadeh and Bashiri, 2016). Moreover, the humanitarian relief network could be considered as a connection between the preparedness and response phases, which increases the ability of relief organizations to implement high-performance disaster relief operations (i.e., establishing relief facilities at appropriate locations and storing suitable amount of relief supplies in the open relief facilities) (see Thomas, 2008). In this paper, we consider the humanitarian relief network design problem for strategic planning purpose.

In the disaster relief context, relief organizations are faced with huge time pressure due to the fact that once a disaster occurs, time is life and relief supplies should be delivered to the affected areas as quickly as possible (see Van Wassenhove, 2006), thus alleviating human suffering which is the main goal for any humanitarian relief operations (see Wang et al., 2017). In addition, according to the National Comprehensive Disaster Prevention and Mitigation Plan (2016-2020), it is essential to guarantee that the affected people should be rescued within 12 hours after the occurring of a disaster.[2] In order to ensure that the affected people can receive relief supplies in time and thus alleviate the suffering of people in need, we deal with the issue of timely rescue by defining rescue radius, i.e., if an affected area is within the pre-specified rescue radius of a relief facility, it can be served by the relief facility; otherwise, the affected area cannot be covered by the relief facility.

Apart from the timely supply of relief resources, it is of significance to take into account the sufficient supply of relief resources, ensuring that the demand can be fulfilled at a high service level. As it is very difficult to predict the time and severity of a disaster, the number of people affected and thus the demand for relief supplies is uncertain. Besides, the design of humanitarian relief network is carried out in the pre-disaster stage and the pre-disaster relief funding is financially restricted (see Balcık and Beamon, 2008). In the disaster relief context, considering the budgetary constraints in the pre-disaster stage, it is essential to ensure that the uncertain demand can be satisfied at a high service level and a cost-inefficient humanitarian relief network can be avoided.

In the design of a humanitarian relief network, it is critical to capture the characteristic of the inherent uncertainty in demand for relief supplies. The significance of managing demand uncertainty in the disaster relief environment is also emphasized by Noyan (2012). To this end, we use stochastic programming to cope with the demand uncertainty and utilize a joint chance constraint to ensure that the demand for relief supplies in the affected areas can be met at a highest possible service level under the budget limitation for disaster preparedness.

In this paper, we develop a chance-constrained stochastic programming model to study humanitarian relief network design. Given a certain cost budget, the model determines the locations of the relief facilities, the amount of relief supplies stored at each open relief facility, as well as the assignments between the open relief facilities and the affected areas, so as to maximize the responsiveness. It is noteworthy that both the supply delivery time and the demand fulfillment reflect the responsiveness of a humanitarian relief network (see Bastian et al., 2016). In our model, the supply delivery time are explicitly taken into account by imposing an effective rescue radius. Therefore, we use the probability to serve demand without shortage (i.e., the service level) to represent the responsiveness of the designed humanitarian relief network. To maximize the utilization of the pre-positioned resources, the demand for relief supplies in an affected area can be satisfied by more than one relief facility. The model also handles the uncertainty in demand with a joint chance constraint, which guarantees that the uncertain demand in each affected area can be met at a service level determined by the responsiveness of the network. We approximate the proposed model using another model with joint chance constraints, which can be solved based on two different cases:

- Case 1. **The demand distribution in each affected area is known.** By assuming that the uncertain demand in each affected area follows independent Normal (uniform, resp.)

distribution, we develop the Normal-distribution-based (Uniform-distribution-based, resp.) approach to solve the chance-constrained stochastic programming model.

- Case 2. **Partial information about the demand in each affected area is known.** Suppose that we only know the information such as the expectation, the finite support, the variance of the uncertain demand in each affected area. We develop the Hoeffding and the one-sided Chebyshev approximations to solve the chance-constrained stochastic programming model.

In each case, the chance-constrained stochastic programming model can be transformed into a linear mixed-integer program (MIP), and thus can be solved by CPLEX directly.

Our paper contributes to the literature in the following two aspects: (1) We develop a chance-constrained stochastic programming model for humanitarian relief network design and implement it using a case study of the 2014 Typhoon Rammasun in China; and (2) To tackle the computational challenges, we approximate the proposed model using another model with joint chance constraints. The resulting approximation model can be solved based on two settings of the demand information in each affected area: (i) The demand distribution is given; and (ii) The partial demand information, e.g., the mean, the variance, and the support, is known.

The rest of the paper is organized as follows. We review the relevant literature in Section 2. In Section 3, we describe the humanitarian relief network design problem and develop the chance-constrained stochastic programming model. The solution approaches are proposed in Section 4. We use a case study in Section 5 and its variants in Section 6 to illustrate the application of the model. Finally, we conclude the paper in Section 7. The appendices, which include all the proofs, the procedure to generate inputs in the case study of the 2014 Typhoon Rammasun, and the endnotes, are available in the online supplemental file.

2 Literature review

There exists a rich amount of literatures that develop optimization models to study various disaster relief management problems. Those interested in a comprehensive review of it can refer to, e.g., Altay and Green (2006), Galindo and Batta (2013), Anaya-Arenas et al. (2014), Gupta et al. (2016), Ye et al. (2019), Wamba (2020), and Dönmez et al. (2021). We primarily review the relevant literature on humanitarian relief network design. Horner and Downs (2007) propose an integer programming model to study the humanitarian relief network design problem. The problem determines the locations of relief facilities and assignments between relief facilities and demand points. Their model minimizes the cost of assigning relief supplies from relief facilities to demand points and requires that each demand point is served by only one relief facility, i.e., the single-sourcing strategy is adopted. Yushimito et al. (2012) also use the single-sourcing strategy to develop a facility location model that decides the locations of relief facilities and which relief facility serves each affected area. The model maximizes the coverage of affected areas while minimizing the human suffering that is measured by a social cost function depending on the distance between the relief facility and the affected area. In addition, Marcelin et al. (2016) propose a single-sourcing facility location optimization model, which minimizes the total transportation costs of providing relief supplies from relief facilities to demand points and imposes an upper bound on the total number of the relief facilities open. Other single-sourcing models developed to study the humanitarian relief network design problem can be found in, e.g., Horner and Downs (2010), Horner and Widener (2011), and Erbeyoğlu and Bilge (2020). In contrast, our model allows that the demand in each affected area can be satisfied by more than one relief facility, i.e., the multi-sourcing strategy is used in our study. Notably, Balcık and Beamon (2008) apply the multi-sourcing strategy to develop a maximal covering location model integrating relief facility location and emergency inventory pre-positioning decisions. The uncertain demand is represented by a set of scenarios, each of which is assumed to be realized by a given probability. The objective is to maximize the total expected demand covered by the established relief facilities. Their model has an implicit assumption that in each scenario there is only one demand point and the implementation is illustrated by an earthquake case. In general, there is an epicenter in an earthquake, the affected area covered by which is relatively small compared with other disasters such as hurricanes, typhoons or floods. Consequently, their model may not be applicable to those disasters that are generally characterized by multiple affected areas.

Another stream of research that relates to our study focuses on developing two-stage stochastic/robust models, in which the first- and second-stage decisions correspond to the pre- and post-disaster relief operations, respectively (see, e.g., Rawls and Turnquist, 2010; Ben-Tal et al., 2011; Rawls and Turnquist, 2011; Döyen et al., 2012; Bozorgi-Amiri et al., 2013; Elçi and Noyan, 2018; Ni et al., 2018; Noham and Tzur, 2018). In these models, the pre-disaster decisions include the relief facility location and inventory pre-positioning, and the post-disaster decisions are related to the distribution of the relief supplies. These models, however, are built within the outbound emergency logistics context and do not take into account the assignments between the affected areas and the open relief facilities in the pre-disaster stage.

In this paper, we develop a stochastic programming model to study the humanitarian relief network design problem. A joint chance constraint is employed to model the responsiveness of the network, which we intend to maximize under a budget constraint. In general, a stochastic programming model with a joint chance constraint is significantly more challenging to solve than that with individual chance constraints (see Elçi et al., 2018). For a comprehensive review on the chance-constrained stochastic programming, we refer to Prékopa (1995), Prékopa (2003), Dentcheva (2006), Birge and Louveaux (2011), and Shapiro et al. (2014).

3 Problem description and model formulation

We consider a humanitarian relief network design problem that involves a set of affected areas and a set of potential locations of relief facilities. The supply capacity of each relief facility is given. Each affected area has an uncertain demand of relief supply, which is represented by a set of demand scenarios. The relief supply is regarded as a disaster relief commodity package that can be a bundle of critical relief necessities such as tents, quilts, medical kits, etc. Note that the disaster relief commodity package used in our study is defined in Appendix B.3 of the online supplemental file. We assume that the demand of each affected area can be served by more than one relief facility.

The following three types of costs are considered in the humanitarian relief network design problem.

- Fixed location and operation costs. There is a fixed cost of locating and operating each relief facility.
- Inventory pre-positioning costs. We need to acquire relief supplies and store them in the open relief facilities, which leads to the inventory pre-positioning costs.
- Assignment costs. In the disaster relief context, in order to ensure that affected people can be effectively rescued after a disaster, relief supplies should be delivered to affected areas through specific transportation modes (trucks or helicopters) within the effective rescue time. The speed of the transportation mode and the effective rescue time determine the effective rescue radius of a relief facility. If the distance between a relief facility and an affected area does not exceed the effective rescue radius, i.e., the relief facility can effectively rescue (serve)

Table 1: Model notations

Sets and Indices	
$\mathcal{F}$	set of potential locations of relief facilities; $i \in \mathcal{F}$
$\mathcal{A}$	set of affected areas; $j \in \mathcal{A}$
Ω	set of demand scenarios; $\omega \in \Omega$
Parameters	
$D_j(\omega)$	realized demand for relief supplies in affected area j under the scenario ω, $\forall j \in \mathcal{A}$, $\omega \in \Omega$
f_i	fixed cost of locating and operating a relief facility at location i, $\forall i \in \mathcal{F}$
h_i	inventory pre-positioning cost for each unit of relief supply at relief facility i, $\forall i \in \mathcal{F}$, which includes the cost to acquire and store one unit of relief supply
Q_i	supply capacity of relief facility i, $\forall i \in \mathcal{F}$
c_{ij}	fixed cost of assigning relief facility i to affected area j, $\forall i \in \mathcal{F}$, $\forall j \in \mathcal{A}$
B	cost budget for preparedness
Decision variables	
ϵ	$1-\epsilon$ corresponds to the responsiveness of a humanitarian relief network
Y_i	$Y_i = 1$ if a relief facility is located at location i, and $Y_i = 0$ otherwise, $\forall i \in \mathcal{F}$
X_{ij}	$X_{ij} = 1$ if relief facility i serves affected area j, and $X_{ij} = 0$ otherwise, $\forall i \in \mathcal{F}, j \in \mathcal{A}$
I_i	amount of relief supplies stored at open relief facility i, $\forall i \in \mathcal{F}$
$\theta_{ij}(\omega)$	amount of relief supplies shipped form relief facility i to its assigned affected area j when the demand is realized as $D_j(\omega)$, $\forall i \in \mathcal{F}$, $\forall j \in \mathcal{A}, \omega \in \Omega$

the affected area, the assignment cost between them is set to be 0; otherwise, we set the assignment cost to be a large number.

Given a certain cost budget for preparedness, the problem is to simultaneously determine: (1) the locations of the open relief facilities, (2) the amount of relief supplies to be stored in each open relief facility, and (3) which set of open relief facilities serves each affected area so that the responsiveness is maximized.

With the notations defined in Table 1, the humanitarian relief network design problem can be formulated as follows.

$$\mathcal{P}_1: \quad \max \quad 1-\epsilon \tag{1}$$

$$\text{s.t.} \quad \sum_{i\in\mathcal{F}} f_i Y_i + \sum_{i\in\mathcal{F}} h_i I_i + \sum_{i\in\mathcal{F}}\sum_{j\in\mathcal{A}} c_{ij} X_{ij} \le B, \tag{2}$$

$$\text{Prob}\left\{ \begin{array}{ll} \sum_{j\in\mathcal{A}} \theta_{ij}(\omega) \le I_i & \forall i \in \mathcal{F} \\ \sum_{i\in\mathcal{F}} \theta_{ij}(\omega) \ge D_j(\omega) & \forall j \in \mathcal{A} \end{array} ;\ \forall \omega \in \Omega \right\} \ge 1-\epsilon, \tag{3}$$

$$0 \le \theta_{ij}(\omega) \le M X_{ij},\ \forall i \in \mathcal{F}, j \in \mathcal{A}, \omega \in \Omega, \tag{4}$$

$$X_{ij} \le Y_i,\ \forall i \in \mathcal{F}, j \in \mathcal{A}, \tag{5}$$

$$I_i \le Q_i Y_i,\ \forall i \in \mathcal{F}, \tag{6}$$

$$I_i \ge 0,\ \forall i \in \mathcal{F}, \tag{7}$$

$$Y_i, X_{ij} \in \{0,1\},\ \forall i \in \mathcal{F}, j \in \mathcal{A}, \tag{8}$$

where M is a big number. Constraint (2) specifies the budget limitation on the total costs of relief facility location, relief supply pre-positioning, and assignment. The set of inequalities in constraint (3) represents an event such that under each demand scenario ω ($\omega \in \Omega$) in this event, the total amount of relief supplies shipped from each relief facility to its assigned affected areas does not exceed its available inventory and the demand of each affected area can be satisfied. Constraint (3) is a joint chance constraint which ensures that the probability of the occurrence of the event, i.e., the probability that no shortage occurs at any affected area, is at least $1-\epsilon$. Constraint (4) means a relief facility could only supply the linked affected areas. Constraint (5) ensures that an affected area can only be assigned to the open relief facilities. Constraint (6) requires that relief supplies can only be stored in the open relief facilities with limited supply capacity. Constraints (7) and (8) are the standard non-negative and binary restrictions. The objective function (1) maximizes the responsiveness of a humanitarian relief network, which, as shown in constraint (3), corresponds to the probability that the demands in all affected areas could be fulfilled by the relief supplies shipped to these areas.

4 Solution methods

Model $\mathcal{P}_1$ presented in Section 3 integrates the decisions of relief facility location, inventory pre-positioning, and relief facility to affected area assignment. It is very difficult to find the optimal solution to model $\mathcal{P}_1$ because it contains a joint chance constraint and integer variables. The key difficulty comes from the joint chance constraint. We first develop another model with chance constraints to approximate model $\mathcal{P}_1$.

The humanitarian relief network can be represented by a bipartite graph $\mathcal{G} := \{\mathcal{A} \cup \mathcal{F}, \Theta\}$, where $\Theta \subseteq \mathcal{A} \times \mathcal{F} = \{(i, j) : i \in \mathcal{F}, j \in \mathcal{A}\}$ denotes the set of links in $\mathcal{G}$. Each link $(i, j) \in \Theta$ means that relief facility i serves affected area j. Let $\Gamma(S)$ be the set of relief facilities that can serve the affected areas in set S for $S \subseteq \mathcal{A}$, i.e., $\Gamma(S) := \{i : (i, j) \in \Theta, j \in S \subseteq \mathcal{A}\}$.

Definition 1. *A humanitarian relief network $\mathcal{G} = \{\mathcal{A} \cup \mathcal{F}, \Theta\}$ is a feasible humanitarian relief network to model $\mathcal{P}_1$ if $\Gamma(j) \neq \emptyset$ for all $j \in \mathcal{A}$, and $(i, j) \in \Theta$ if and only if $i \in \Gamma(j)$ for all $j \in \mathcal{A}$.*

Obviously, a feasible humanitarian relief network $\mathcal{G}$ is corresponding to a feasible solution (X_{ij}^0, Y_i^0) to model $\mathcal{P}_1$, where

$$Y_i^0 = \begin{cases} 1, & \text{if } i \in \Gamma(S); \\ 0, & \text{otherwise;} \end{cases} \quad \text{and} \quad X_{ij}^0 = \begin{cases} 1, & \text{if } (i, j) \in \Theta; \\ 0, & \text{otherwise.} \end{cases}$$

Proposition 1. *For a given feasible solution (X_{ij}^0, Y_i^0), the joint chance constraint of model $\mathcal{P}_1$*

$$\text{Prob}\left\{ \begin{array}{ll} \sum_{j \in \mathcal{A}} \theta_{ij}(\omega) \leq I_i & \forall i \in \mathcal{F} \\ \sum_{i \in \mathcal{F}} \theta_{ij}(\omega) \geq D_j(\omega) & \forall j \in \mathcal{A} \end{array} ;\ \forall \omega \in \Omega \right\} \geq 1 - \epsilon$$

is equivalent to

$$\text{Prob}\left\{ \sum_{j \in S} D_j(\omega) \leq \sum_{i \in \Gamma(S)} I_i, \forall S \subseteq \mathcal{A}, \omega \in \Omega \right\} \geq 1 - \epsilon. \tag{9}$$

The chance constraint (9) implies that for any $S \subseteq \mathcal{A}$ of the affected areas, the linked relief facilities should have adequate relief supplies to satisfy all the demands in S with a probability of at least $1 - \epsilon$. Chance constraint (9) is still difficult to solve since it needs to evaluate the probability that $2^{|\mathcal{A}|}$ inequalities hold simultaneously. We then develop another model with chance constraints to approximate model $\mathcal{P}_1$ as follows.

$$\begin{aligned} \mathcal{P}_2: \quad \max \quad & 1 - \epsilon/|\mathcal{A}| \\ \text{s.t.} \quad & (2), (5), (6), (7), (8), \\ & \text{Prob}\left\{ D_j(\omega) \leq \sum_{i \in \mathcal{F}} I_{ij}, \omega \in \Omega \right\} \geq 1 - \epsilon/|\mathcal{A}|,\ \forall j \in \mathcal{A}, & (10) \\ & \sum_{j \in \mathcal{A}} I_{ij} = I_i,\ \forall i \in \mathcal{F}, & (11) \\ & I_{ij} \leq M X_{ij},\ \forall i \in \mathcal{F}, j \in \mathcal{A}, & (12) \\ & I_{ij} \geq 0,\ \forall i \in \mathcal{F}, j \in \mathcal{A}, & (13) \end{aligned}$$

where I_{ij} denotes the amount of relief supplies kept for affected area j in relief facility i for all $i \in \mathcal{F}$ and $j \in \mathcal{A}$. Note that I_{ij} is fixed before the realization of $D_j(\omega)$ in model $\mathcal{P}_2$. Constraint (10) is a chance constraint which ensures that under each demand scenario $\omega \in \Omega$, the demand at each affected area can be satisfied with a probability of at least $1 - \epsilon/|\mathcal{A}|$. Constraint (11) guarantees that the total amount of relief supplies stored in each open relief facility for its linked affected areas is equal to its available inventory. Constraint (12) requires that each open relief facility only stores relief supplies for the affected areas assigned to it. Constraint (13) is the standard non-negative restriction.

It is easy to see that any feasible solution to model $\mathcal{P}_2$ is also feasible to model $\mathcal{P}_1$. We next propose several approaches to solve model $\mathcal{P}_2$ based on two different available demand information settings: (1) the demand distribution in each affected area is known and (2) some partial information about the demand in each affected area is known.

4.1 Demand-distribution-based approach

If the distribution of $D_j(\omega)$ is known, we can obtain δ_j such that Prob $(D_j(\omega) \geq \delta_j) \leq \epsilon/|\mathcal{A}|$ and the chance constraint (10) of model $\mathcal{P}_2$ can be written as

$$\sum_{i \in \mathcal{F}} I_{ij} \geq \delta_j.$$

- **Uniform-distribution-based approach**. Suppose that demand realization $D_j(\omega)$ follows uniform distribution, i.e., $D_j(\omega) \sim U(a_j, b_j)$, where a_j and b_j correspond to the lower and upper bounds of the uncertain demand $D_j(\omega)$ for each $j \in \mathcal{A}$, respectively.

  Proposition 2. *The chance constraint* (10) *of model* $\mathcal{P}_2$ *is equivalent to*

  $$\sum_{i \in \mathcal{F}} I_{ij} \geq a_j + (b_j - a_j)(1 - \epsilon/|\mathcal{A}|), \tag{14}$$

  for all $j \in \mathcal{A}$.

  Note that (14) is a linear constraint. Replacing (10) with (14) in model $\mathcal{P}_2$ yields an equivalent formulation of model $\mathcal{P}_2$, which is a linear binary program. The service level of the relief network is at least $1 - \epsilon^+/|\mathcal{A}|$, where ϵ^+ is defined as $\max\{0, \epsilon\}$.

- **Normal-distribution-based approach**. Suppose that demand realization $D_j(\omega)$ follows Normal distribution, i.e., $D_j(\omega) \sim N(\mu_j, \sigma_j)$, in which μ_j and σ_j denote the mean and the standard deviation of the uncertain demand $D_j(\omega)$ for each $j \in \mathcal{A}$, respectively.

Proposition 3. *The chance constraint* (10) *of model* $\mathcal{P}_2$ *is equivalent to*

$$\sum_{i\in\mathcal{F}} I_{ij} \geq \mu_j + z_\alpha \sigma_j, \tag{15}$$

for all $j \in \mathcal{A}$*., where* z_α *corresponds to the service level of* $1-\alpha = 1-\epsilon/|\mathcal{A}|$ *, i.e.,* $\Phi(z_\alpha) = 1-\epsilon/|\mathcal{A}|$ *in which* $\Phi(\cdot)$ *is the distribution function of the standard Normal distribution. Note that the value of* z_α *can be obtained in the standard Normal distribution table in DeGroot (1975).*

Observe that (15) is a linear constraint of z_α and z_α is a strictly decreasing function of ϵ. Therefore, model $\mathcal{P}_2$ is equivalent to

$$\begin{aligned} \max \quad & z_\alpha \\ \text{s.t.} \quad & (2), (5), (6), (7), (8), (11), (12), (13), (15), \end{aligned}$$

which is also a linear binary program. The service level of the relief network is at least $1 - |\mathcal{A}|(1-\Phi(z_\alpha))$.

Note that the approach of solving model $\mathcal{P}_2$ based on demand distribution is not limited to the uniform and Normal distributions. It is also applicable to other probability distributions. In this paper, we consider these two types of demand distributions for illustration.

4.2 Hoeffding approximation

- Suppose that we know $E[D_j(\omega)] = \mu_j$ and $\text{Prob}(D_j(\omega) \in [a_j, b_j]) = 1$.

Theorem 1 (Hoeffding's inequality)**.** *Let* $X_1, X_2, ..., X_n$ *be independent random variables bounded by the interval* $[0,1]$*. Let*

$$\overline{X} = \frac{1}{n}(X_1 + X_2 + \cdots + X_n).$$

Then

$$\text{Prob}(\overline{X} - E[\overline{X}] \geq t) \leq e^{-2nt^2}$$

for any $t \geq 0$*.*

Proposition 4. *The chance constraint* (10) *of model* $\mathcal{P}_2$ *is satisfied if*

$$\sum_{i\in\mathcal{F}} I_{ij} \geq \mu_j + (b_j - a_j)\sqrt{\frac{-\ln(\epsilon/|\mathcal{A}|)}{2}} \tag{16}$$

for all $j \in \mathcal{A}$*.*

Similar to the case with Normal-distributed demand, as $\sqrt{-\ln(\epsilon/|\mathcal{A}|)/2}$ is a strictly decreasing function of ϵ, we can introduce a new variable z to represent this term. Applying Proposition 4, we obtain the following conservative approximation of model $\mathcal{P}_2$:

$$\begin{aligned} \max \quad & z \\ \text{s.t.} \quad & (2), (5), (6), (7), (8), (11), (12), (13), \\ & \sum_{i \in \mathcal{F}} I_{ij} \geq \mu_j + (b_j - a_j) z, \ \forall j \in \mathcal{A}. \end{aligned}$$

Note that this approximation remains a linear binary program. The service level of the relief network is at least $1 - |\mathcal{A}| e^{-2z^2}$.

4.3 One-sided Chebyshev approximation

- Suppose that we know $E[D_j(\omega)] = \mu_j$ and $\text{Var}(D_j(\omega)) = \sigma_j^2$.

Theorem 2 (One-sided Chebyshev inequality)**.** *Let $a > 0$ and X be a real-numbered random variable. Then*

$$\text{Prob}\big(X - \mathbb{E}[X] \geq a\big) \leq \frac{Var(X)}{Var(X) + a^2}$$

for any $a \geq 0$.

Proposition 5. *The chance constraint (10) of model $\mathcal{P}_2$ is satisfied if*

$$\sum_{i \in \mathcal{F}} I_{ij} \geq \mu_j + \sqrt{\sigma_j^2 \left(\frac{1}{\epsilon/|\mathcal{A}|} - 1 \right)} \tag{17}$$

for all $j \in \mathcal{A}$.

Same as the Hoeffding approximation, Proposition 5 shows that model $\mathcal{P}_2$ can be approximated conservatively by the following linear binary program:

$$\begin{aligned} \max \quad & z \\ \text{s.t.} \quad & (2), (5), (6), (7), (8), (11), (12), (13), \\ & \sum_{i \in \mathcal{F}} I_{ij} \geq \mu_j + \sigma_j z, \forall j \in \mathcal{A}, \end{aligned}$$

where z represents the term $\sqrt{|\mathcal{A}|/\epsilon - 1}$. The service level of the relief network is at least $1 - |\mathcal{A}|/(1 + z^2)$.

4.4 Evaluation of the effectiveness of the proposed approaches

We use two performance measures, i.e., fill rate and chance, to evaluate the effectiveness of the approaches outlined in Sections 4.1-4.3. The fill rate is defined as the percentage of the demand that is fulfilled by the pre-positioned relief supplies. The chance represents the probability that the realized demand is satisfied by the pre-positioned relief supplies.

Suppose that the humanitarian relief network and the inventory level of each open relief facility obtained by solving model $\mathcal{P}_2$ are $\mathcal{G}^* = \{\mathcal{A} \cup \mathcal{F}^*, \Theta^*\}$ and I_i^*, $\forall i \in \mathcal{F}^*$, respectively. Through solving the following maximum flow problem, we can compute the fill rate and the chance for the humanitarian relief network $\mathcal{G}^*$ under realized demand $D_j(\omega)$ for all $j \in \mathcal{A}$:

$$\begin{aligned}
Z(\mathcal{G}^*, I_i^*, \omega) \quad = \quad \max \quad & \sum_{i \in \mathcal{F}^*} \sum_{j \in \mathcal{A}} \theta_{ij}(\omega) \\
\text{s.t.} \quad & \theta_{ij}(\omega) \leq M X_{ij}, \forall i \in \mathcal{F}^*, j \in \mathcal{A}, \\
& \sum_{j \in \mathcal{A}} \theta_{ij}(\omega) \leq I_i, \forall i \in \mathcal{F}^*, \\
& \sum_{i \in \mathcal{F}^*} \theta_{ij}(\omega) \leq D_j(\omega), j \in \mathcal{A}, \\
& \theta_{ij}(\omega) \geq 0, \forall i \in \mathcal{F}^*, j \in \mathcal{A}.
\end{aligned}$$

The fill rate and the chance can be calculated, respectively, as follows:

$$\text{Fill rate} := \mathbb{E}_\omega \left[Z(\mathcal{G}^*, I_i^*, \omega) \Big/ \sum_{j \in \mathcal{A}} D_j(\omega) \right]$$

and

$$\text{Chance} := \text{Prob} \left\{ Z(\mathcal{G}^*, I_i^*, \omega) = \sum_{j \in \mathcal{A}} D_j(\omega) \right\}.$$

5 Case study

In this section, the 2014 Typhoon Rammasun is considered as the case to illustrate the application of the proposed model. The destructive typhoon affected 11.07 million people in Guangdong Province, Hainan Province, Yunnan Province, and Guangxi Zhuang Autonomous Region, which are illustrated in Figure 1.[3] The direct economic losses reached 38.48 billion CNY in PR China.[3] Using inputs generated from this case, we study the performances of the Uniform- and Normal-distribution-based approaches as well as the Hoeffding and one-sided Chebyshev approximations.

We further conduct experiments of deterministic humanitarian relief network design models and compare their performances with those of the chance-constrained stochastic programming models. We close this section by conducting sensitivity analysis on the effective rescue radius to show its impact on the optimization results. All the mathematical programming models are implemented in C++ and solved by the CPLEX 12.6 solver. All numerical experiments in our study are conducted on a Dell desktop with 3.40GHz Intel i7 CPU and 16G memory running the Windows 7 Professional 64bit operating system.

Figure 1: Affected areas in three provinces and one autonomous region

5.1 Computational results

In this part, we would like to investigate the performance of the humanitarian relief network design model with the four proposed approaches using the case study of the 2014 Typhoon Rammasun. We consider 42 affected areas and 26 potential locations of relief facilities, which are illustrated in Figure 2 (see also Appendices B.1 and B.2 of the online supplemental file). To determine the forecasted demand for each affected area, we first estimate the most likely demand D_j^M for each affected area j using the procedure presented in Appendix B.4 of the online supplemental file. The values of D_j^M are displayed in Table 9 of Appendix B in the online supplemental file. Let $U(a, b)$

denote a uniform distribution in $[a,b]$. Let $N(\mu,\sigma,a,b)$ represent a truncated Normal distribution where μ and σ are the mean and the standard deviation of the "parent" Normal distribution, respectively, and the truncated interval is $[a,b]$. Let $T(a,b,c)$ be a triangular distribution in which a, b, and c correspond to the lower bound, the most likely value, and the upper bound, respectively. The forecasted demand for each affected area $j \in \mathcal{A}$ is then generated using the following approach:

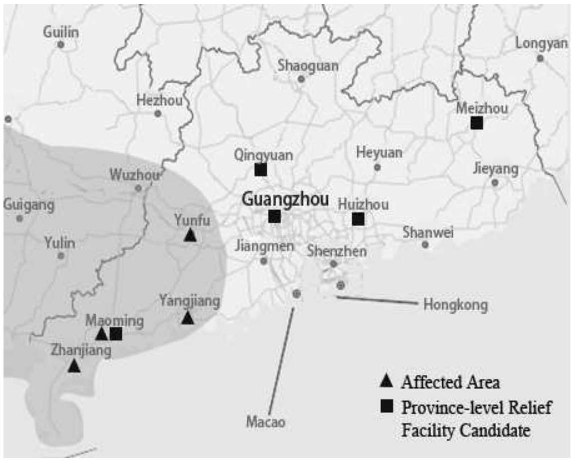
- Uniform-distribution-based approach: Let a_j and b_j be the minimum and maximum of 100 independent samples drawn from $N(\mu_j, \sigma_j, 0, +\infty)$, where $\mu_j \sim U(0.9D_j^M, 1.1D_j^M)$ and $\sigma_j \sim U(10, 30)$ for each $j \in \mathcal{A}$. The random demand $D_j(\omega)$ of affected area $j \in \mathcal{A}$ follows an independent uniform distribution in $[a_j, b_j]$, i.e., $D_j(\omega) \sim U(a_j, b_j)$.

- Normal-distribution-based approach: The random demand $D_j(\omega)$ of affected area $j \in \mathcal{A}$ follows an independent Normal distribution with mean μ_j and standard deviation σ_j, i.e., $D_j(\omega) \sim N(\mu_j, \sigma_j)$, where μ_j and σ_j are generated by $\mu_j \sim U(0.9D_j^M, 1.1D_j^M)$ and $\sigma_j \sim U(10, 30)$, respectively, for each $j \in \mathcal{A}$.

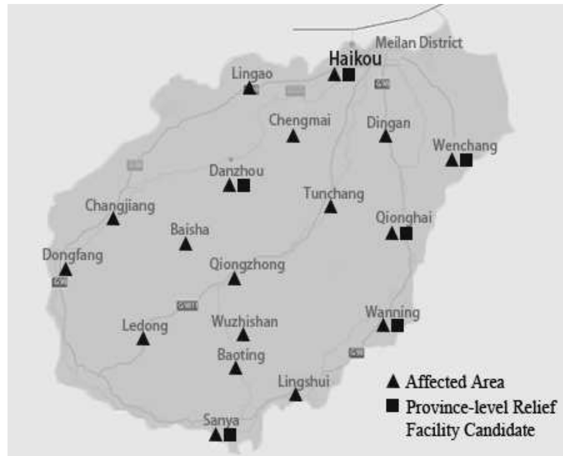
- Hoeffding approximation: The mean μ_j of random demand $D_j(\omega)$ is generated by $\mu_j \sim U(0.9D_j^M, 1.1D_j^M)$ for affected area $j \in \mathcal{A}$. Let a_j and b_j are the minimum and maximum of 100 independent samples drawn from $N(\mu_j, \sigma_j, 0, +\infty)$, where $\sigma_j \sim U(10, 30)$ for each $j \in \mathcal{A}$. The range of $D_j(\omega)$ is set to $[a_j, b_j]$.

- One-sided Chebyshev approximation: The mean μ_j and the standard deviation σ_j of random demand $D_j(\omega)$ are generated by $\mu_j \sim U(0.9D_j^M, 1.1D_j^M)$ and $\sigma_j \sim U(10, 30)$, respectively, for each $j \in \mathcal{A}$.

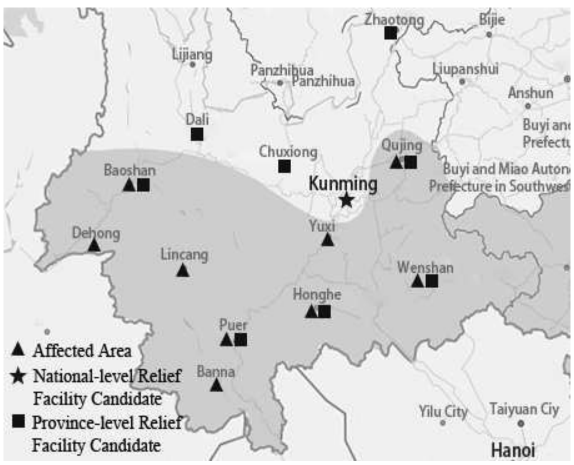
For each potential location for relief facility, we generate the cost parameters in our case study, i.e., per unit inventory pre-positioning cost h_i, fixed location and operation cost of each relief facility f_i for all $i \in \mathcal{F}$, and assignment cost c_{ij} for all $i \in \mathcal{F}$ and $j \in \mathcal{A}$, using the procedure presented in Appendix B.5 of the online supplemental file. The capacity for each potential facility Q_j is obtained using the procedure in Appendix B.6 of the online supplemental file. To generate the cost budget for preparedness, we first determine a base budget BB for each of the four approaches by solving



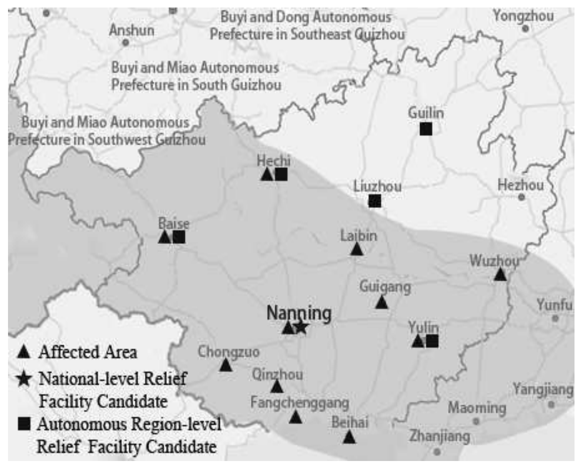
(a) Affected areas and relief facility candidates in Guangdong Province



(b) Affected areas and relief facility candidates in Hainan Province



(c) Affected areas and relief facility candidates in Yunnan Province



(d) Affected areas and relief facility candidates in Guangxi Zhuang Autonomous Region

Figure 2: Affected areas and relief facility candidates in the case study

the following optimization problem:

$$
\begin{aligned}
BB \quad = \quad \min \quad & \sum_{i \in \mathcal{F}} f_i Y_i + \sum_{i \in \mathcal{F}} h_i I_i + \sum_{i \in \mathcal{F}} \sum_{j \in \mathcal{A}} c_{ij} X_{ij} \\
\text{s.t.} \quad & (5), (6), (7), (8), (11), (12), (13), \\
& \sum_{i \in \mathcal{F}} I_{ij} \geq D_j^L, \ \forall j \in \mathcal{A},
\end{aligned}
$$

where D_j^L denotes a pre-set demand of relief supply in affected area j. By choosing D_j^L properly, we can get a base budget BB under which the responsiveness maximization problem is guaranteed to be feasible. Here D_j^L is set to a_j ($\mu_j - 3\sigma_j$, μ_j, μ_j, resp.) for the Uniform-distribution-based approach (the Normal-distribution-based approach, the Hoeffding approximation, the one-sided Chebyshev approximation, resp.). It is straightforward that the resulting base budget BB ensures the feasibility of the corresponding responsiveness maximization problem for each of the four approaches. After determining the base budget BB for each of the four approaches, we can vary the total budget for preparedness by multiplying an adjustment coefficient θ ($\theta \geq 1$) to BB, i.e., set $B := \theta \times BB$, to study the impact of budget on the responsiveness of humanitarian relief network. In our case study, we let θ take values in the set $\{1.00, 1.04, 1.08, 1.12, 1.16\}$.

We generate 100 random instances for each value of θ. For each of instance, the four approaches outlined in Section 4 to solve model $\mathcal{P}_2$ are evaluated using the following procedure.

Step 1. Based on the four approaches developed in Section 4, we solve all the corresponding linear binary reformulation/approximation of model $\mathcal{P}_2$ and obtain the humanitarian relief network solution for each of the models. Note that the obtained responsiveness of the humanitarian relief network is denoted by R.

Step 2. We generate 10,000 realizations of $D_j(\omega)$ as follows.

- Uniform-distribution-based approach: We set D_j^L and D_j^U to be the minimum and maximum of 200 independent samples drawn from $N(\mu_j, \sigma_j, 0, +\infty)$, where $\mu_j \sim U(0.9D_j^M, 1.1D_j^M)$ and $\sigma_j \sim U(10, 30)$ for each $j \in \mathcal{A}$. Note that the value of D_j^M for each $j \in \mathcal{A}$ is listed in Table 9 of Appendix B in the online supplemental file. Each realization of $D_j(\omega)$ is then generated by $D_j(\omega) \sim U(D_j^L, D_j^U)$ for each $j \in \mathcal{A}$.
- Normal-distribution-based approach: Given D_j^M for each $j \in \mathcal{A}$ in Table 9 of Appendix B, let $\bar{\mu}_j$ be the average of 200 independent samples drawn from $N(\mu_j, \sigma_j, 0, +\infty)$, where $\mu_j \sim U(0.9D_j^M, 1.1D_j^M)$ and $\sigma_j \sim U(10, 30)$ for each $j \in \mathcal{A}$. Each realization of $D_j(\omega)$ is generated by $D_j(\omega) \sim N(\bar{\mu}_j, \bar{\sigma}_j, 0, +\infty)$, where $\bar{\sigma}_j \sim U(10, 30)$ for each $j \in \mathcal{A}$.
- Hoeffding and one-sided Chebyshev approximations: Similar to the Uniform-distribution-based approach, we let D_j^L and D_j^U be the minimum and maximum of 200 independent samples drawn from $N(\mu_j, \sigma_j, 0, +\infty)$, where $\mu_j \sim U(0.9D_j^M, 1.1D_j^M)$ and $\sigma_j \sim U(10, 30)$ for each $j \in \mathcal{A}$. Each realization of $D_j(\omega)$ is generated by $D_j(\omega) \sim T(D_j^L, D_j^A, D_j^U)$, where $D_j^A \sim U(0.9D_j^M, 1.1D_j^M)$ for each $j \in \mathcal{A}$.

For each of the humanitarian relief network solutions obtained in Step 1 and each of the realization of $D_j(\omega), \forall j \in \mathcal{A}$, we solve the corresponding maximum flow problem defined in

Section 4.4, and calculate the fill rate and the chance according to this demand realization.

Step 3. For each of the models built up in Step 1, we compute the average of the fill rate and the chance for each instance based on the 10,000 realizations obtained in Step 2.

For all instances, the humanitarian relief network design model can be solved based on the four approaches within reasonable amount of CPU times. Table 2 presents the computational results of the humanitarian relief network design model solved using the four approaches. In Table 2, the first column titled "θ" represents the adjustment coefficient of the budget for preparedness. The second column labelled "Approach" indicates the approach used to obtain the values in the corresponding row. The Uniform-distribution-based, Normal-distribution-based, Hoeffding approximation, and one-sided Chebyshev approximation approaches are abbreviated as the "Unif.", "Norm.", "Hoef.", and "Cheb.", respectively. The columns of "Fac. open", "Arc", and "#F" report the average number of relief facilities open, the average number of selected links, and the average number of affected areas that are multi-sourced (i.e., the demand for relief supplies in an affected area is satisfied by more than one relief facility), respectively. The column titled "R" presents the average guaranteed responsiveness implied by the optimal values of the humanitarian relief network design model. The average fill rate and the average chance of the 100 instances are reported in the columns titled "FR" and "Chance", respectively.

Table 2 demonstrates the effectiveness of our proposed chance-constrained models for humanitarian relief network design. Firstly, as we can see from Table 2, when we take the value of θ to be 1.00 (i.e., we use the base budget B as the budget for preparedness), the resulting humanitarian relief networks yielded by all the four approaches have poor effectiveness performances. Specifically, the average responsiveness of all four approaches is equal to 0, and their corresponding average chance is also close to or equal to 0. These results are reasonable and align with our intuition due to the particular way of generating the base budget BB.

Secondly, the effectiveness performances of humanitarian relief networks would increase with the budget for preparedness under all cases. For example, when the adjustment coefficient θ increases from 1.00 to 1.16, the average responsiveness of all the proposed approaches increases from 0.00 to 1.00. In the meantime, the average chance of the Uniform-distribution-based approach (the Normal-distribution-based approach, the Hoeffding approximation, the one-sided Chebyshev approximation, resp.) increases from 0.00% (0.00%, 1.94%, 1.68%, resp.) to 94.07% (95.23%, 95.16%, 98.00%, resp.), while the corresponding average fill rate also increases from 97.42% (96.99%,

Table 2: Computational results of chance-constrained humanitarian relief network design models

θ	Approach	R	Fac. open	Arc	#F	FR (%)	Chance (%)
1.00	Unif.	0.00	10.46	47.90	5.61	97.42	0.00
	Norm.	0.00	10.20	43.62	5.02	96.99	0.00
	Hoef.	0.00	11.00	47.86	5.32	98.76	1.94
	Cheb.	0.00	10.98	47.20	4.86	98.63	1.68
1.04	Unif.	0.76	11.09	48.27	5.59	99.41	18.99
	Norm.	0.78	10.99	48.47	5.74	99.23	19.24
	Hoef.	0.71	11.40	49.00	6.34	99.65	51.64
	Cheb.	1.00	11.36	48.64	5.98	99.70	53.18
1.08	Unif.	1.00	11.92	48.65	5.93	99.81	63.00
	Norm.	1.00	11.65	48.99	6.28	99.84	60.91
	Hoef.	0.99	12.06	48.80	5.84	99.89	73.28
	Cheb.	1.00	12.12	48.80	6.14	99.85	77.00
1.12	Unif.	1.00	12.95	49.13	6.49	99.96	88.13
	Norm.	1.00	12.18	48.99	6.38	99.94	84.36
	Hoef.	1.00	13.40	49.24	6.38	99.94	84.08
	Cheb.	1.00	13.36	49.28	6.42	99.99	95.72
1.16	Unif.	1.00	13.91	49.58	6.86	99.98	94.07
	Norm.	1.00	13.57	49.25	6.55	99.99	95.23
	Hoef.	1.00	13.94	49.60	6.96	99.98	95.16
	Cheb.	1.00	13.84	49.82	7.10	99.99	98.00

98.76%, 98.63%, resp.) to 99.98% (99.99%, 99.98%, 99.99%, resp.).

Thirdly, from Table 2, we can also conclude that the humanitarian relief networks yielded by all four approaches tend to be denser when the preparedness budget increases. Take the Uniform-distribution-based approach as an example. The average number of relief facilities open, the average number of selected links, and the average number of multi-sourced affected areas increase from 10.46, 47.90, and 5.61 to 13.91, 49.58, and 6.68, respectively, when θ increases from 1.00 to 1.16. Intuitively, a denser humanitarian relief network performs better against uncertain disasters than a sparse one, which explains the second observation discussed above.

5.2 Comparison between the chance-constrained stochastic programming model and the deterministic model

This part is dedicated to justify the effectiveness of the proposed chance-constrained stochastic programming models with respect to the deterministic models based on demand expectation, i.e., $E[D_j(\omega_j)] = \mu_j$ for all $j \in \mathcal{A}$. As it is impossible to capture the probability of fulfilling demand in a deterministic setting, the deterministic models target to minimize the shortage under a given budget. In particular, the deterministic model is formulated as follows:

$$
\begin{aligned}
\min \quad & \sum_{j\in\mathcal{A}} s_j \\
\text{s.t.} \quad & (2), (5), (6), (7), (8), \\
& \sum_{j\in\mathcal{A}} \theta_{ij} \leq I_i, \ \forall i \in \mathcal{F}, \\
& \sum_{i\in\mathcal{F}} \theta_{ij} + s_j \geq \mu_j, j \in \mathcal{A}, \\
& 0 \leq \theta_{ij} \leq MX_{ij}, \forall i \in \mathcal{F}, \ \forall j \in \mathcal{A}, \\
& s_j \geq 0, \ \forall j \in \mathcal{A}.
\end{aligned}
$$

In the comparison experiments, we set θ to be 1.16 and compare the corresponding performances of the deterministic models with those of the four chance-constrained stochastic programming models, respectively. The detailed computational results are reported in Table 3. The rows titled "Dete." display the results of the deterministic models.

As shown in Table 3, it is noteworthy that the deterministic models have very poor performances of chance (equal to 0.00%) under all cases, while the average chance for the chance-constrained stochastic programming models is at least 94.07%. In addition, the chance-constrained models also achieve a higher average fill rate (at least 99.98%) than the corresponding deterministic models. These computational results indicate that the chance-constrained stochastic programming models are much more effective than the deterministic model for humanitarian relief network design.

Table 3: Comparison between the chance-constrained stochastic humanitarian relief network design model and the deterministic humanitarian relief network design model ($\theta = 1.16$)

Approach	Fac. open	Arc	#F	FR (%)	Chance (%)
Unif.	13.91	49.58	6.86	99.98	94.07
Dete.	15.66	45.84	3.52	98.17	0.00
Norm.	13.57	49.25	6.55	99.99	95.23
Dete.	15.78	45.51	3.27	98.17	0.00
Hoef.	13.94	49.60	6.96	99.98	95.16
Dete.	15.50	45.22	2.88	97.87	0.00
Cheb.	13.84	49.82	7.10	99.99	98.00
Dete.	15.50	45.22	2.88	97.87	0.00

5.3 Sensitivity analysis

In Section 5.1, we temporarily assume the truck speed to be 50km per hour and 2 hours lead time for the preparation of relief supplies (see also Appendix B.5 in the online supplemental file). Because both the truck speed and the preparation lead time for relief supplies determine the effective rescue radius of relief facilities, we further implement sensitivity analysis on the effective rescue radius to study its impact on the optimization results in the case study of Typhoon Rammasun. Specifically, we let the effective rescue radius (unit:km) varies within the set $\{450, 500, 550, 600\}$. In addition, we set θ to be 1.08 in the sensitivity analysis experiments. Computational results of the sensitivity analysis are reported in Table 4. Note that the second column titled "ERR" indicates the effective rescue radius.

As shown in Table 4, when the effective rescue radius decreases from 600km to 450km, all four approaches show a tendency of opening more facilities and having less affected areas multi-sourced and less number of selected links. Specifically, the average number of open facilities of

Table 4: Computational results of sensitivity analysis on effective rescue radius ($\theta = 1.08$)

Approach	ERR (km)	R	Fac. open	Arc	#F	FR (%)	Chance (%)
Unif.	450	1.00	14.31	47.63	5.21	99.72	40.24
	500	1.00	11.92	48.65	5.93	99.81	63.00
	550	1.00	11.88	50.06	7.17	99.86	72.91
	600	1.00	12.22	50.88	7.50	99.95	83.41
Norm.	450	1.00	13.88	47.18	4.89	99.63	33.99
	500	1.00	11.65	48.99	6.28	99.84	60.91
	550	1.00	11.72	49.53	6.71	99.88	71.73
	600	1.00	11.93	51.24	8.17	99.89	78.58
Hoef.	450	0.99	14.48	48.10	5.60	99.75	50.24
	500	0.99	12.06	48.80	5.84	99.83	73.28
	550	0.99	12.08	49.26	6.54	99.85	74.22
	600	0.99	12.20	49.06	6.30	99.86	76.89
Cheb.	450	1.00	14.64	48.18	5.78	99.76	49.54
	500	1.00	12.12	48.80	6.14	99.85	77.00
	550	1.00	12.00	48.32	5.64	99.90	79.31
	600	1.00	12.32	50.22	7.20	99.94	81.68

the Uniform-distribution-based approach (the Normal-distribution-based approach, the Hoeffding approximation, the one-sided Chebyshev approximation, resp.) decreases from 14.31 (13.88, 14.48, 14.64, resp.) to 12.22 (11.93, 12.20, 12.32, resp.) when the effective rescue radius increases from 450km to 600km. Meanwhile, the average number of selected links increases from 47.63 (47.18, 48.10, 48.18, resp.) to 50.88 (51.24, 49.06, 50.22, resp.) and the average number of affected areas that are multi-sourced also increases from 5.21 (4.89, 5.60, 5.78, resp.) to 7.50 (8.17, 6.30, 7.20, resp.).

Furthermore, under the same budget for preparedness, the responsiveness of the humanitarian relief network yielded by all four approaches would improve with the increase of effective rescue radius. For example, when the effective rescue radius increases from 450km to 600km, the average fill rate and the average chance of the Uniform-distribution-based approach (the Normal-distribution-based approach, the Hoeffding approximation, the one-sided Chebyshev approximation, resp.) increase from 99.72% (99.63%, 99.75%, 99.76%, resp.) and 40.24% (33.99%, 50.24%, 49.54%, resp.) to 99.95% (99.89%, 99.86%, 99.94%, resp.) and 83.84% (78.58%, 76.89%, 81.68%, resp.), respectively.

To summarize, given a fixed budget for preparedness, the sensitivity analysis indicates that when the effective rescue radius is small, all four approaches tend to open more facilities and have less affected areas multi-sourced and less number of selected links. Additionally, the responsiveness of the humanitarian relief network yielded by all four approaches would improve with the increase of effective rescue radius.

6 Experiment variants

In this section, further computational experiments are carried out to investigate the performance of the chance-constrained humanitarian relief network design models based on random instances with a larger scale. For each instance considered in this section, we generate the required inputs using the following procedure. First, we label the 42 affected areas in the case study of the 2014 Typhoon Rammasun (see Appendix B.1 of the online supplemental file) from 0 to 41 according to their alphabetical order, and let ξ ($\xi \in \Xi$) denote the number associated with each affected area, i.e., $\xi \in \Xi := \{0, 1, \ldots, 41\}$. Similarly, the 26 relief facility candidates in the case study (see Appendix B.2 of the online supplemental file) are labeled from 0 to 25 according to their alphabetical order, and let τ ($\tau \in T$) denote the number associated with each relief facility candidate, i.e., $\tau \in T := \{0, 1, \ldots, 25\}$. We use $U(\Delta)$ to denote a discrete uniform distribution that takes values in a finite set Δ. For each instance with $|\mathcal{F}|$ relief facility candidates and $|\mathcal{A}|$ affected areas, we generate the inputs in this computational experiment as follows.

(1) The locations of relief facility candidate i and affected area j are uniformly distributed over the square [0, 700] $\times$ [0, 700], $\forall i \in \mathcal{F}$ and $\forall j \in \mathcal{A}$.

(2) The forecasted demand inputs: The most likely demand of affected area j (i.e., D_j^M) is equal to that of the affected area labelled ξ, i.e., $D_j^M = D_\xi^M$ for each $j \in \mathcal{A}$, where ξ is generated by $\xi \sim U(\Xi)$ and D_ξ^M is displayed in Table 9 of Appendix B in the online supplemental file. Then the forecasted demand inputs of the four approaches are generated using the same procedure outlined in Appendix B.4 of the online supplemental file.

(3) We use the same method introduced in Section 5.1 to generate budgets for each of approach. In our large scale case, we set D_j^L to be a_j ($\mu_j - 3\sigma_j$, μ_j, μ_j, resp.) to calculate base budget BB for the Uniform-distribution-based approach (the Normal-distribution-based approach, the Hoeffding approximation, the one-sided Chebyshev approximation, resp.). We also let θ take values in the set $\{1.00, 1.04, 1.08, 1.12, 1.16\}$.

(4) Cost parameters:

- Fixed location and operation cost: The fixed location and operation cost of relief facility candidate i is generated by $f_i \sim U(m_i, n_i)$, where m_i and n_i are equivalent to those of the relief facility candidate labelled τ, i.e., $m_i = m_\tau$ and $n_i = n_\tau$ for each $i \in \mathcal{F}$, where τ is generated by $\tau \sim U(T)$ and the values of m_τ and n_τ are available in Table 12 of Appendix B in the online supplemental file.
- Unit inventory pre-positioning cost: The unit inventory pre-positioning cost h_i of relief facility candidate i is generated by $h_i \sim U(2.4, 4.4)$ for each $i \in \mathcal{F}$, i.e., the same as that in Appendix B.5 of the online supplemental file.
- Assignment cost: If the Euclidean distance between relief facility candidate i and affected area j does not exceed 600, the assignment cost c_{ij} of the arc (i, j) is set to be 0; otherwise, the assignment cost c_{ij} is assumed to be a big number, $\forall i \in \mathcal{F}$ and $\forall j \in \mathcal{A}$.

(5) The supply capacity of relief facility candidate i is generated by $Q_i \sim U(k_i, l_i)$, where k_i and l_i are equivalent to those of the relief facility candidate labelled τ, i.e., $k_i = k_\tau$ and $l_i = l_\tau$ for each $i \in \mathcal{F}$, where τ is generated by $\tau \sim U(T)$ and the values of k_τ and l_τ are calculated according to the procedure in Appendix B.6 of the online supplemental file.

Following the procedure described in Section 5.1, we conduct the computational experiment with $|\mathcal{F}| = 80$ and $|\mathcal{A}| = 120$ for the chance-constrained humanitarian relief network design models. For each given budget and each approach, we generate 100 random instances. Table 5 reports the computational results. All the chance-constrained models can be solved within reasonable amount of time. The responsiveness performances of all four approaches also increase monotonically with the budget for preparedness. The fill rate is always above 97% and the chance exceeds 70% when θ reaches 1.12. These results further demonstrate the effectiveness of the solution approaches for instances with a larger scale.

7 Conclusions

An effective and cost-efficient humanitarian relief network is critical for relief organizations to implement high-performance disaster relief operations (i.e., establishing relief facilities at appropriate locations and pre-positioning suitable amount of relief supplies in the open relief facilities). This paper aims at supporting relief organizations in designing a humanitarian relief network, in which the demand for relief supplies in each affected area can be met by more than one relief facility. We cope with the demand uncertainty in each affected area using a joint chance constraint, which can be used to measure the responsiveness of the humanitarian relief network. We develop a chance-constrained stochastic programming model that determines the locations of the relief facilities, the amount of relief supplies stocked at each open relief facility, and which set of relief facilities serves each affected area. The proposed model maximizes the responsiveness under a given cost budget for preparedness. We approximate the proposed model using another model with chance constraints, which can be solved based on two settings of the demand information: (1) The Normal- and Uniform-distribution-based approaches are developed if the demand distribution in each affected area is given; (2) The Hoeffding (one-sided Chebyshev, resp.) approximation is developed if the mean and the support (the mean and the variance, resp.) of the demand in each affected area is given. We illustrate the application of the model and the solution approaches using a case study of the 2014 Typhoon Rammasun. Computational results show that the proposed solution approaches are effective for solving the chance-constrained humanitarian relief network design models. In addition, comparison experiments demonstrate that the chance-constrained stochastic programming models are superior to deterministic models for humanitarian relief network design under the same budget for preparedness. Sensitivity analysis experiments show that the respon-

Table 5: Computational results of chance-constrained humanitarian relief network design models ($|\mathcal{F}| = 80$ and $|\mathcal{A}| = 120$)

θ	Approach	R	Fac. open	Arc	#F	FR (%)	Chance (%)
1.00	Unif.	0.00	28.48	141.36	23.92	97.18	0.00
	Norm.	0.00	28.12	130.40	21.12	97.00	0.00
	Hoef.	0.00	29.12	148.74	22.84	98.89	1.92
	Cheb.	0.01	29.14	149.80	24.06	98.85	2.70
1.04	Unif.	0.73	30.54	162.30	26.98	99.62	23.50
	Norm.	0.78	29.24	149.76	23.38	99.80	27.86
	Hoef.	0.62	34.18	224.00	34.46	99.74	24.42
	Cheb.	1.00	33.22	267.90	33.26	99.75	26.76
1.08	Unif.	1.00	30.74	151.34	24.42	99.97	72.54
	Norm.	1.00	33.58	191.90	36.26	99.99	80.60
	Hoef.	0.99	31.36	160.74	26.80	99.89	54.00
	Cheb.	1.00	32.38	163.84	27.72	99.93	61.16
1.12	Unif.	1.00	31.88	153.76	27.00	99.99	89.32
	Norm.	1.00	32.74	167.26	29.64	100.00	93.60
	Hoef.	1.00	33.52	168.74	30.08	99.96	74.64
	Cheb.	1.00	34.48	178.84	33.26	99.95	73.30
1.16	Unif.	1.00	33.06	154.92	27.60	99.99	92.44
	Norm.	1.00	32.96	160.82	29.48	100.00	98.14
	Hoef.	1.00	34.58	167.82	28.46	99.97	84.96
	Cheb.	1.00	33.66	158.76	29.42	99.99	89.82

siveness obtained by chance-constrained stochastic programming models would improve with the increase of the effective rescue radius.

This paper studies a humanitarian relief network design problem in the presence of demand uncertainties. Our proposed model, however, does not consider the possible facility failure caused by devastating disasters as well as fairness issues, both of which are important components in humanitarian relief network design. Considering these two concerns will result in a more sophisticated model. Its solution approach will be an interesting topic for future research.

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A Proofs

Proof of Proposition 1. Given a feasible humanitarian relief network corresponding to (X_{ij}^0, Y_i^0), for any $\omega \in \Omega$, we could construct a linear programming (LP) model

$$\begin{aligned} LP1: \quad \max \quad & 0 \\ \text{s.t.} \quad & \sum_{j \in \mathcal{A}} \theta_{ij}(\omega) \leq I_i, \ \forall i \in \mathcal{F}, \\ & \sum_{i \in \mathcal{F}} \theta_{ij}(\omega) \geq D_j(\omega), \ \forall j \in \mathcal{A}, \\ & \theta_{ij}(\omega) \geq 0, \ \forall (i,j) \in \Theta. \end{aligned}$$

Obviously model $LP1$ is equivalent to the following LP

$$\begin{aligned} LP2: \quad \max \quad & -\sum_{i \in \mathcal{F}} p_i - \sum_{j \in \mathcal{A}} q_j \\ \text{s.t.} \quad & \sum_{j \in \mathcal{A}} \theta_{ij}(\omega) - p_i \leq I_i, \ \forall i \in \mathcal{F}, \\ & \sum_{i \in \mathcal{F}} \theta_{ij}(\omega) + q_j \geq D_j(\omega), \ \forall j \in \mathcal{A}, \\ & \theta_{ij}(\omega) \geq 0, \ \forall (i,j) \in \Theta, \\ & p_i, q_j \geq 0, \ \forall i \in \mathcal{F}, j \in \mathcal{A}, \end{aligned}$$

because we could regard p_i and q_j as artificial variables, and their values will be zero if model $LP1$ is feasible.

The dual problem of model $LP2$ is

$$\begin{aligned} DP2: \quad \min \quad & \sum_{i \in \mathcal{F}} I_i \gamma_i - \sum_{j \in \mathcal{A}} D_j(\omega) \varphi_j \\ \text{s.t.} \quad & \gamma_i - \varphi_j \geq 0, \ \text{if } (i,j) \in \Theta, \\ & 0 \leq \gamma_i, \varphi_j \leq 1, \ \forall i \in \mathcal{F}, j \in \mathcal{A}. \end{aligned}$$

It is easy to see that model $DP2$ must have an integer solution because the constraints are network flow conservation constraints and the right-hand side of the constraints are integers.

For any subset $S \subseteq \mathcal{A}$, we can get a corresponding feasible solution to model $DP2$ as the following:

$$\varphi_j = \begin{cases} 1, & \text{if } j \in S; \\ 0, & \text{otherwise;} \end{cases} \quad \text{and} \quad \gamma_i = \begin{cases} 1, & \text{if } i \in \Gamma(S); \\ 0, & \text{otherwise.} \end{cases}$$

If model $LP1$ has feasible solutions and thus the optimal solution, model $DP2$ also has an optimal solution that is equal to zero. Therefore, for any subset S, the corresponding solution's objective satisfies

$$\sum_{i\in\Gamma(S)} I_i - \sum_{j\in S} D_j(\omega) \geq 0.$$

Hence, for any $\omega \in \Omega$,

$$\begin{cases} \sum_{j\in\mathcal{A}} \theta_{ij}(\omega) \leq I_i, \ \forall i \in \mathcal{F} \\ \sum_{i\in\mathcal{F}} \theta_{ij}(\omega) \geq D_j(\omega), \ \forall j \in \mathcal{A} \\ \theta_{ij}(\omega) \geq 0 \end{cases}$$

is equivalent to

$$\sum_{i\in\Gamma(S)} I_i \geq \sum_{j\in S} D_j(\omega), \ \forall S \subseteq \mathcal{A}. \qquad \square$$

Proof of Proposition 2. We use $F_j(\cdot)$ to denote the distribution function of the random variable $D_j(\omega)$. Since the demand realization $D_j(\omega)$ follows uniform distribution, i.e., $D_j(\omega) \sim U(a_j, b_j)$, then we have

$$F_j^{-1}(1 - \epsilon/|\mathcal{A}|) = a_j + (b_j - a_j)(1 - \epsilon/|\mathcal{A}|).$$

The chance constraint (10) suggests that

$$\text{Prob}\left\{ D_j(\omega) \leq \sum_{i\in\mathcal{F}} I_{ij} \right\} = F_j\left(\sum_{i\in\mathcal{F}} I_{ij} \right) \geq 1 - \epsilon/|\mathcal{A}|.$$

As $F_j(\cdot)$ is monotonically increasing, we have

$$\sum_{i\in\mathcal{F}} I_{ij} \geq a_j + (b_j - a_j)(1 - \epsilon/|\mathcal{A}|). \qquad \square$$

Proof of Proposition 3. Since the demand realization $D_j(\omega)$ follows Normal distribution, i.e., $D_j(\omega) \sim N(\mu_j, \sigma_j)$, then the chance constraint (10) suggests that

$$\begin{aligned} \text{Prob}\left\{ D_j(\omega) \leq \sum_{i\in\mathcal{F}} I_{ij} \right\} &= \text{Prob}\left\{ \frac{D_j(\omega) - \mu_j}{\sigma_j} \leq \frac{\sum_{i\in\mathcal{F}} I_{ij} - \mu_j}{\sigma_j} \right\} \\ &= \Phi\left(\frac{\sum_{i\in\mathcal{F}} I_{ij} - \mu_j}{\sigma_j} \right) \geq 1 - \epsilon/|\mathcal{A}|. \end{aligned}$$

Note that $\Phi(z_\alpha) = 1 - \epsilon/|\mathcal{A}|$. Then, we have

$$\frac{\sum_{i\in\mathcal{F}} I_{ij} - \mu_j}{\sigma_j} \geq z_\alpha,$$

and hence

$$\sum_{i\in\mathcal{F}} I_{ij} \geq \mu_j + z_\alpha \sigma_j. \qquad \square$$

Proof of Proposition 4. Under the condition in (16), we have

$$\frac{\sum_{i\in\mathcal{F}} I_{ij} - \mu_j}{b_j - a_j} \geq \sqrt{\frac{-\ln(\epsilon/|\mathcal{A}|)}{2}} \geq 0.$$

Note that

$$\begin{aligned}
\text{Prob}\left\{ D_j(\omega) \geq \sum_{i\in\mathcal{F}} I_{ij} \right\} &= \text{Prob}\left\{ \frac{D_j(\omega) - a_j}{b_j - a_j} - \frac{\mu_j - a_j}{b_j - a_j} \geq \frac{\sum_{i\in\mathcal{F}} I_{ij} - a_j}{b_j - a_j} - \frac{\mu_j - a_j}{b_j - a_j} \right\} \\
&= \text{Prob}\left\{ \frac{D_j(\omega) - a_j}{b_j - a_j} - \frac{\mu_j - a_j}{b_j - a_j} \geq \frac{\sum_{i\in\mathcal{F}} I_{ij} - \mu_j}{b_j - a_j} \right\}.
\end{aligned}$$

As $\frac{D_j(\omega)-a_j}{b_j-a_j}$ is a random variable in $[0,1]$ with expectation $\frac{\mu_j-a_j}{b_j-a_j}$, Hoeffding's inequality yields

$$\begin{aligned}
\text{Prob}\left\{ D_j(\omega) \geq \sum_{i\in\mathcal{F}} I_{ij} \right\} &\leq \exp\left(-2\left(\frac{\sum_{i\in\mathcal{F}} I_{ij} - \mu_j}{b_j - a_j} \right)^2 \right) \leq \exp\left(-2\left(\sqrt{\frac{-\ln(\epsilon/|\mathcal{A}|)}{2}} \right)^2 \right) \\
&= \epsilon/|\mathcal{A}|,
\end{aligned}$$

which is equivalent to the constraint (10). $\square$

Proof of Proposition 5. Under the condition in (17), we have

$$\sum_{i\in\mathcal{F}} I_{ij} - \mu_j \geq \sqrt{\sigma_j^2 \left(\frac{1}{\epsilon/|\mathcal{A}|} - 1 \right)} \geq 0.$$

Note that

$$\text{Prob}\left\{ D_j(\omega) \geq \sum_{i\in\mathcal{F}} I_{ij} \right\} = \text{Prob}\left\{ D_j(\omega) - \mu_j \geq \sum_{i\in\mathcal{F}} I_{ij} - \mu_j \right\}.$$

As $D_j(\omega)$ is a random variable with expectation μ_j, the one-sided Chebyshev inequality yields

$$\begin{aligned}
\text{Prob}\left\{ D_j(\omega) \geq \sum_{i\in\mathcal{F}} I_{ij} \right\} &\leq \frac{\sigma_j^2}{\sigma_j^2 + \left(\sum_{i\in\mathcal{F}} I_{ij} - \mu_j\right)^2} \leq \frac{\sigma_j^2}{\sigma_j^2 + \sigma_j^2\left(\frac{1}{\epsilon/|\mathcal{A}|} - 1\right)} \\
&= \epsilon/|\mathcal{A}|,
\end{aligned}$$

which is equivalent to the constraint (10). $\square$

B Input generation

This part provides the details on how we generate the sets of affected areas and potential locations as well as the parameters for demand, cost, and capacity in the case study.

B.1 Set of affected areas

As introduced in Section 5, the destructive Typhoon Rammasun caused large-scale social and economic losses across Guangdong Province, Hainan Province, Yunnan Province, and Guangxi Zhuang Autonomous Region. The specific affected areas in the three provinces and one autonomous region are shown as follows.

- Guangdong Province: The affected cities in Guandong Province are Maoming, Yangjiang, Yunfu, and Zhanjiang, which are shown in Figure 2(a) in Section 5.1.[4] Let $\mathcal{A}_1$ denote the set of affected areas in Guangdong Province.

- Hainan Province: The affected areas in Hainan Province include two cities, i.e., Haikou and Sanya, and 16 counties directly under the jurisdiction of the province.[3] According to the Hainan Statistical Yearbook 2014, the 16 counties are Baisha, Baoting, Changjiang, Chengmai, Danzhou, Dingan, Dongfang, Ledong, Lingao, Lingshui, Qionghai, Qiongzhong, Tunchang, Wanning, Wenchang, and Wuzhishan.[5] The 18 affected areas in Hainan Province are specifically illustrated in Figure 2(b) in Section 5.1. Let $\mathcal{A}_2$ denote the set of affected areas in Hainan Province.

- Yunnan Province: The 9 affected cities in Yunnan Province are Banna, Baoshan, Dehong, Honghe, Lincang, Puer, Qujing, Wenshan, and Yuxi, which are presented in Figure 2(c) in Section 5.1.[6] We use $\mathcal{A}_3$ to represent the set of affected areas in Yunnan Province.

- Guangxi Zhuang Autonomous Region: There are 11 cities affected by the Typhoon Rammasun in Guangxi Zhuang Autonomous Region, namely, Baise, Beihai, Chongzuo, Fangchenggang, Guigang, Hechi, Laibin, Nanning, Qinzhou, Wuzhou, and Yulin.[7] All of them are shown in Figure 2(d) in Section 5.1. The set of affected areas in Guangxi Zhuang Autonomous Region is denoted by $\mathcal{A}_4$.

Note that the set of affected area $\mathcal{A}$ is composed of four sets, i.e., $\mathcal{A} = \mathcal{A}_1 \cup \mathcal{A}_2 \cup \mathcal{A}_3 \cup \mathcal{A}_4$. Based on the above description, the set $\mathcal{A}$ contains 42 affected areas.

B.2 Set of potential locations of relief facilities

The Ministry of Civil Affairs of PR China has set up national-level relief facilities in Yunnan Province[8] and Guangxi Zhuang Autonomous Region.[9] In addition, province (autonomous region)-level relief facilities have also been established in Guangdong Province,[10] Hainan Province,[11] Yunnan Province,[12] and Guangxi Zhuang Autonomous Region.[13] The potential locations of relief facilities in this case study can be determined by referring to the locations of the national-level and province (autonomous region)-level relief facilities in the three provinces and one autonomous region, which are shown in detail as follows.

- Guangdong Province: The Department of Civil Affairs of Guangdong Province set up province-level relief facilities in Guangzhou, eastern Guangdong, northern Guangdong, western Guangdong, and the Pearl River Delta.[10] The province-level relief facility in the eastern (northern, western, Pearl River Delta, resp.) part of Guangdong Province is situated in Meizhou (Qingyuan, Maoming, Huizhou, resp.).[14] The 5 potential locations of relief facilities in Guangdong Province are shown in Figure 2(a) in Section 5.1.

- Hainan Province: The province-level relief facilities in Hainan Province are built up in Danzhou, Haikou, Qionghai, Sanya, Wanning, and Wenchang, respectively.[11] The 6 potential locations of relief facilities in Hainan Province are displayed in Figure 2(b) in Section 5.1.

- Yunnan Province: One national-level relief facility is located in Kunming, Yunnan Province.[8] The Department of Civil Affairs of Yunnan Province has established province-level relief facilities in Baoshan, Chuxiong, Dali, Honghe, Puer, Qujing, Wenshan, and Zhaotong.[12] The 9 cities are regarded as the potential locations of relief facilities in Yunnan Province, which are presented in Figure 2(c) in Section 5.1.

- Guangxi Zhuang Autonomous Region: There is one national-level relief facility in Nanning, Guangxi Zhuang Autonomous Region.[9] Five autonomous region-level relief facilities are built up in the central, northern, northwestern, southeastern, and western part of Guangxi Zhuang Autonomous Region.[13] The central Guangxi consists of Laibin[15] and Liuzhou.[16] The northern Guangxi includes Guilin[17] and Hezhou,[18] and the northwestern Guangxi invloves Hechi.[19] The southeastern Guangxi is composed of Guigang[20] and Yulin,[21] and the western Guangxi refers to Baise.[22] According to the Guangxi Statistical Yearbook 2014, we obtain the information about the resident population and administrative region land area of each city in the central, northern, northwestern, southeastern, and western part of Guangxi Zhuang Autonomous Region, which are given in Table 6.[23] Then we can calculate the population density (number of people per square kilometer) of each city in the central, northern, northwestern, southeastern, and western part of Guangxi Zhuang Autonomous Region, which is also provided in Table 6. According to Balcık and Beamon (2008), relief facilities should be located in areas with high population density. Thus, it is reasonable to choose the location with higher population density as the potential location of an autonomous region-level relief facility in the central, northern, northwestern, southeastern, and western part of Guangxi Zhuang Autonomous Region. Based on the population density information provided in Table 6, the potential location of an autonomous region-level relief facility in the central (northern, northwestern, southeastern, western, resp.) part of Guangxi Zhuang Autonomous Region is Liuzhou (Guilin, Hechi, Yulin, Baise, resp.). The 6 potential locations of relief facilities in Guangxi Zhuang Autonomous Region are given in Figure 2(d) in Section 5.1.

Table 6: Resident population, administrative region land area, and population density of each city in the central, northern, northwestern, southeastern, and western part of Guangxi Zhuang Autonomous Region

Area	City	Resident population (10,000 persons)	Administrative region land area (sq km)	Population density (person/sq km)
Central Guangxi	Laibin	214.9	13,411.0	160
	Liuzhou	385.6	18,597.0	207
Northern Guangxi	Guilin	488.1	27,809.0	176
	Hezhou	200.0	11,855.0	169
Northwestern Guangxi	Hechi	343.2	33,476.0	103
Southeastern Guangxi	Guigang	422.1	10,602.0	398
	Yulin	562.3	12,838.0	438
Western Guangxi	Baise	354.5	36,202.0	98

Note that the set $\mathcal{F}$ consists of the set of the national-level relief facility candidates and the set of the province (autonomous region)-level relief facility candidates, which are denoted by $\mathcal{F}_1$ and $\mathcal{F}_2$, respectively. Based on the above information, the set $\mathcal{F} = \mathcal{F}_1 \cup \mathcal{F}_2$ contains 26 potential locations of relief facilities, 2 (24, resp.) of which belong to the set $\mathcal{F}_1$ ($\mathcal{F}_2$, resp.).

B.3 Disaster relief commodity package

According to the Construction Standards for Relief Facilities, the disaster relief commodities used to rescue the emergency transfer and resettlement population mainly include tents, quilts, survival kits, folding beds, mobile toilets, life jackets, and cotton suits.[24] In addition, the standard also provides the unit volume for each kind of disaster relief commodity as listed in Table 7.[24] The unit price for each type of the disaster relief commodity shown in Table 7 is obtained from JD.com. We assume that one tent can accommodate 5 people and 10 people share one mobile toilet. Suppose that the disaster relief commodities delivered to the affected areas can be bundled into disaster relief commodity packages, each unit of which can satisfy the demand of 10 people. The amount of each kind of disaster relief commodity in one disaster relief commodity package is also displayed in Table 7. Note that the relief supply and the disaster relief commodity package are used interchangeably in the case study.

Table 7: The unit volume, unit price, and amount for each kind of disaster relief commodity in a disaster relief commodity package

Item	Unit volume (m^3)	Unit price (CNY)	Amount
Tent	0.312	1400.0	2
Quilt	0.030	129.0	10
Survival kit	0.008	460.0	10
Folding bed	0.044	199.0	10
Mobile toilet	0.706	1,680.0	1
Life jacket	0.015	168.0	10
Cotton suit	0.016	149.0	10

The set of disaster relief commodities is denoted by E, indexed by $e \in E$. Let V_e and N_e denote the unit volume and the amount of disaster relief commodity e ($e \in E$) in one disaster relief commodity package. Based on the information provided in Table 7, we can calculate that the volume for one disaster relief commodity package (denoted by V) is 2.46m^3, i.e., $V := \sum_{e\in E} V_e \times N_e$. Let P_e denote the unit price of disaster relief commodity e ($e \in E$) in one disaster relief commodity package. The shelf life of these disaster relief commodities is estimated to be 5 years by experience. Then, we can compute that the annual depreciation cost for one disaster relief commodity package (denoted by C^{dep}) is 3,106 CNY, i.e., $C^{dep} := (\sum_{e\in E} P_e \times N_e)/5$.

B.4 Most likely demand

According to the Construction Standards for Relief Facilities, relief supplies are mainly used to rescue the emergency transfer and resettlement population in a disaster.[24] To determine the mostly likely demand in each affected area, we first obtain the emergency transfer and resettlement population in each affected area. The total emergency transfer and resettlement population in Guangdong Province (Hainan Province, Yunnan Province, Guangxi Zhuang Autonomous Region, resp.) is 157,000 (381,200, 6,600, 317,000, resp.).[3] There are 4 (18, 9, 11, resp.) affected areas in Guangdong Province (Hainan Province, Yunnan Province, Guangxi Zhuang Autonomous Region, resp.), which have been described in detail in Appendix B.1. We use RP_j to denote the resident population in affected area j for all $j \in \mathcal{A}$ in the year of 2014. According to the Guangdong Statistical Yearbook 2014,[25] Hainan Statistical Yearbook 2014,[26] Yunnan Statistical Yearbook 2014,[27] and Guangxi Statistical Yearbook 2014,[23] we can obtain the resident population of each affected area in Guangdong Province, Hainan Province, Yunnan Province, and Guangxi Zhuang Autonomous Region, which is shown in Table 8. Let EP_j denote the emergency transfer and resettlement population in affected area j for each $j \in \mathcal{A}$. We assume that EP_j is proportional to RP_j and the proportional coefficient is $157,000/\sum_{j\in\mathcal{A}_1} RP_j$ for each $j \in \mathcal{A}_1$, i.e., $EP_j := 157,000 \times RP_j/\sum_{j\in\mathcal{A}_1} RP_j$ for each $j \in \mathcal{A}_1$. Similarly, we have $EP_j := 381,200 \times RP_j/\sum_{j\in\mathcal{A}_2} RP_j$ for each $j \in \mathcal{A}_2$, $EP_j := 6,600 \times RP_j/\sum_{j\in\mathcal{A}_3} RP_j$ for each $j \in \mathcal{A}_3$, and $EP_j := 317,000 \times RP_j/\sum_{j\in\mathcal{A}_4} RP_j$ for each $j \in \mathcal{A}_4$.

Now consider D_j^M denoting the most likely demand of relief supply in affected area j for each $j \in \mathcal{A}$. As defined in Appendix B.3, each disaster relief commodity package can satisfy the demand of 10 people. Therefore, we set D_j^M to be 1/10 of the emergency transfer and resettlement population in the corresponding affected area, i.e., $D_j^M := EP_j/10$ for all $j \in \mathcal{A}$. The value of D_j^M is shown in Table 9.

Table 8: The resident population of each affected area in Guangdong Province, Hainan Province, Yunnan Province, and Guangxi Zhuang Autonomous Region

Province (Autonomous region)	Guangdong Province				Hainan Province	
Affected area	Maoming	Yangjiang	Yunfu	Zhanjiang	Baisha	Baoting
Resident population (10,000 persons)	601.3	248.0	242.8	716.7	17.0	14.9

Province (Autonomous region)	Hainan Province					
Affected area	Changjiang	Chengmai	Danzhou	Dingan	Dongfang	Haikou
Resident population (10,000 persons)	22.7	47.7	96.1	28.8	41.5	217.1

Province (Autonomous region)	Hainan Province					
Affected area	Ledong	Lingao	Lingshui	Qionghai	Qiongzhong	Sanya
Resident population (10,000 persons)	46.6	43.6	32.4	49.5	17.5	73.2

Province (Autonomous region)	Hainan Province				Yunnan Province	
Affected area	Tunchang	Wanning	Wenchang	Wuzhishan	Banna	Baoshan
Resident population (10,000 persons)	26.0	55.6	54.7	10.5	115.2	255.4

Province (Autonomous region)	Yunnan Province					
Affected area	Dehong	Honghe	Lincang	Puer	Qujing	Wenshan
Resident population (10,000 persons)	124.5	459.1	247.9	258.4	597.4	357.8

Province (Autonomous region)	Yunnan Province	Guangxi Zhuang Autonomous Region				
Affected area	Yuxi	Baise	Beihai	Chongzuo	Fangchenggang	Guigang
Resident population (10,000 persons)	234.0	354.5	159.0	202.81	89.9	422.1

Province (Autonomous region)	Guangxi Zhuang Autonomous Region					
Affected area	Hechi	Laibin	Nanning	Qinzhou	Wuzhou	Yulin
Resident population (10,000 persons)	343.2	214.9	685.4	315.9	295.4	562.3

Table 9: Value of D_j^M, $j \in \mathcal{A}$

Province (Autonomous region)	Guangdong Province				Hainan Province	
Affected area j	Maoming	Yangjiang	Yunfu	Zhanjiang	Baisha	Baoting
D_j^M	5218.8	2152.3	2107.8	6221.0	721.7	632.3
Province (Autonomous region)	Hainan Province					
Affected area j	Changjiang	Chengmai	Danzhou	Dingan	Dongfang	Haikou
D_j^M	964.5	2029.8	4092.0	1225.0	1765.0	9244.7
Province (Autonomous region)	Hainan Province					
Affected area j	Ledong	Lingao	Lingshui	Qionghai	Qiongzhong	Sanya
D_j^M	1982.1	1857.4	1380.5	2108.2	746.9	3116.9
Province (Autonomous region)	Hainan Province				Yunnan Province	
Affected area j	Tunchang	Wanning	Wenchang	Wuzhishan	Banna	Baoshan
D_j^M	1108.0	2367.5	2330.4	447.1	28.7	63.6
Province (Autonomous region)	Yunnan Province					
Affected area j	Dehong	Honghe	Lincang	Puer	Qujing	Wenshan
D_j^M	31.0	114.4	61.7	64.4	148.8	89.1
Province (Autonomous region)	Yunnan Province	Guangxi Zhuang Autonomous Region				
Affected area j	Yuxi	Baise	Beihai	Chongzuo	Fangchenggang	Guigang
D_j^M	58.3	3082.9	1382.8	1763.6	781.8	3670.1
Province (Autonomous region)	Guangxi Zhuang Autonomous Region					
Affected area j	Hechi	Laibin	Nanning	Qinzhou	Wuzhou	Yulin
D_j^M	2984.4	1868.8	5960.0	2747.2	2569.1	4889.3

B.5 Cost parameters

In this part, we generate the cost parameters in our case study, i.e., per unit inventory pre-positioning cost h_i, fixed location and operation cost of each relief facility f_i for all $i \in \mathcal{F}$, and assignment cost c_{ij} for all $i \in \mathcal{F}$ and $j \in \mathcal{A}$. We assume that each unit of cost in our case study is equal to 1,000 CNY.

(1) **Unit inventory pre-positioning cost:** The inventory pre-positioning cost includes the annual depreciation and operating costs, in which the latter is set to be 10% of the annual depreciation cost (see Ni et al., 2018). Note that the annual depreciation cost for each unit of the relief supply is 3,106 CNY, which is given in Appendix B.3. Then the average unit cost for inventory pre-positioning can be calculated as $C = 3,106 \times (1 + 10\%)/1,000 = 3.4$. Therefore, we generate the unit inventory pre-positioning cost by $h_i \sim U(2.4, 4.4)$ for all $i \in \mathcal{F}$.

(2) **Fixed location and operation cost:** According to the Construction Standards for Relief Facilities, a relief facility is composed of storage rooms and non-storage auxiliary rooms, in which the storage rooms are used to store relief supplies.[24]

- National-level relief facility: National-level relief facilities are classified into three categories: small, medium, and large,[24] in which the medium ones are considered as illustration in our case study. The minimum and maximum total construction areas of a national-level relief facility are displayed in Table 10.[24] Then we can compute the average total construction area of a national-level relief facility, which is also given in Table 10.
- Province (Autonomous region)-level relief facility: The minimum and maximum total construction areas of a province (autonomous region)-level relief facility are shown in Table 3.[24] Then we can calculate the average total construction area of a province (autonomous region)-level relief facility, which is also provided in Table 10.

Let S_i^t denote the average total construction area of relief facility i, i.e., S_i^t = 18,250m^2 (S_i^t = 6,400m^2, resp.) for each $i \in \mathcal{F}_1$ ($i \in \mathcal{F}_2$, resp.). Assume that a relief facility consists of 70% brick-concrete structure and 30% brick-wood structure, whose construction costs are 1,800 CNY/m^2 and 1,600 CNY/m^2, respectively (see Wang, 2010). In addition, let P_i^l be the price per square meter of industrial land in potential location of relief facility i for each $i \in \mathcal{F}$, the value of which is given in Table 11. Then we can calculate the average total construction cost of

Table 10: Construction area of relief facilities

Relief facility	Total construction area (m^2)			Construction area of storage rooms (m^2)		
	Min	Max	Average	Min	Max	Average
National-level (medium)	16,700	19,800	18,250	14,673	17,661	16,167
Province (Autonomous region)-level	5,000	7,800	6,400	3,985	6,641	5,313

relief facility i (denoted by C_i^{tc}) for all $i \in \mathcal{F}$, i.e., $C_i^{tc} := (1,800 \times 70\% + 1,600 \times 30\% + P_i^l) \times S_i^t$ for all $i \in \mathcal{F}$. The asset life of a relief facility is set to 50 years. Let C_i^{dc} denote the average annual depreciation cost of relief facility i for each $i \in \mathcal{F}$, then we have $C_i^{dc} := C_i^{tc}/50$ for each $i \in \mathcal{F}$. We assume that the annual fixed cost of locating and operating a relief facility is 120% of the annual depreciation cost (see Ni et al., 2018). Then we can calculate the number of units cost of relief facility i for each $i \in \mathcal{F}$, i.e., $C_i := C_i^{dc} \times 120\%/1,000$ for each $i \in \mathcal{F}$. Thus, we generate the fixed location and operation cost of relief facility i by $f_i \sim U(m_i, n_i)$, where $m_i := C_i - 200$ and $n_i := C_i + 200$ for each $i \in \mathcal{F}$ as shown in Table 12.

(3) **Assignment cost:** As mentioned in Section 1, it is essential to ensure that the affected areas can receive relief supplies within 12 hours after the occurrence of a disaster. Assume that the preparation lead time, which is needed to collect disaster information, load relief supplies, etc., before performing transportation operations, is 2 hours. We assume that relief supplies are shipped by trucks, the speed of which is 50km per hour. Then we can compute that the effective rescue radius of a relief facility is 500km. The distance between a relief facility candidate and an affected area is obtained by the shortest truck travel distance in Baidu Map. The distance from relief facility candidate i to affected area j is denoted by d_{ij} for all $i \in \mathcal{F}$ and $j \in \mathcal{A}$, whose value is given in Tables 13 and 14. If the distance d_{ij} does not exceed 500km, i.e., $d_{ij} \leq 500$, the assignment cost c_{ij} of the arc (i, j) is assumed to be 0; otherwise we set the assignment cost c_{ij} to a big number, $\forall i \in \mathcal{F}$ and $\forall j \in \mathcal{A}$.

Table 11: Industrial land price in each potential location of relief facility

Province (Autonomous region)	Level of relief facility	Potential location of relief facility	Industrial land price (CNY/m^2)
Guangdong Province	Province-level	Guangzhou	917.0[28]
		Huizhou	955.3[29]
		Maoming	402.0[30]
		Meizhou	216.1[31]
		Qingyuan	432.1[32]
Hainan Province	Province-level	Danzhou	512.9[33]
		Haikou	681.9[34]
		Qionghai	489.4[35]
		Sanya	1,559.3[36]
		Wanning	380.0[37]
		Wenchang	494.9[38]
Yunnan Province	National-level	Kunming	780.0[39]
	Province-level	Baoshan	261.5[40]
		Chuxiong	210.0[41]
		Dali	525.0[42]
		Honghe	380.0[43]
		Puer	270.0[44]
		Qujing	424.1[45]
		Wenshan	161.2[46]
		Zhaotong	195.0[47]
Guangxi Zhuang Autonomous Region	National-level	Nanning	435.0[48]
	Autonomous region-level	Baise	268.3[49]
		Guilin	467.0[50]
		Hechi	324.7[51]
		Liuzhou	373.0[52]
		Yulin	214.3[53]

Table 12: Fixed location and operation cost of relief facility i, $i \in \mathcal{F}$

Province (Autonomous region)	Level of relief facility	Potential location of relief facility i	C_i	$f_i \sim U(m_i, n_i)$
Guangdong Province	Province-level	Guangzhou	408.1	$f_i \sim U(208.1, 608.1)$
		Huizhou	414.0	$f_i \sim U(214.0, 614.0)$
		Maoming	329.0	$f_i \sim U(129.0, 529.0)$
		Meizhou	300.5	$f_i \sim U(100.5, 500.5)$
		Qingyuan	333.6	$f_i \sim U(133.6, 533.6)$
Hainan Province	Province-level	Danzhou	346.0	$f_i \sim U(146.0, 546.0)$
		Haikou	372.0	$f_i \sim U(172.0, 572.0)$
		Qionghai	342.4	$f_i \sim U(142.4, 542.4)$
		Sanya	506.8	$f_i \sim U(306.8, 706.8)$
		Wanning	325.6	$f_i \sim U(125.6, 525.6)$
		Wenchang	343.3	$f_i \sim U(143.3, 543.3)$
Yunnan Province	National-level	Kunming	1103.8	$f_i \sim U(903.8, 1303.8)$
	Province-level	Baoshan	307.4	$f_i \sim U(107.4, 507.4)$
		Chuxiong	299.5	$f_i \sim U(99.5, 499.5)$
		Dali	347.9	$f_i \sim U(147.9, 547.9)$
		Honghe	325.6	$f_i \sim U(125.6, 525.6)$
		Puer	308.7	$f_i \sim U(108.7, 508.7)$
		Qujing	332.4	$f_i \sim U(132.4, 532.4)$
		Wenshan	292.0	$f_i \sim U(92.0, 492.0)$
		Zhaotong	297.2	$f_i \sim U(97.2, 497.2)$
Guangxi Zhuang Autonomous Region	National-level	Nanning	952.7	$f_i \sim U(752.7, 1152.7)$
	Autonomous region-level	Baise	308.5	$f_i \sim U(108.5, 508.5)$
		Guilin	339.0	$f_i \sim U(139.0, 539.0)$
		Hechi	317.1	$f_i \sim U(117.1, 517.1)$
		Liuzhou	324.6	$f_i \sim U(124.6, 524.6)$
		Yulin	300.2	$f_i \sim U(100.2, 500.2)$

Table 13: The distance from each affected area to each relief facility candidate in Guangdong and Hainan

Affected area	Relief facility candidates in Guangdong and Hainan										
	Danzhou	Guangdong	Haikou	Huizhou	Maoming	Meizhou	Qingyuan	Qionghai	Sanya	Wanning	Wenchang
Baise	816	799	701	936	626	1,180	836	799	972	857	785
Baisha	53.7	778	176	861	427	1,135	812	173	264	155	214
Banna	1,700	1,745	1,586	1,882	1,510	2,126	1,777	1,682	1,856	1,736	1,668
Baoshan	1,817	1,823	1,703	1,960	1,628	2,204	1,855	1,799	1,974	1,853	1,785
Baoting	186	821	261	934	495	1,199	881	156	73	99	213
Beihai	444	563	330	697	244	953	615	427	601	485	413
Changjiang	107	772	175	858	423	1,131	808	265	205	315	357
Chengmai	117	635	48	731	296	1,004	682	141	312	197	133
Chongzuo	632	694	518	831	443	1,075	726	616	789	669	601
Danzhou	0	713	127	810	375	1,083	761	217	236	276	209
Dehong	1,953	1,959	1,839	2,096	1,764	2,340	1,991	1,935	2,110	1,989	1,921
Dingan	164	630	57	740	305	1,009	690	55	229	114	66
Dongfang	146	801	213	896	461	1,169	847	303	169	279	296
Fangchenggang	522	642	408	776	333	1,032	694	506	679	559	489
Guigang	582	470	468	592	342	832	489	566	738	618	549
Haikou	131	587	0	698	263	967	650	97	285	151	84
Hechi	828	678	714	814	638	975	652	811	984	869	797
Honghe	1,180	1,225	1,066	1,366	991	1,606	1,257	1,164	1,337	1,216	1,148
Laibin	697	541	583	661	472	901	549	697	853	733	666
Ledong	269	808	336	908	473	1,177	859	194	94	203	235

Table 13: (Continued) The distance from each affected area to each relief facility candidate in Guangdong and Hainan

Affected area	Relief facility candidates in Guangdong and Hainan										
	Danzhou	Guangdong	Haikou	Huizhou	Maoming	Meizhou	Qingyuan	Qionghai	Sanya	Wanning	Wenchang
Lincang	1,847	1,853	1,733	1,990	1,597	2,234	1,885	1,829	2,004	1,884	1,815
Lingao	67	664	78	761	326	1,034	712	168	304	226	160
Lingshui	169	791	217	900	466	1,169	851	115	74	56	172
Maoming	376	342	262	480	0	736	398	358	533	418	345
Nanning	591	562	477	696	401	940	591	574	747	627	560
Puer	1,578	1,623	1,464	1,760	1,389	2,004	1,671	1,560	1,734	1,614	1,546
Qinzhou	478	598	365	724	289	988	650	462	635	521	448
Qionghai	216	685	111	794	359	1,063	744	0	182	67	56
Qiongzhong	80.4	721	139	824	386	1,090	772	107	160	81	148
Qujing	1,262	1,249	1,147	1,386	1,072	1,589	1,266	1,243	1,418	1,298	1,229
Sanya	294	857	285	968	535	1,237	919	185	0	124	241
Tunchang	110	676	93	776	341	1,046	727	58	247	132	99
Wanning	270	748	165	848	414	1,117	798	63	123	0	119
Wenchang	206	670	103	779	344	1,048	729	56	237	122	0
Wenshan	1,976	1,128	962	1,254	887	1,502	1,153	1,059	1,233	1,112	1,044
Wuzhishan	139	794	213	894	459	1,163	845	180	86	135	221
Wuzhou	616	256	506	396	255	630	254	598	770	655	585
Yangjiang	488	226	374	338	130	605	299	469	644	529	457
Yulin	490	382	625	515	165	759	410	473	646	526	459
Yunfu	601	145	486	287	240	527	178	584	757	637	570

Table 13: (Continued) The distance from each affected area to each relief facility candidate in Guangdong and Hainan

Affected area	Relief facility candidates in Guangdong and Hainan										
	Danzhou	Guangdong	Haikou	Huizhou	Maoming	Meizhou	Qingyuan	Qionghai	Sanya	Wanning	Wenchang
Yuxi	1,366	1,410	1,252	1,544	1,176	1,791	1,443	1,348	1,522	1,402	1,333
Zhanjiang	289	428	175	529	93	808	480	273	446	325	257

Table 14: The distance from each affected area to each relief facility candidate in Yunnan and Guangxi

Affected area	Relief facility candidates in Yunnan and Guangxi														
	Baise	Baoshan	Chuxiong	Dali	Guilin	Hechi	Honghe	Kunming	Liuzhou	Nanning	Puer	Qujing	Wenshan	Yulin	Zhaotong
Baise	0	1,029	694	863	551	235	436	546	411	244	833	454	331	448	627
Baisha	893	1,891	1,557	1,725	958	906	1,230	1,377	819	668	1,651	1,340	1,126	568	1,512
Banna	957	976	643	810	1,496	1,203	525	520	1,358	1,198	127	665	641	1,411	868
Baoshan	1,033	0	341	178	1,457	1,254	724	500	1,437	1,268	858	627	797	1,472	831
Baoting	936	1,934	1,599	1,768	1,001	948	1,299	1,446	863	711	1,697	1,383	1,195	611	1,555
Beihai	451	1,450	1,115	1,283	516	464	815	990	378	226	1,213	898	711	215	1,071
Changjiang	877	1,876	1,541	1,709	942	890	1,227	1,373	804	652	1,639	1,325	1,122	553	1,497
Chengmai	751	1,749	1,415	1,582	818	766	1,117	1,246	678	526	1,512	1,198	996	426	1,370
Chongzuo	275	1,186	854	1,022	514	370	554	701	374	130	974	722	449	343	894
Danzhou	830	1,827	1,493	1,661	894	842	1,193	1,325	756	604	1,591	1,277	1,074	505	1,449
Dehong	1,169	142	480	315	1,588	1,399	861	638	1,573	1,404	677	763	934	1,608	968
Dingan	745	1,744	1,409	1,577	812	758	1,108	1,255	672	520	1,506	1,192	1,004	420	1,365
Dongfang	916	1,914	1,579	1,747	980	928	1,265	1,411	843	690	1,677	1,363	1,160	591	1,535
Fangchenggang	369	1,367	1,033	1,200	504	381	733	879	366	144	1,129	814	628	294	988
Guigang	392	1,399	1,065	1,233	320	324	829	912	186	150	1,231	825	698	113	1,012
Haikou	704	1,702	1,368	1,535	768	716	1,067	1,213	631	478	1,465	1,151	963	379	1,323
Hechi	236	1,253	916	1,086	304	0	684	884	162	246	1,081	677	579	403	744
Honghe	437	721	386	555	977	683	0	258	839	678	402	295	121	874	582
Laibin	342	1,363	1,027	1,196	217	224	766	875	80	165	1,163	787	662	227	959
Ledong	914	1,912	1,577	1,745	978	926	1,277	1,423	841	688	1,675	1,361	1,172	589	1,533

Table 14: (Continued) The distance from each affected area to each relief facility candidate in Yunnan and Guangxi

Affected area	Relief facility candidates in Yunnan and Guangxi														
	Baise	Baoshan	Chuxiong	Dali	Guilin	Hechi	Honghe	Kunming	Liuzhou	Nanning	Puer	Qujing	Wenshan	Yulin	Zhaotong
Lincang	1063	268	371	291	1,482	1,284	611	533	1,469	1,298	289	657	737	1,502	864
Lingao	780	1,779	1,444	1,612	845	793	1,142	1,276	707	554	1,542	1,228	1,025	456	1,399
Lingshui	906	1,905	1,570	1,737	973	919	1,269	1,416	833	681	1,667	1,353	1,165	581	1,526
Maoming	627	1,625	1,291	1,458	537	644	991	1,137	478	401	1,388	1,072	886	162	1,246
Nanning	243	1,265	928	1,098	379	247	668	777	239	0	1,073	689	571	207	863
Puer	835	555	521	688	1,374	1,081	403	398	1,236	1,080	0	543	519	1,272	746
Qinzhou	357	1,355	1,021	1,189	453	365	721	867	313	127	1,118	804	616	250	976
Qionghai	799	1,798	1,463	1,631	863	812	1,162	1,309	726	574	1,560	1,246	1,058	474	1,419
Qiongzhong	827	1,825	1,491	1,658	891	839	1,189	1,336	754	602	1,588	1,274	1,085	502	1,446
Qujing	455	628	291	458	828	676	295	152	859	690	541	0	345	894	304
Sanya	974	1,971	1,637	1,805	1,040	988	1,340	1,483	901	748	1,760	1,421	1,232	649	1,593
Tunchang	782	1,780	1,446	1,614	847	795	1,145	1,292	709	557	1,543	1,229	1,041	457	1,401
Wanning	853	1,852	1,517	1,685	918	866	1,216	1,363	780	628	1,614	1,300	1,112	529	1,473
Wenchang	785	1,783	1,448	1,616	849	797	1,147	1,293	711	560	1,545	1,232	1,043	459	1,403
Wenshan	331	797	462	632	872	579	121	310	731	574	519	345	0	770	632
Wuzhishan	899	1,898	1,563	1,731	964	912	1,263	1,409	827	674	1,661	1,347	1,158	575	1,519
Wuzhou	586	1,599	1,260	1,433	308	428	1,011	1,118	249	367	1,399	1,025	906	191	1,140
Yangjiang	738	1,741	1,402	1,574	566	691	1,103	1,249	507	501	1,499	1,184	998	320	1,358
Yulin	449	1,471	1,134	1,304	398	405	874	993	261	207	1,271	895	770	0	1,069
Yunfu	658	1,683	1,347	1,517	432	564	1,086	1,214	372	419	1,484	1,107	982	238	1,281

Table 14: (Continued) The distance from each affected area to each relief facility candidate in Yunnan and Guangxi

Affected area	Relief facility candidates in Yunnan and Guangxi														
	Baise	Baoshan	Chuxiong	Dali	Guilin	Hechi	Honghe	Kunming	Liuzhou	Nanning	Puer	Qujing	Wenshan	Yulin	Zhaotong
Yuxi	620	537	204	370	1,049	841	191	78	1,024	855	322	224	307	1,059	428
Zhanjiang	547	1,545	1,211	1,379	612	560	911	1,058	474	322	1,308	993	807	222	1,167

B.6 Supply capacity

In the Construction Standards for Relief Facilities, we can obtain the minimum and maximum construction areas of storage rooms of a national-level (medium) and province (autonomous region)-level relief facility, which are shown in Table 10.[24] Then we can calculate the average construction area of storage rooms of relief facility i (denoted by S_i^{sr}), i.e., $S_i^{sr} = 16,167\text{m}^2$ ($S_i^{sr} = 5{,}313\text{m}^2$, resp.) for each $i \in \mathcal{F}_1$ ($i \in \mathcal{F}_2$, resp.). According to the Construction Standards for Relief Facilities, the storage room of a relief facility should not exceed three floors and the height of the storage room should not be less than 6 meters.[24] In our case study, we assume that the storage room of each relief facility has 2 floors and the height of each floor is set to 3.5 meters. Note that the volume for each unit of the relief supply is 2.46m^3, which is given in Appendix B.3. Assume that the storage utilization ratio for the storage room of a relief facility is 90%. Then we can calculate the average storage capacity of relief facility i (denoted by CAP_i), i.e., $CAP_i := (S_i^{sr} \times 2 \times 3.5 \times 0.9)/2.46$ for each $i \in \mathcal{F}$. We obtain the value of CAP_i and generate the supply capacity Q_i for each relief facility $i \in \mathcal{F}$ as follows.

- National-level relief facility: $CAP_i = 41,403.3$ for each $i \in \mathcal{F}_1$. We generate supply capacity of relief facility i by $Q_i \sim U(k_i, l_i)$, where $k_i := CAP_i - 6,000$ and $l_i := CAP_i + 6,000$ for each $i \in \mathcal{F}_1$.

- Province (Autonomous region)-level relief facility: $CAP_i = 13,606.5$ for each $i \in \mathcal{F}_2$. We generate supply capacity of relief facility i by $Q_i \sim U(k_i, l_i)$, where $k_i := CAP_i - 4,000$ and $l_i := CAP_i + 4,000$ for each $i \in \mathcal{F}_2$.

Notes

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