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Bi-objective multi-layer location–allocation model for the immediate aftermath of sudden-onset disasters

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ABSTRACT

Locating distribution centers is critical for humanitarians in the immediate aftermath of a sudden-onset disaster. A major challenge lies in balancing the complexity and uncertainty of the problem with time and resource constraints. To address this problem, we propose a location–allocation model that divides the topography of affected areas into multiple layers; considers constrained number and capacity of facilities and fleets; and allows decision-makers to explore trade-offs between response time and logistics costs. To illustrate our theoretical work, we apply the model to a real dataset from the 2015 Nepal earthquake response. For this case, our method results in a considerable reduction of logistics costs.

1. Introduction and research question

Locating temporary distribution centers is among the first critical decisions that humanitarian logisticians have to make in the aftermath of a sudden-onset disaster (Maharjan and Hanaoka, 2018). Observations from the 2015 Nepal earthquake (Paul et al., 2017) and the 2016 Ecuador earthquake (USAID, 2016) confirm that pre-positioned warehouses and distribution centers are often overwhelmed by incoming cargo, not suitable to accommodate dispersed demand points, and the requirement of the incoming humanitarian organizations (HOs). To address these challenges, the Logistics Cluster, which coordinates logistics activities in large-scale humanitarian responses (Jahre and Jensen, 2010), locates and sets up temporary distribution centers, i.e., staging areas (SAs).

As the location of SAs have to be decided at the start of the operations, they fall under the immediate response phase. Generally, one distinguishes immediate response and relief (Kovács and Spens, 2007). The immediate response phase is the first chaotic phase after a disaster. Its duration depends on the complexity of the response and level of destruction (Gralla et al., 2013). The relief phase covers the time after the immediate response up to the early recovery. In this phase, as a result of rapid needs assessments, demands and beneficiaries are often prioritized and hence, relief operations are more structured (Kovács and Spens, 2007).

The decision-making environment in the immediate response phase is particularly challenging. This is due to decision density (exceptional number of decisions to be made (Comes, 2016)), urgency (many decisions must be taken under time pressure (Gralla et al., 2016)), uncertainty (about the current and the future situation (Van de Walle and Comes, 2015)), limited resource (monetary and non-monetary (Chakravarty, 2014)), and potential consequences (decisions taken early on can continue to impact the entire response (Kowalski-Trakofler et al., 2003)). While the complexity of the location decision (Loree and Aros-Vera, 2018) highlights the need for decision support systems (DSSs) to support field-based decision-makers (hereinafter DMs) in the immediate response

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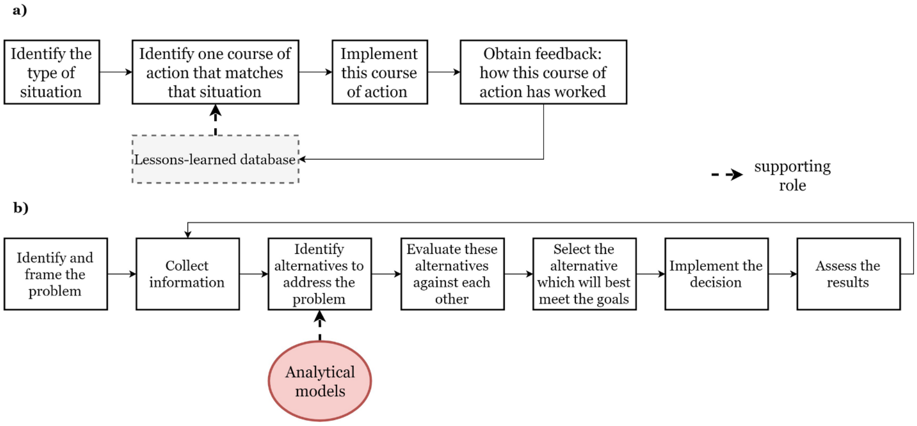

Fig. 1. Naturalistic (a) vs. analytic (b) decision-making in humanitarian response (inspired by Campbell and Clarke (2018)) and the potential of models to support the analytic process.

(Thompson et al., 2006), the above challenges pose specific requirements on DSSs (Van de Walle and Turoff, 2008).

Because most computational DSSs are not designed for these conditions, DMs often use naturalistic approaches for decision-making (Campbell and Clarke, 2018), see Fig. 1a. But the appropriateness of these approaches has been criticized as they (1) may be prone to biases, (2) rely on the experience and intuition of the DM, (3) are not transparent (challenging accountability), and (4) do not support discussion and deliberative processes. Analytic approaches, as described in the Fig. 1b, can have several advantages as they (1) use a clear analytic process, (2) allow others to see how the result was achieved, and (3) are helpful in group decision-making (Klein, 2011).

The contribution of this paper is developing a methodology which can support the location decision in severely time- and resource-constrained contexts, as of immediate response phase, given the challenges of decision-making in such environments.

Several operations research (OR) location–allocation models have been developed over the last decades to support decision-making in disaster response (Galindo and Batta, 2013; Anaya-Arenas et al., 2014; Gutjahr and Nolz, 2016; Boonmee et al., 2017). These models cover different data modeling types (deterministic, stochastic, or robust) and modelling methodologies (single- and multi-objective) (Galindo and Batta, 2013).

However, these models have been described as not applicable in practice: "too narrow, too rigid, too consumptive in terms of resources and cognitive capacity, or simply ineffective" (Comes, 2016), or "poorly adapted to decisions taken in disasters response" (Campbell and Clarke, 2018). The reasons can be first, improper framing of the problem (Klein, 2011), second, wrong data assumptions to address uncertainty (Lu, 2017), and third, limited usefulness for the responders who often look for a set of robust solutions rather than one optimal option (Woodward et al., 2014). Developing a model that can support DMs while addressing the specific constraints of immediate response motivates our research question: How can HOs balance the response time and logistics costs when they want to locate temporary relief distribution centers in the immediate response phase? This trade-off is motivated by first, the importance of considering logistics costs from the beginning of operations due to the increasing gap between funds and appeals for humanitarian response after sudden onset disasters (GHA, 2018) and second, the rush of HOs to deliver relief items to beneficiaries to save more lives and alleviate the sufferings (Kunz et al., 2017).

In this paper, we propose a multi-commodity multi-layer bi-objective location–allocation model to locate temporary relief distribution centers in the immediate response phase for sudden-onset disasters. We consider uncertainty by developing a rapid model which considers multiple time-steps in the operation's timeline. This approach enables decision-makers to account for the possible changes in the parameters due to uncertainties (Huang et al., 2015) and support re-parametrization of the model when updated information is available.

To support trade-offs, we follow an a posteriori paradigm. While traditionally decision support relies on *a priori* agreement on (or imposition of) assumptions about the probability of alternative states of the world and the way in which competing objectives are to be aggregated with the aim of producing a preference ranking of decision alternative, an *a posteriori* approach enables decision-makers to explore trade-offs among objectives and the robustness of performance (e.g., (Shortridge and Zaitchik, 2018)).

We apply our model to the 2015 Nepal earthquake case and use the data from the United Nations World Food Program (UN WFP), the lead agency of the Logistics Cluster. We compare our results with what practitioners actually decided in the Nepal earthquake and discuss the differences. We analyze the sensitivity of the solutions of the model to the variations in the parameters and examine the stability of the results.

Methodologically, our research have been informed by an empirical study after the 2015 Nepal earthquake to develop a relevant and validated model. We used an empirical case study as a method to establish a theoretically and empirically relevant research question (Eisenhardt and Graebner, 2007). Model development is informed by our field research, and assumptions were validated by practitioners. Data on cost and time parameters of the model is based on practitioners' inputs, and the model is validated through benchmarking our results against UN WFP's relief operations in the Nepal case.

The remainder of the paper is structured as follows. A literature review to identify the characteristics of an immediate response and the research gaps in the OR location–allocation models is given in Section 2. In Section 3, the proposed location–allocation model is discussed and the solution approach is explained. We apply our model to the 2015 Nepal earthquake case and present the results in Section 4. We discuss our results in Section 5. Finally, the conclusions and implications for theory and practice are presented in Section 6.

2. Background

Here, first we explore the contextual characteristics of an immediate response from the literature and our empirical work. Then, we review two core features of OR models for the location–allocation problem in disaster response over the last decade: (1) the criteria and assumptions considered and (2) the data modelling approaches.

2.1. Constraints and requirements of the sudden-onset disaster response context

The context of operations after sudden-onset natural disasters is dynamic, complex and uncertain. Due to the impacts on livelihoods, a disaster can lead to different demand profiles in the affected areas (Kovács and Spens, 2007). Moreover, priority relief items (type and quantity) can change over the course of response depending on conditions, such as weather and livelihood recovery (Campbell and Clarke, 2018). Similarly, the infrastructure status (transportation and communication) may change rapidly (Comes et al., 2013). Such characteristics highlight that developed models need to account for constantly changing conditions in the response to be able to support DMs.

A successful sudden-onset disaster response meets the needs of the population (effectiveness) in the shortest amount of time (time efficiency) with the least amount of resources (cost efficiency) (Hu et al., 2016; Kunz et al., 2017). In the immediate response, time pressure is high to ensure that the most urgent humanitarian needs can be met (Gralla et al., 2014). However, since there is an increasing shortage of funding (GHA, 2014), minimizing logistics costs from the beginning contributes to reaching more beneficiaries and helping more lives in the subsequent phases.

In addition, we found from our interviews that the models should have the capacity to address the specific characteristics of the affected area, such as the topography, and the features of the relief operations. As we will explain in Section 2.2.1, models that consider a single type of transportation and commodity and/or facilities with an unlimited capacity do not represent the constraints of the relief operations in the field. This can be a reason for why practitioners are often reluctant to use analytical models. In this regard, verifying and validating the proposed models with experts and benchmarking the outcomes against real cases are crucial for ensuring the benefits of using DSSs.

2.2. Location–allocation models for disaster response

OR location–allocation models are developed in the HL literature for different purposes such as shelters, medical facilities, distribution centers, vehicle hubs, and debris containers (Galindo and Batta, 2013; Anaya-Arenas et al., 2014; Boonmee et al., 2017). However, the characteristics of these problems differ from one to another and in distinct disaster management phases. The location–allocation problem related to distribution centers in disasters response (i.e., after the event of the disaster) is typically discrete, i.e. facilities can be established only at candidate locations (Hu et al., 2016). In the following, we only review OR models for discrete location-allocation problem in disasters response for the last 10 years. Literature reviews with wider scopes can be found in (Galindo and Batta, 2013; Anaya-Arenas et al., 2014; Boonmee et al., 2017).

2.2.1. Criteria and assumptions

Criteria: OR models determine the number and locations of the facilities and allocate resources to them primarily by considering a single objective (Anaya-Arenas et al., 2014; Boonmee et al., 2017); e.g., minimization of logistics costs (Noham and Tzur, 2018) or

Table 1
Criteria (in the form of objectives and/or constraints) in reviewed OR location–allocation models for disaster response.

Paper	Response time	Logistics costs	Demand coverage	Risk	Fairness
Tzeng et al. (2007)	✓	✓	✓	–	–
Nolz et al. (2011)	✓	–	✓	✓	–
Zhan and Liu (2011)	✓	–	✓	–	–
Vitoriano et al. (2011)	✓	✓	–	✓	✓
Lin et al. (2012)	✓	✓	✓	–	–
Najafi et al. (2013)	–	✓	✓	–	–
Abounacer et al. (2014)	✓	–	✓	–	–
Barzinpour and Esmaeili (2014)	–	✓	✓	–	–
Ahmadi et al. (2015)	✓	✓	✓	–	–
Huang et al. (2015)	–	✓	✓	–	–
Cao et al. (2017)	✓	–	✓	–	✓
Maharjan and Hanaoka (2018)	–	✓	✓	–	–
Loree and Aros-Vera (2018)	–	✓	–	–	✓

Table 2
Unrealistic assumptions of reviewed OR location–allocation models.

Paper	Assumption(s)
Tzeng et al. (2007)	Unlimited fleets capacity (size and/or quantity); minimizing time and costs are not the objectives and only reflected as soft constraints to ensure the effective use of the resources
Nolz et al. (2011)	Unlimited fleets capacity (size and/or quantity); Unlimited facility capacity (size and/or quantity); Single commodity; unlimited time
Zhan and Liu (2011)	Combined location-routing; facility location decision is made before the disaster occurs
Vitoriano et al. (2011)	Single commodity; combined location-routing; facility location decision is made before the occurrence of a disaster
Lin et al. (2012)	Unlimited facility capacity (size and/or quantity)
Najafi et al. (2013)	Combined location-routing; same trucks and helicopters can be used to transport injured people and relief items; facility location decision is made prior to the occurrence of a disaster
Abounacer et al. (2014)	Unlimited time
Barzinpour and Esmaeili (2014)	Unlimited fleets capacity (size and/or quantity); demand coverage in the urban districts is the first priority
Ahmadi et al. (2015)	Unlimited facility capacity (size and/or quantity); single transportation mean
Huang et al. (2015)	Unlimited facility capacity (size and/or quantity); combined location-routing; fairness is the only objective
Cao et al. (2017)	Unlimited fleets capacity (size and/or quantity); Unlimited facility capacity (size and/or quantity); combined location-routing
Maharjan and Hanaoka (2018)	Unlimited fleets capacity (size and/or quantity); Unlimited facility capacity (size and/or quantity); single commodity; single transportation mean
Loree and Aros-Vera (2018)	Unlimited fleets capacity (size and/or quantity); single commodity; single transportation mean

unmet demands (Chapman and Mitchell, 2018). Some studies that consider multiple objectives are listed in Table 1. Although minimizing the response time and logistics costs are of high importance for the logisticians in the immediate response phase (cf. Section 2.1), few studies (Tzeng et al., 2007; Lin et al., 2012; Ahmadi et al., 2015; Vitoriano et al., 2011) address these two objectives simultaneously. Some objectives, such as fairness or equity, require access to reliable information about the demography and assessed needs, thus, they can be considered in phases after the immediate response. However, to ensure that the demands are met with these models and effectiveness is addressed, a certain level of demand coverage is commonly applied as a constraint.

Assumptions: Models are always a simplification of reality. However, some important assumptions have previously already been characterized as unrealistic (Galindo and Batta, 2013; Martinez et al., 2011; Holguín-Veras et al., 2012; Gralla et al., 2014). These assumptions are listed in Table 2.

Unlimited capacity in transportation or facilities is unrealistic; available fleet and facilities both have been shown to severely constrain and impact the immediate response (Martinez et al., 2011; Boonmee et al., 2017), even if mobile storage units are used (Baharmand et al., 2016). Moreover, assuming a single commodity does not consider the fact that some beneficiaries can have an urgent need for different food and non-food items, and that HOs often aim at distributing multiple commodities in their operations (Prasad et al., 2017). Because such items can have different requirements for storage, handling, or transportation, considering them as a single commodity makes the proposed model inapplicable in reality.

The duration for the operations is critical because relief operations are generally defined as projects with a pre-defined timeline and budget (Baharmand et al., 2016). Because accomplishing each task is time consuming (e.g., setting up depots), a model cannot reflect the reality if the time factor is not considered in the parameters.

Finally, an issue with combining location and distribution is that the status of transportation often changes rapidly in the immediate response phase (Gralla et al., 2014). Thus, routing and scheduling plans require more frequent updates than the location decision.

2.2.2. Data modelling approaches

In the reviewed papers (cf. Table 1), data is modelled either by deterministic (Tzeng et al., 2007; Balcik et al., 2008; Nolz et al., 2011; Vitoriano et al., 2011; Lin et al., 2012; Abounacer et al., 2014; Cao et al., 2017; Maharjan and Hanaoka, 2018; Loree and Aros-Vera, 2018) or stochastic (Zhan and Liu, 2011; Barzinpour and Esmaeili, 2014; Ahmadi et al., 2015) approaches, as shown in Fig. 2. One of the papers in Table 1 used a robust model (Najafi et al., 2013). The data is said to be deterministic when there are no uncertainties associated with any of the variables, whereas in a stochastic model, certain first-order variables are represented by probability distributions. Robust models, however, identify sets of alternatives that perform well across a range of assumptions on deeply uncertain variables (Herman, 2013).

The following two methods have been widely adopted in the location–allocation literature to model a dynamic network flow with deterministic data: time period planning horizon (Tzeng et al., 2007; Balcik et al., 2008; Lin et al., 2012; Najafi et al., 2013; Maharjan and Hanaoka, 2018; Loree and Aros-Vera, 2018) and rolling planning horizon (Huang et al., 2015; Cao et al., 2017). The first approach divides the response into several fixed time units (Hoyos et al., 2015). In the second approach, multiple planning horizons are considered and the parameters of the model can change in each horizon. According to Huang et al. (2015), the second approach allows dealing with the uncertainties in disaster response effectively because decisions can be revised at several time points based on the available real-time information (adding or closing locations compared with a previously established network).

Stochastic methods are recommended to address uncertainties when probability distributions are available (Manopiniwes and Irohara, 2017). However, such information is not accessible in the context of sudden-onset disasters when the uncertainty is deep (Liberatore et al., 2013). Furthermore, stochastic methods are typically difficult to implement and solve, so that they are not

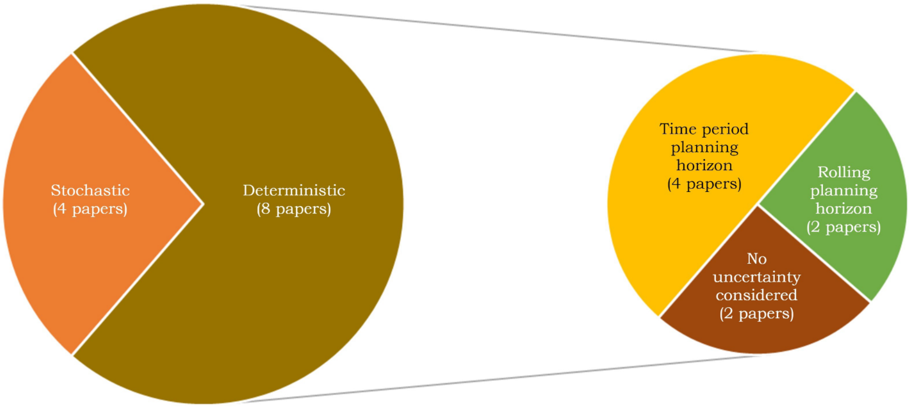

Fig. 2. Overview of data modelling approaches.

immediately applicable (Charles et al., 2016).

According to Charles et al. (2016), robust models have a limited applicability in the immediate response owing to the computational requirements. Robustness is referred to as a "measure of the insensitivity of the performance of a given strategy to future conditions" (Maier et al., 2016). Therefore, robust modelling approaches necessitates running thousands of scenarios which is not feasible in the operational level given limitations in time and computational resources to run thousands of scenarios (Peters et al., 2016). Scenario analysis largely targets long-term decision-making and strategic planning purposes (e.g., Charles et al. (2016) and Ransikarbum and Mason (2016)). Only a very few studies have considered rapid scenario updates for decision-making in crises (Comes et al., 2015, 2012).

2.3. Gap analysis

Despite the significance of supporting the decision to locate temporary relief distribution centers in the immediate response phase, literature does not address adequately constraints and requirements from disaster management, and several extensions have to be included in terms of objectives and constraints.

The reviewed papers primarily consider the response as a single planning horizon and employ the deterministic data modelling approach for the entire timeline. Thus, the uncertainty of parameters in the chaotic context of the immediate response is not effectively addressed. Huang et al. (2015), Cao et al. (2017), Maharjan and Hanaoka (2018), Loree and Aros-Vera (2018) assumed that the demands and resources may change for the time intervals in the response. However, the first two studies focused only on fairness related objectives and did not investigate the time and cost efficiency. Moreover, Loree and Aros-Vera (2018) and Maharjan and Hanaoka (2018) considered minimizing logistics and deprivation costs, and logistics costs and unmet demands as objectives of their models, respectively. However, response time has been often reported as one of the main concerns of DMs in the immediate response phase (Gralla et al., 2014).

Furthermore, in the reviewed papers commonly only a single layer is considered in the distribution networks, or it is assumed that all the affected areas are accessible by a single transportation mode. However, multiple transportation modes (ground, air, and water) may be required based on the topography of the affected area and infrastructure status. For instance, opposed to the features of a flat region, for an area composed of several islands, e.g. Philippines, a combination of trucks, helicopters, and boats will be necessary to deliver relief items to those affected (Lum and Margesson, 2014).

Moreover, none of the reviewed papers that apply the suggested models to use cases or benchmark their results with real operations in the field. Instead, papers often confine their studies to randomly generated numerical applications. Comparing results can provide helpful insights for practitioners regarding how using DSSs can contribute to improving relief operations and eventually, can help to save more lives (Pedraza-Martinez and Van Wassenhove, 2016; Kunz et al., 2017).

3. Model development

This study aims at developing an approach to locate temporary relief distribution centers that respects the constraints and specifics of a disaster. Our approach ensures that the complexities of the response, such as multiple criteria, multiple time periods, multiple commodities, and multiple layers are taken into account, while at the same time ensuring that the requirements in terms of run-time, computational resources and data can be met. In other words, our modeling approach focuses on balancing detail and complexity of the model with rapidly generating results.

3.1. Modelling methodology

To develop our location–allocation model, we followed Baharmand et al. (2017b)'s exploratory mixed-method research design, and conducted a field study after the 2015 Nepal earthquake. Our on-site data collection included semi-structured interviews (with logisticians), observations, and documents review. For analyzing the data, we used the content analysis approach and coded the empirically collected data based on the keywords such as “location” which were driven from our primary theoretical framework. The analysis provided supporting evidence for the following elements of this study: the research question, problem definition, data modeling, decision criteria, time-line, assumptions, and modeling requirements.

We developed an optimization model in close collaboration with practitioners over a course of approximately two years. The experts were five logisticians working on planning the relief operations in the UN WFP and International Federation of Red Cross and Red Crescent Societies (IFRC). After several iterative discussions, we were able to identify the required capabilities, model them, and ensure that they are implemented correctly. In the model development process, we compared the model calculations with practitioners’ data, and investigated those cost or time components that were estimated differently or were left un-modeled. Following the discussions with the practitioners, we finally ensured that the un-modeled costs and times were integrated in the model.

Although the specific characteristics of disasters contexts may imply constraints regarding datasets, disasters are not any more totally data lacking contexts (Van de Walle and Comes, 2015). The data that we used in our paper to build and validate the model is often available for different type of disasters through information sharing platforms. Typically, HOs would be provided maps, distances, and logistics prices through the Logistics Cluster in the early stages of response. Such information is also often shared on websites such as ReliefWeb,[1] LogCluster,[2] HumanitarianDataExchange (HDX)[3]as open data. In situations where data is not available or it is incomplete, practitioners use estimates, according to our interviews.

3.2. Problem definition

Fig. 3 illustrates the distribution network in the affected region during the immediate response. In the aftermath of disasters, relief materials are normally received through the main entry points such as international airports, borders, or ports. To facilitate the distribution of the received items, the DMs must determine the location for setting up the SAs, and decide the allocation of the scarce resources to them. An SA is often observed as a temporary location in the affected region/country between the main entry points/pre-positioned warehouses and demand points to store, sort, consolidate, de-consolidate, and distribute relief items (Maharjan and Hanaoka, 2018). The impact of such locations on the effectiveness and efficiency of relief distribution has been noted several times (Lin et al., 2012; Holguín-Veras et al., 2012; Cao et al., 2017; Paul et al., 2017).

Depending on the topography of the affected region, the locations in the relief distribution network can be divided into three layers.

i Locations that remain accessible by the main entry points (MEPs) via the highways or main roads. Relief items are normally sent to these locations by high-capacity trucks and/or trailers.
ii Locations that are not accessible by the MEPs via the highways or main road. These places can be reached from the locations in layer 1 using smaller trucks (e.g., 4×4 trucks or tractors). If necessary, air transport can also be utilized to access these locations.
iii Remote and hard-to-reach locations, where ground transportation is impossible or highly risky. The only approach to reach the beneficiaries in these locations is through air transport, porters, or a combination thereof from the SAs in layer 1.

3.3. Assumptions

To develop our mathematical model, we made the following assumptions based on our observations in the field. All the assumptions are discussed and challenged in our interviews with field practitioners and then eventually approved.

- Each point of demand (POD) is accessible from at least one SA. PODs in the first and second layer should be reached in a time less than or equal to the maximum covering time (the time required to reach a certain location). We assume that this maximum covering time δ refers to access time by trucks. PODs in the third layer should be accessible by the SA(s) within a distance less than the maximum reaching radius ω.
- Mobile storage units (MSUs) are assumed as storing structures in the SAs. MSUs have been successfully and rapidly erected in recent response operations (for instance in 2015 Nepal earthquake response (UNWFP, 2016)), and thus, they can expedite the relief operations. We also assume that the act of erecting MSUs is conducted by volunteers and does not impose any logistics costs.
- Moving items from one SA to another SA is not allowed in the immediate response. The only possible material flow is either from the MEPs to PODs (only in the first layer), from the MEPs to SAs, or from the SAs to PODs (in all layers).
- In the immediate response, the plan is to cover all (or certain amount of) the targeted demands. According to interviews, the objective for the immediate response often is to address targeted demands completely (100% demand coverage) which we highlight as a constraint in our model.
- The demands are assumed to be measured by ratio for each individual beneficiary at the PODs, and the number of individuals is known from the most recent pre-disaster census report.

[1] https://reliefweb.int/.
[2] https://logcluster.org/.
[3] https://data.humdata.org/.

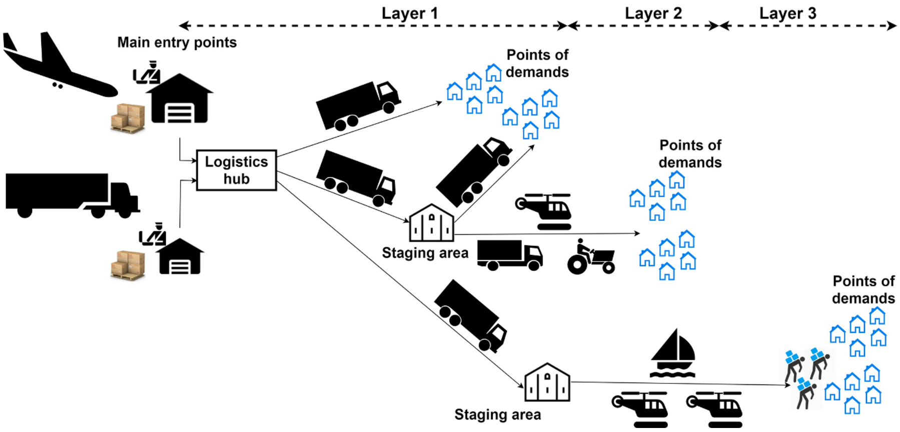

Fig. 3. Schematic presentation of our location–allocation problem.

- Ground and air transportation modes are assumed for shipping relief items. This is due to potential topography layers that may be seen in different countries.
- Required times for handling the relief items (customs control and packaging) are assumed to be negligible for the location–allocation decision (all internationally-sourced commodities have to get through).
- Ground fleets are assumed to be allocated in each SA with a limited number (locally limited). Helicopters can travel from every SA to the PODs in layers 2 and 3 but the total number of helicopters in the region and their daily tours are limited.
- All the available transportation modes at each SA can leave and reach their destinations on the same day. On the next day, the same number of means are available for operation.
- It is assumed that the time horizon of the operation can be divided into multiple time steps, such as days, weeks, or months. However, the shortest time step can be one single day.

3.4. Notations

3.4.1. Index sets

To formulate the model, a number of sets are defined in relation to the problem's illustration. As Fig. 3 shows, five distinct sets of nodes can be recognized in the relief distribution network; MEP, SA, and three layers of PODs. Furthermore, the duration of immediate response phase can be represented by a set of discrete time steps, $\mathbb{T}$, to (1) enable updating uncertain parameters of network such as demands (cf. Section 2.2.2), and (2) facilitate the determination of overall operations time. Also, a set of multiple commodities is assumed to be targeted for distribution in the network. Relevant indices are presented as follows.

$\mathbb{B}$ Set of main entry points ($b \in \mathbb{B} = \{1, 2, ..., B\}$)
$\mathbb{I}$ Set of potential locations for staging areas ($i \in \mathbb{I} = 1, 2, ..., I\}$)
$\mathbb{P}$ Set of demand points in POD layer 1 ($p \in \mathbb{P} = \{1, 2, ..., P\}$)
$\mathbb{J}$ Set of demand points in POD layer 2 ($j \in \mathbb{J} = \{1, 2, ..., J\}$)
$\mathbb{H}$ Set of demand points in POD layer 3($h \in \mathbb{H} = \{1, 2, ..., H\}$)
$\mathbb{T}$ Set of time steps ($t \in \mathbb{T} = \{1, 2, ..., T\}$)
$\mathbb{C}$ Set of relief commodity types ($c \in \mathbb{C} = \{1, 2, ..., C\}$)
$\mathbb{G}$ Set of ground transportation types available at field ($g \in \mathbb{G} = \{1, 2, ..., G\}$)
$\mathbb{A}$ Set of air transportation types available at field ($a \in \mathbb{A} = \{1, 2, ..., A\}$)

3.4.2. Model parameters

Parameters basically provide the known information of the problem to the model. This information includes travel distances and times between nodes, estimation of different costs, the quantity of demand, and characteristics of available MSUs and transportation modes (e.g. number and capacity).

$d_{b,i}$	Distance from the bth MEP to ith SA in km
$d_{b,p}$	Distance from the bth MEP to pth POD layer 1 in km
$d_{i,p}$	Distance from the ith SA to pth POD layer 1 in km
$d_{i,j}$	Distance from the ith SA to jth POD layer2 in km
$t_{b,i}$	Transit time from the bth MEP to ith SA in min
$t_{b,p}$	Transit time from the bth MEP to pth POD layer 1 in min
$t_{i,p}$	Transit time from the ith SA to pth POD layer 1 in min
$t_{i,j}$	Transit time from the ith SA to jth POD layer 2 in min
α^a	Estimates air transportation costs in USD/tour
α^g	Estimated ground transportation costs in USD/km
υ	Estimated human resources(HR) costs during the operations in *USD* per one *SA*
φ	Estimated recurring costs including the costs for rental, equipment, utilities, and supplies in USD per one *MSU* during the operations
m_h^c	Demand of commodity c in the hth POD layer 3 in kg
m_j^c	Demand of commodity c in the jth POD layer 2 in kg
m_p^c	Demand of commodity c in the pth POD layer 1 in kg
β_t	Maximum possible number of MSUs that can be erected simultaneously in tth time step
γ	Estimated required time for setting up an MSU in *timesteps*
ζ	Volume capacity of every MSU in m^3
π_i	Maximum number of MSUs that can be erected in the ith SA in *units*
σ	Total number of available MSUs in *units*
cap^a	Weight capacity of an air transportation of type a *in* mTons
cap^g	Weight capacity of a ground transportation of type g *in* mTons
τ_i^a	Number of helicopters of type $a$available in the ith SA in *units*
τ_b^g	Number of trucks of type $g$available in the bth MEP in *units*
τ_i^g	Number of trucks of type g available in the ith SA in *units*
δ	Maximum allowed driving time in min
ω	Maximum allowed distance for every helicopter tour in km
k^c	Weight of the cth commodity in kg/m^3
U	A very big number

3.4.3. Decision variables

As the model tries to locate SAs and allocate resources to them, four categories of decision variables are required. First, the location of selected SAs and the PODs which will be supported by these SAa, have to identified among the lists of potential places and layered PODs, respectively. Second, the required capacity in each selected SA to support allocated PODs has to be determined. Third, the suggested duration of operation should to be calculated. Fourth, the commodities and transportation flows have to be determined to align demand coverage in each layer with available shipment modes and capacities. Further explanation of decision variables are provided in the following.

Binary variables

LOC_i	1, if the ith candidate SA is opened;0, otherwise
$X_{b,p}$	1 if there is ground shipment between the bth MEP and pth POD(layer 1);0 otherwise
$X_{b,i}$	1 if there is ground shipment between the bth MEP and ith SA; 0 otherwise
$Y_{i,p}$	1 if there is ground shipment between the ith SA and pth POD(layer 1);0 otherwise
$Y_{i,j}$	1 if there is ground shipment between the ith SA and jth POD(layer2);0 otherwise
$Z_{i,j}$	1 if there is air shipment between the ith SA and jth POD(layer 2);0 otherwise
$Z_{i,h}$	1 if there is air shipment between the ith SA and hth POD (layer 3);0 otherwise
L_t	1 if there is an operation in the tth time step; 0 otherwise
E_t	1 if at least one MSU is erected in the tth time step; 0 otherwise

Continuous variables

$F^{c}_{t,b,p}$ Amount of cth item to be shipped from the bth MEP to pth POD (layer 1)by ground transportation in m^3

$M^{c}_{t,b,i}$ Amount of cth item to be shipped from the bth MEP to ith SA by ground transportation in m^3

$O^{c}_{t,i,p}$ Amount of cth item to be shipped from the ith SA to pth POD (layer 1)by ground transportation in m^3

$O^{c}_{t,i,j}$ Amount of cth item to be shipped from the ith SA to jth POD (layer 2)by ground transportation in m^3

$R^{c}_{t,i,j}$ Amount of cth item to be shipped from the ith SA to jth POD (layer 2)by air transportation in m^3

$R^{c}_{t,i,h}$ Amount of cth item to be shipped from the ith SA to hth POD (layer 3)by air transportation in m^3

$W_{t,i}$ Available inventory at SA at the end of t in m^3

Integer variables

$N_{t,i}$ Number of MSUs in the ith SA at tth time step in integers

$S^{g}_{t,b,i}$ Number of ground shipment of type g from the bth MEP to the ith SA

$S^{g}_{t,b,p}$ Number of ground shipment of type g from the bth MEP to the pth POD(layer 1)

$S^{g}_{t,i,p}$ Number of ground shipment of type g from the ith SA to the pth POD (layer 1)

$S^{g}_{t,i,j}$ Number of ground shipment of type g from the ith SA to the jthPOD (layer 2)

$Q^{a}_{t,i,j}$ Number of air shipment tours of type a from the ith SA to the jthPOD (layer 2)

$Q^{a}_{t,i,h}$ Number of air shipment tours of type $a$from the ith SA to the hthPOD (layer 3)

3.5. Objective function

The objective of the model is to determine the optimum location of SAs and the number of MSUs to be erected on them, the flow of commodities between different layers and inventory at SAs such that the total logistics costs and response time are minimized. The two objective functions of model have conflicting natures.

First objective

The minimization of logistics costs is the first objective which consists of ground transportation cost, air transportation cost, recurring cost and human resource cost. The ground transportation cost, which is represented by Eq. (1), includes the cost from MEPs to SAs, MEPs to PODs in layer 1 and SAs to PODs in Layers 1 and 2. Air transportation cost, i.e., Eq. (2), consists of costs related to shipping items from SAs to PODs in level 2 and 3 through air fleets. Recurring cost and human resource cost per location are rough estimations for the duration of the project and they are included in the model through Eqs. (3) and (4), respectively. The logistics costs objective function is formulated as below.

$$\begin{aligned} \textit{Minimize total logistics costs} = & \textit{Ground transportation cost} \\ & + \textit{Air transportation cost} \\ & + \textit{recurring cost} \\ & + \textit{Human resource cost} \end{aligned}$$

where

$$Ground\ transportation\ costs = \sum_{g=1}^{G} \alpha^g \ (\sum_{t=1}^{T} \sum_{b=1}^{B} \sum_{i=1}^{I} S_{t,b,i}^{g} d_{b,i} + \sum_{t=1}^{T} \sum_{b=1}^{B} \sum_{p=1}^{P} S_{t,b,p}^{g} d_{b,p} + \sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{p=1}^{P} S_{t,i,p}^{g} d_{i,p} + \sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{j=1}^{J} S_{t,i,j}^{g} d_{i,j}) \tag{1}$$

$$Air\ transportation\ costs = \sum_{a=1}^{A} \alpha^a \ (\sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{j=1}^{J} Q_{t,i,j}^{a} + \sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{h=1}^{H} Q_{t,i,h}^{a}) \tag{2}$$

$$Recurring\ cost = \varphi \sum_{t=1}^{T} \sum_{i=1}^{I} N_{t,i} \tag{3}$$

$$Human\ resource\ costs = \upsilon \sum_{i=1}^{I} LOC_i \tag{4}$$

Second objective

The second objective is the minimization of response time and consists of two components. The first component, Eq. (5), consists of the required time for setting up MSUs at located staging areas. Eq. (5) includes the result of multiplying required days for erecting one MSU (or multiple MSUs simultaneously) and the summation of the binary variable E_t. This variable is calculated by constraints (34) and (35), and refers to every attempt to erect one MSU (or multiple MSUs simultaneously). The second component, Eq. (6), refers to the busy time steps during the operation. Eq. (6) represents the summation of the binary variable L_t. This variable counts every time step in the network that includes a shipment from MEPs to SAs/PODs and/or from SAs to PODs. The binary variable L_t is determined through the constraints (43)–(45) which will be explained later.

$$Minimize\ total\ response\ time = MSU\ setup\ time + Operation\ time$$

where

$$MSU\ setup\ time = \gamma \sum_{t=1}^{T} E_t \tag{5}$$

$$Operation\ time = \sum_{t=1}^{T} L_t \tag{6}$$

In order to minimize the second objective function, the number of busy days has to be decreased as many as possible. This cannot be done unless the maximum number of transportation means be allocated to the operation in every busy day to complete the delivery as soon as possible. However, this contradicts with the nature of the first objective function which tries to decrease the number of allocated transportation means to minimize logistics costs.

Subject to constraints

$$F_{t,b,p}^{c} \leqslant UX_{b,p} \qquad \forall\ t \in \mathbb{T},\ c \in \mathbb{C},\ b \in \mathbb{B},\ p \in \mathbb{P} \tag{7}$$

$$M_{t,b,i}^{c} \leqslant UX_{b,i} \qquad \forall\ t \in \mathbb{T},\ c \in \mathbb{C},\ b \in \mathbb{B},\ i \in \mathbb{I} \tag{8}$$

$$X_{b,i} \leqslant LOC_i \qquad \forall\ b \in \mathbb{B},\ i \in \mathbb{I} \tag{9}$$

Constraints (7) and (8) ensure that relief items can be transferred from MEPs to PODs (first layer) and SAs only if MEP is connected to these locations, respectively. Similarly, Constraint (9) makes sure that the MEP can be connected to a SA only if the SA is located there.

$$\sum_{c=1}^{C} \sum_{p=1}^{P} O_{t,i,p}^{c} + \sum_{c=1}^{C} \sum_{j=1}^{J} O_{t,i,j}^{c} + \sum_{c=1}^{C} \sum_{j=1}^{J} R_{t,i,j}^{c} + \sum_{c=1}^{C} \sum_{h=1}^{H} R_{t,i,h}^{c} \leqslant W_{t,i} \qquad \forall\ t \in \mathbb{T},\ i \in \mathbb{I} \tag{10}$$

Constraint (10) shows that the amount of relief items transferred from established SAs is less than or equal to the maximum inventory available at given SA during that time step.

$$O^c_{t,i,p} \leqslant UY_{i,p} \qquad \forall\, t \in \mathbb{T},\, c \in \mathbb{C},\, i \in \mathbb{I},\, p \in \mathbb{P} \tag{11}$$

$$O^c_{t,i,j} \leqslant UY_{i,j} \qquad \forall\, t \in \mathbb{T},\, c \in \mathbb{C},\, i \in \mathbb{I},\, j \in \mathbb{J} \tag{12}$$

$$R^c_{t,i,j} \leqslant UZ_{i,j} \qquad \forall\, t \in \mathbb{T},\, c \in \mathbb{C},\, i \in \mathbb{I},\, j \in \mathbb{J} \tag{13}$$

$$R^c_{t,i,h} \leqslant UZ_{i,h} \qquad \forall\, t \in \mathbb{T},\, c \in \mathbb{C},\, i \in \mathbb{I},\, h \in \mathbb{H} \tag{14}$$

Constraints (11)–(14) imply that relief items can be shipped from SAs to PODs only if they are connected.

$$Y_{i,p} \leqslant LOC_i \qquad \forall\, i \in \mathbb{I},\, p \in \mathbb{P} \tag{15}$$

$$Y_{i,j} \leqslant LOC_i \qquad \forall\, i \in \mathbb{I},\, j \in \mathbb{J} \tag{16}$$

$$Z_{i,j} \leqslant LOC_i \qquad \forall\, i \in \mathbb{I},\, j \in \mathbb{J} \tag{17}$$

$$Z_{i,h} \leqslant LOC_i \qquad \forall\, i \in \mathbb{I},\, h \in \mathbb{H} \tag{18}$$

Constraints (15)–(18) ensure that a SA can be assigned to a POD only if the SA is established.

$$W_{t-1,i} + \sum_{c=1}^{C}\sum_{b=1}^{B} M^c_{t,b,i} \leqslant \zeta N_{t,i} \qquad \forall\, t \in \mathbb{T},\, i \in \mathbb{I} \tag{19}$$

$$\begin{aligned} W_{t-1,i} + \sum_{c=1}^{C}\sum_{b=1}^{B} M^c_{t,b,i} &- \sum_{c=1}^{C}\sum_{p=1}^{P} O^c_{t,i,p} - \sum_{c=1}^{C}\sum_{j=1}^{J} O^c_{t,i,j} \\ &- \sum_{c=1}^{C}\sum_{j=1}^{J} R^c_{t,i,j} - \sum_{c=1}^{C}\sum_{h=1}^{H} R^c_{t,i,h} \leqslant W_{t,i} \qquad \forall\, t \in \mathbb{T},\, i \in \mathbb{I} \end{aligned} \tag{20}$$

Constraints (19) and (20) make sure that inventory at SA does not exceed the storing capacity.

$$k^c\left(\sum_{t=1}^{T}\sum_{i=1}^{I} O^c_{t,i,p} + \sum_{t=1}^{T}\sum_{b=1}^{B} F^c_{t,b,p}\right) \geqslant m^c_p \qquad \forall\, c \in \mathbb{C},\, p \in \mathbb{P} \tag{21}$$

$$k^c\left(\sum_{t=1}^{T}\sum_{i=1}^{I} O^c_{t,i,j} + \sum_{t=1}^{T}\sum_{i=1}^{I} R^c_{t,i,j}\right) \geqslant m^c_j \qquad \forall\, c \in \mathbb{C},\, j \in \mathbb{J} \tag{22}$$

$$k^c\left(\sum_{t=1}^{T}\sum_{i=1}^{I} R^c_{t,i,h}\right) \geqslant m^c_h \qquad \forall\, c \in \mathbb{C},\, h \in \mathbb{H} \tag{23}$$

Constraints (21)–(23) ensure that the demands in each layer are 100% met. The constraint for addressing 100% of estimated demands is driven from our interviews with practitioners regarding what objectives they often target in the immediate response.

$$\begin{aligned} \sum_{t=1}^{T}\sum_{p=1}^{P} O^c_{t,i,p} &+ \sum_{t=1}^{T}\sum_{j=1}^{J} O^c_{t,i,j} + \sum_{t=1}^{T}\sum_{j=1}^{J} R^c_{t,i,j} \\ &+ \sum_{t=1}^{T}\sum_{h=1}^{H} R^c_{t,i,h} \leqslant \sum_{t,b} M^c_{t,b,i} \qquad \forall\, c \in \mathbb{C},\, i \in \mathbb{I} \end{aligned} \tag{24}$$

Constraint (24) guarantees the balance between the items delivered to the demand points and items supplied to the SAs.

$$\sum_{i=1}^{I} Y_{i,p} + \sum_{b=1}^{B} X_{b,p} \geqslant 1 \qquad \forall\, p \in \mathbb{P} \tag{25}$$

$$\sum_{i=1}^{I} Y_{i,j} + \sum_{i=1}^{I} Z_{i,j} \geqslant 1 \qquad \forall\, j \in \mathbb{J} \tag{26}$$

$$\sum_{i=1}^{I} Z_{i,h} \geqslant 1 \qquad \forall\, h \in \mathbb{H} \tag{27}$$

Constraints (25)–(27) ensure that the demand points in layers 1– 3 are covered by at least one SA.

$$X_{b,i} t_{b,i} \leqslant \delta \qquad \forall\, b \in \mathbb{B},\, i \in \mathbb{I} \tag{28}$$

Constraint (28) ensures that MEPs support only those SAs that can be accessed within a certain driving time, δ.

$$Y_{i,p} t_{i,p} \leqslant \delta \qquad \forall\, i \in \mathbb{I},\, p \in \mathbb{P} \tag{29}$$

$$X_{b,p} t_{b,p} \leqslant \delta \qquad \forall\, b \in \mathbb{B},\, p \in \mathbb{P} \tag{30}$$

Constraints (29) and (30) state which PODs in the layer 1 can be potentially supported by every SA and MEP by truck, respectively.

$$Y_{i,j} t_{i,j} \leqslant \delta \qquad \forall\, i \in \mathbb{I},\, j \in \mathbb{J} \tag{31}$$

Constraint (31) ensures the travel time between potential SAs and allocated PODs to them in layer 2 for ground transportation are less than δ.

$$Z_{i,j} d_{i,j} \leqslant \omega \qquad \forall\, i \in \mathbb{I},\, j \in \mathbb{J} \tag{32}$$

Constraint (32) guarantees that air transportation (e.g., helicopters) are only allocated for transporting items to PODs within a certain distance.

$$N_{t,i} \leqslant LOC_i \pi_i \qquad \forall\, t \in \mathbb{T},\, i \in \mathbb{I} \tag{33}$$

$$\sum_{i=1}^{I} (N_{t,i} - N_{t-1,i}) \leqslant \beta_t E_t \qquad \forall\, t \in \mathbb{T} \tag{34}$$

$$N_{t-1,i} \leqslant N_{t,i} \qquad \forall\, t \in \mathbb{T},\, i \in \mathbb{I} \tag{35}$$

Constraint (33) limits the number of MSUs in each SA to the space constraint. Sometimes it would not be possible to erect as many MSUs as we want in an SA. Constraint (34) ensures that only β number of MSUs can be erected simultaneously in the SAs. For the simplicity of computation, Constraint (35) guarantees that the number of MSUs in each SA can only remain the same or increase in each time step.

$$\sum_{i=1}^{I} N_{t,i} \leqslant \sigma \qquad \forall\, t \in \mathbb{T} \tag{36}$$

Constraint (36) ensures that the total number of proposed MSUs is less than available MSUs for the operation.

$$\sum_{c=1}^{C} M_{t,b,i}^{c} \frac{k^c}{1000} \leqslant \sum_{g=1}^{G} S_{t,b,i}^{g} cap^g \qquad \forall\, t \in \mathbb{T},\, b \in \mathbb{B},\, i \in \mathbb{I} \tag{37}$$

$$\sum_{c=1}^{C} F_{t,b,p}^{c} \frac{k^c}{1000} \leqslant \sum_{g=1}^{G} S_{t,b,p}^{g} cap^g \qquad \forall\, t \in \mathbb{T},\, b \in \mathbb{B},\, p \in \mathbb{P} \tag{38}$$

$$\sum_{c=1}^{C} O_{t,i,p}^{c} \frac{k^c}{1000} \leqslant \sum_{g=1}^{G} S_{t,i,p}^{g} cap^g \qquad \forall\, t \in \mathbb{T},\, i \in \mathbb{I},\, p \in \mathbb{P} \tag{39}$$

$$\sum_{c=1}^{C} O_{t,i,j}^{c} \frac{k^c}{1000} \leqslant \sum_{g=1}^{G} S_{t,i,j}^{g} cap^g \qquad \forall\, t \in \mathbb{T},\, i \in \mathbb{I},\, j \in \mathbb{J} \tag{40}$$

Constraints (37)–(40) guarantee that the shipped items do not exceed the capacity of ground transportation with respect to the weight limitation.

$$\sum_{c=1}^{C} R_{t,i,j}^{c} \frac{k^c}{1000} \leqslant \sum_{a=1}^{A} Q_{t,i,j}^{a} cap^a \qquad \forall\, t \in \mathbb{T},\, i \in \mathbb{I},\, j \in \mathbb{J} \tag{41}$$

$$\sum_{c=1}^{C} R_{t,i,h}^{c} \frac{k^c}{1000} \leqslant \sum_{a=1}^{A} Q_{t,i,h}^{a} cap^a \qquad \forall\, t \in \mathbb{T},\, i \in \mathbb{I},\, h \in \mathbb{H} \tag{42}$$

Using a similar approach as for ground transportation for air fleets, constraints (41) and (42) state the weight capacity limitation for air transportation systems.

$$\sum_{i=1}^{I} S_{t,b,i}^{g} + \sum_{p=1}^{P} S_{t,b,p}^{g} \leqslant \tau_b^g L_t \qquad \forall\, t \in \mathbb{T},\, b \in \mathbb{B},\, p \in \mathbb{P},\, i \in \mathbb{I},\, g \in G \tag{43}$$

$$\sum_{p=1}^{P} S_{t,i,p}^{g} + \sum_{j=1}^{j} S_{t,i,j}^{g} \leqslant \tau_i^g L_t \qquad \forall\, t \in \mathbb{T},\, i \in \mathbb{I},\, p \in \mathbb{P},\, j \in \mathbb{J},\, g \in G \tag{44}$$

$$\sum_{j=1}^{J} Q_{t,i,j}^{a} + \sum_{h=1}^{H} Q_{t,i,h}^{a} \leqslant \tau_i^a L_t \qquad \forall\, t \in \mathbb{T},\, i \in \mathbb{I},\, j \in \mathbb{J},\, h \in \mathbb{H},\, g \in G \tag{45}$$

Constraints (43)–(45) guarantee that number of transportation between nodes in each time step do not exceed the number of available transportation means. These constraints also ensure that whenever a shipment is taken place in the network at time step t, the counter L_t will consider the time step as an operation day.

$$S^{g}_{t,b,p} \leqslant UX_{b,p} \qquad \forall\ t \in \mathbb{T},\ b \in \mathbb{B},\ p \in \mathbb{P},\ g \in G \tag{46}$$

$$S^{g}_{t,b,i} \leqslant UX_{b,i} \qquad \forall\ t \in \mathbb{T},\ b \in \mathbb{B},\ i \in \mathbb{I},\ g \in G \tag{47}$$

$$S^{g}_{t,i,p} \leqslant UY_{i,p} \qquad \forall\ t \in \mathbb{T},\ i \in \mathbb{I},\ p \in \mathbb{P},\ g \in G \tag{48}$$

$$S^{g}_{t,i,j} \leqslant UY_{i,j} \qquad \forall\ t \in \mathbb{T},\ i \in \mathbb{I},\ j \in \mathbb{J},\ g \in G \tag{49}$$

$$Q^{a}_{t,i,j} \leqslant UZ_{i,j} \qquad \forall\ t \in \mathbb{T},\ a \in \mathbb{A},\ i \in \mathbb{I},\ j \in \mathbb{J} \tag{50}$$

$$Q^{a}_{t,i,h} \leqslant UZ_{i,h} \qquad \forall\ t \in \mathbb{T},\ a \in \mathbb{A},\ i \in \mathbb{I},\ h \in \mathbb{H} \tag{51}$$

Constraints (46)–(51) ensure that transportation takes place only if the two locations are connected.

$$LOC_i \leqslant \sum_{b=1}^{B} X_{b,i} + \sum_{p=1}^{P} Y_{i,p} + \sum_{j=1}^{J} Y_{i,j} + \sum_{j=1}^{J} Z_{i,j} + \sum_{h=1}^{H} Z_{i,h} \qquad \forall\ i \in \mathbb{I} \tag{52}$$

$$LOC_i,\ X_{b,p},\ X_{b,i},\ Y_{i,p},\ Y_{i,j},\ Z_{i,j},\ Z_{i,h} \in 0,\ 1 \qquad \forall\ i \in \mathbb{I},\ b \in \mathbb{B},\ p \in \mathbb{P},\ j \in \mathbb{J},\ h \in \mathbb{H} \tag{53}$$

Constraints (52) and (53) ensure that the values for the binary variables are determined accordingly.

3.6. Solution approach

To solve our linear bi-objective mixed-integer problem, we employed Mavrotas and Florios (2013)'s algorithm, which is called augmented epsilon constraint method version 2 (AUGMECON2). The algorithm has been demonstrated to be very efficient for providing the set of Pareto optimal solutions in multi-objective mixed-integer problems compared with the alternative methods in the literature. Its ready-to-use version is available on the GAMS optimization platform. AUGMECON2 algorithm is developed based on the well-known ϵ-constraint method that optimizes one of the objective functions using the remaining objective functions as constraints, varying their right-hand sides (Deb, 2001). The ϵ-constraint method consists of two phases: (1) generation of the payoff table and (2) usage of the ranges from the payoff table to apply the method. AUGMECON2 employs lexicographic optimization in the construction of the payoff table. This algorithm can be used to generate the exact Pareto set (all the Pareto optimal solutions) if the step size (i.e., the interval between the grid points of the objective functions that are used as constraints) is appropriately chosen. Mavrotas and Florios (2013) suggest setting the step size equal to the range of the integer objective function in the payoff table.

4. Case study

4.1. Overview of the Nepal case

The 2015 Nepal earthquakes cost the lives of about 9000 people, nearly 22,500 were injured, and more than half a million houses collapsed or were damaged (Government of Nepal, 2015). Supplying food to millions who had lost their homes and belongings immediately became the top priority. The Government of Nepal (GoN) requested UN WFP "*to focus on delivering food to the most heavily affected districts outside of the Kathmandu Valley*" (UNWFP, 2015b). The UN WFP proposed Emergency Operation Plan 200668 that had two phases for covering the food demands: immediate relief and structured relief (UNWFP, 2015a). In the immediate relief, the aim was to deliver ten-day food rations within five weeks (April and May 2015) to 1.9 million people in seven severely affected districts "*to support basic caloric needs of earthquake survivors in the hardest hit districts*" (UNWFP, 2015b).

The distribution of relief materials proved challenging owing to remoteness of many affected villages, the widespread destruction of transportation infrastructure, rugged terrain, recurrent landslides, and other logistical difficulties such as insufficient fleets (Paul et al., 2017). Also, observations confirmed a huge backlog at country entry points due to imbalance between the supply and distribution plans (Baharmand et al., 2016). Some HOs even did not have an alternative distribution plan to continue delivering relief items, for instance, when drivers refused to transport commodities to a certain location (Baharmand et al., 2017a). Also, lack of using DSSs was observed in the majority of HOs involved in the Nepal response (Baharmand et al., 2016). Such challenges led to huge backlogs and material convergence in the MEPs (like the international airport) and caused deprivations in affected communities due to delivery delays (Paul et al., 2017; Baharmand et al., 2016).

The Humanitarian Staging Area (HSA), which was located at Kathmandu International Airport, served as the main entry point for the relief items. In total, the Logistics Cluster established eight SAs across the country. The sequence and approximate opening times and number of MSUs in each location are listed in Table 3. According to UNWFP (2015c), the UN WFP mainly utilized two SAs (Deurali and Chautara) for their distribution. The remaining SAs were used either for strategic purposes (Dhulikhel and Bharatpur that were opened to decrease the pressure on the HSA in Kathmandu) or to support partner HOs via the Logistics Cluster (Dhading Besi, Bidur, Dhunche, and Charikot) (UNWFP, 2015a).

We avail the following data sources to estimate the input data for our models: number of households in the PODs (estimated from the 2011 Nepal census report), the Logistics Cluster selected locations for setting up the SAs (as shown in Fig. 4), box sizes for

Table 3
Logistics Cluster staging areas, number of MSUs, and their capacity (m²) during the Nepal response.
source: Logcluster.org

Staging areas	26 April 2015	5 May 2015	10 May 2015	15 May 2015	18 May 2015
HSA Kathmandu	8 × 320	8 × 320	8 × 320	8 × 320	8 × 320
1. Deurali	–	3 × 320	3 × 320	3 × 320	3 × 320
2. Chautara	–	–	1 × 320	4 × 320	4 × 320
3. Dhulikhel	–	–	2 × 320	4 × 320	4 × 320
4. Bharatpur	–	–	1 × 320	4 × 320	4 × 320
5. Dhading Besi	–	–	–	–	1 × 320
6. Bidur	–	–	–	–	1 × 320
7. Dhunche	–	–	–	–	1 × 320
8. Charikot	–	–	–	–	1 × 320

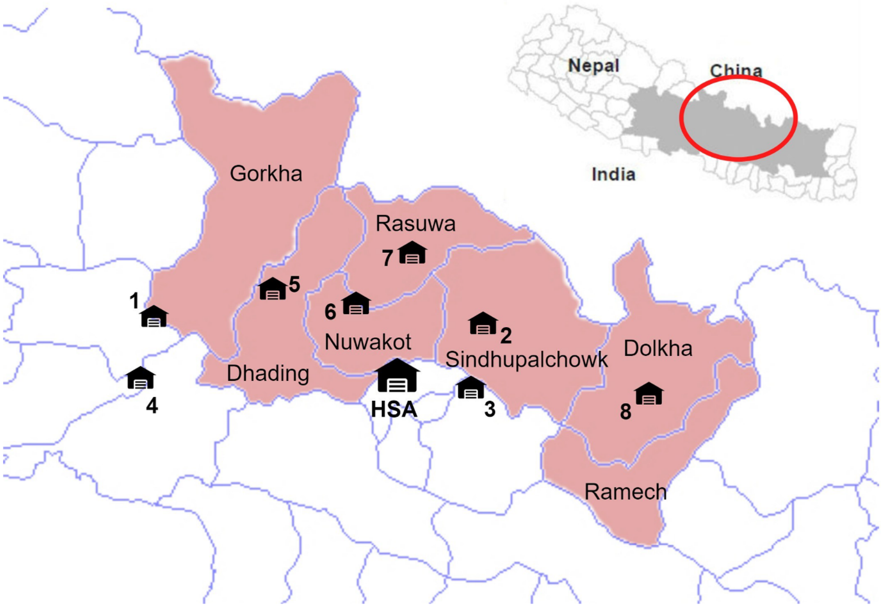

Fig. 4. An overview of affected districts and the location of staging areas established by Logistics Cluster (locations data from Logcluster.org).

delivered food (the UN WFP handbook and interviews), travel times/travel distances (acquired from one Nepalese logistics service provider), and specifications of the MSUs established during the Nepal response (reports from the Logistics Cluster).

The parameters related to the logistics costs are elicited from the business experts of the UN WFP. We ensured that the used parameter values are the "best guess," as depicted in Table 4. In the calculations, the monthly costs were adapted to the estimated timeline of the operation. More details regarding our input data are provided in Appendix A.

4.2. Application results

We implemented our models on GAMS 24.9.1 and used CPLEX 12.7 to solve the model following the AUGMECON2 algorithm. We used a personal laptop with Intel Core i5-4300U processor at 1.90 GHz and 8 GB of RAM operating under Windows 10. To derive the appropriate step size, we solved the immediate response model by setting the number of grid points to an assumed number, 2. From the payoff table, we revised the number of grid points to three (the range for the response time objective function), and then, we

Table 4
Cost parameters for the Nepal case.

Name	Description	Value
Recurring costs	Includes estimates for rental, equipment, utilities, supplies, and preparations in Nepal per day	$850
Trucks costs	Estimating the driving cost for Nepalese drivers per kilometer	$10
Helicopter costs	An estimation of costs for using helicopters per tour	$12000
HR salary	Includes estimates for having both international and national resources in the team per month	$17500
Operation timeline	Maximum estimated days for carrying out the operation	45 days

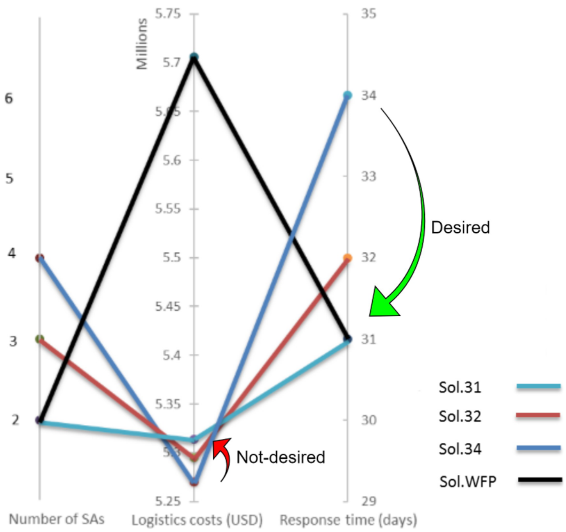

Fig. 5. Comparing model solutions with UN WFP's network for the 2015 Nepal earthquake immediate response and trade-offs.

solved the model while setting the value for the default "relative gap" parameter in GAMS (%10).

By setting "relative gap = 0.1," the AUGMECON2 algorithm could produce the Pareto fronts of the model in 353 s. We note that the required time for collecting the input data of the model and analyzing the results will be added to the time in real operations. Thus, decreasing the solution time for the model is preferred, specifically when the problem size increases. This will be further analyzed in Section 4.3.

Using the actual UN WFP data, we can compare our results with the performance of their network during the immediate response to the 2015 Nepal earthquake, as shown in Fig. 5. Sol.WFP, represents the optimized values of the objective functions for the given location of the SAs that the UN WFP used. Other curves represent the solutions provided by AUGMECON2 algorithm with default value of the relative gap parameter.

Fig. 5 depicts the deviation between the model results and the network of the UN WFP. In this setting, Sol.31 refers to the solution that suggests delivering relief items in 31 days, and it suggests 7% less costs than Sol.WFP. The deviation is further explained in Fig. 6. Indeed, the traveling distance and time from locations 1 and 2 (SAs in Sol.WFP) to densely populated PODs impose more costs

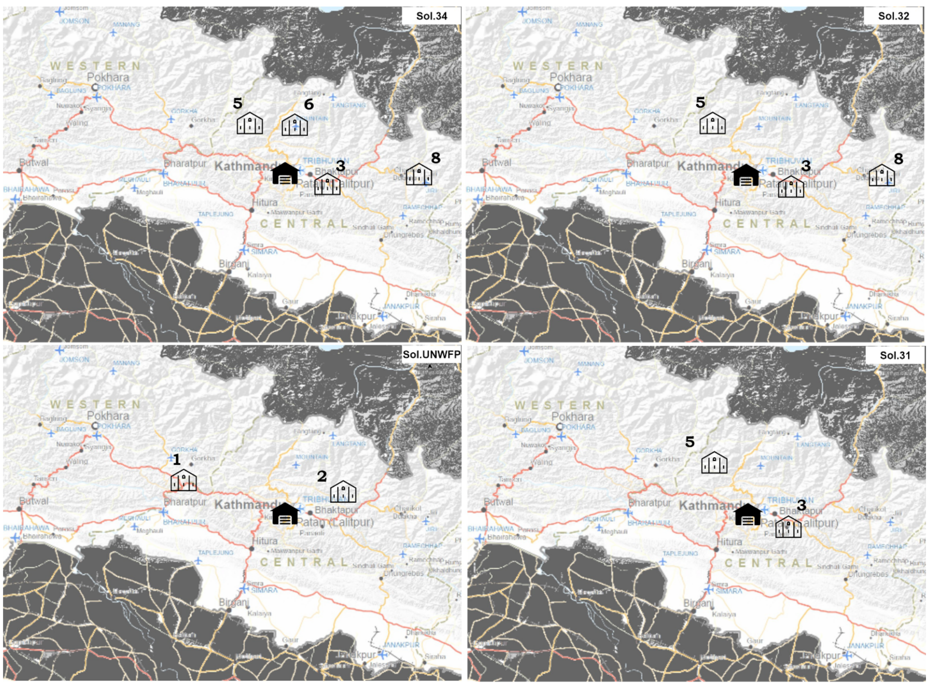

Fig. 6. Network configurations of the Pareto front solutions vs. UN WFP's network in the immediate response.

Table 5
The considered ranges for generating random locations at every instances.

Instance category	Main entry points	Staging areas	Demand points (in each layer)
OC	1	8	8
A	1–3	10–15	10–24
B	4–6	16–21	25–39

comparing with locations 3 and 5 in Sol.31. However, we have to consider that the access constraints from or to location 5 (Dhading Besi) during the first days after the earthquake possibly had delayed the opening dates of this SA (cf. Table 3) and thus, effected the decision of the UN WFP.

We also notice that suggested solutions of the model have similarities in their network structures, as depicted in Fig. 6. Solutions 34 and 32 represent the extended network of solution 31. These solutions basically suggest that more SAs are needed to enable further ground transportation instead of air deliveries as solution 31. Although air deliveries impose more logistics costs compared with ground transportation (Sol.31 costs approximately %1 more than Sol.34), it enables a more rapid demand coverage (3 days), which can have a high priority in the immediate response phase.

Fig. 5 clearly highlights the trade-offs between minimizing logistics costs and response time in the studied problem. Investing %1 more on the logistics costs and opening 4 SAs instead of 2, decreased the response time by approximately %10. Similar conflicts have been noted in the literature between minimizing logistics cost and unsatisfied demand (Maharjan and Hanaoka, 2018) which supports the idea that common objectives in humanitarian response have conflicting nature (Gralla et al., 2014). The trade-offs between multiple objectives can ultimately challenge finding a consensus specifically in the presence of multiple DMs, actors and stakeholders, as in humanitarian response (Campbell and Clarke, 2018).

4.3. Further numerical analysis with example data-sets

We generated five random problem instances based on Maharjan and Hanaoka (2017)'s study of Nepal disaster prone districts to further verify the performance of our proposed model. The main characteristics of the instances are compared with the original case (OC) in Table 5. The number of MEPs were increased in the instances as there can be more entry points like ground borders and airports. The PODs and demands were also increased by assuming that the populations in different disaster prone districts were affected (Maharjan and Hanaoka, 2017). Further potential SA locations are derived based on Maharjan and Hanaoka (2017)'s study. The constraints (43)–(45) (the maximum number of available transportation) and (36) (number of available MSUs) were relaxed when solving the instances of *B* category. The solution approach, computer configuration, and solver parameters settings were kept similar to the analysis of Nepal case.

Table 6 shows the Pareto solution with the earliest response time after solving the model for every instance. The outcomes share some insights regarding the model performance. If we compare OC with A–1, as numbers of SAs and PODs have been increased by 90% and 25% respectively, the solution time has raised significantly. Moreover, although A–2 and A–3 are similar in the number of MEPs, the earliest response time is almost tripled in the later as the number of PODs in A–3 has increased by more than 75%. In instances of *B* category, the response time shows more than 40% increase compared to A–3 despite the relaxation of transportation constraints. This can be due to the raise n the number of demands. Also, the logistics costs have increased by more than 50% if we compare B–1 and A–3.

The results of Table 6 show that by increasing the number of nodes, the solution time increases drastically. However, this can be challenging in the field where DMs have to make critical decisions under stress and time pressure. Some approaches to deal with this issue can be parallelization and running the model on a cluster or simplification and aggregation of nodes. We will discuss these approaches in more details in Section 5.

4.4. Sensitivity analysis

We also conducted a sensitivity analysis to show how varying model parameters would affect the results and objective functions of the proposed model. We analyzed the effects of changing demands, number of available ground transportation, number of available

Table 6
The results of applying the model to some randomly generated instances.

Instance number	Instance components MEP-SA-POD	Total logistics costs (USD)	Total response time (days)	Number of SAs	CPU time (min)
OC	01-08-(08,08,08)	5.31*E*6	31	2	6
A-1	01-15-(10,10,10)	8.1*E*6	44	2	37
A-2	02-10-(13,13,13)	10.2*E*6	44	4	48
A-3	02-14-(23,23,23)	18.9*E*6	113	5	71
B-1	04-20-(27,27,27)	29.1*E*6	159	5	85
B-2	04-18-(35,35,35)	29.3*E*6	268	5	112

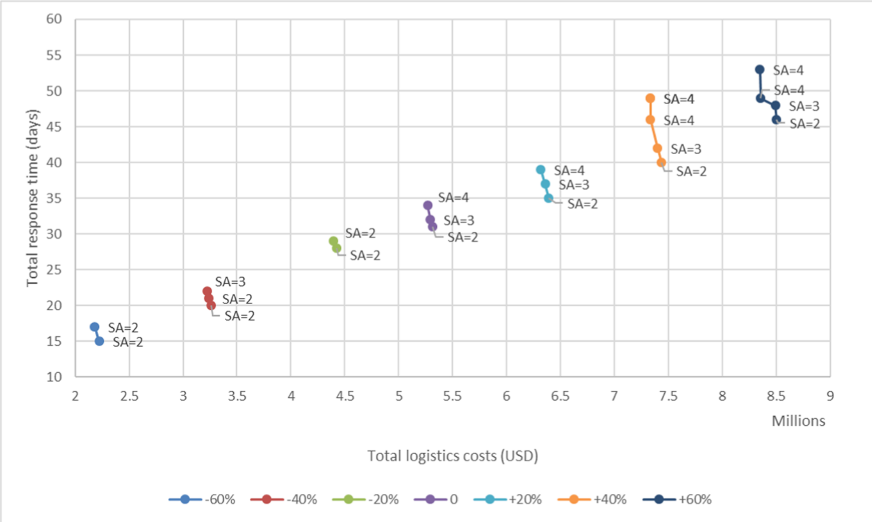

Fig. 7. Impact of changing the demands.

air transportation, ground transportation costs, air transportation costs, recurring and human resource costs, weight of delivered relief packages and MSU setup days. We chose these parameters because (a) any change in the related estimation can affect the values of the objective functions of the model considerably, and (b) the values of these parameters may change suddenly during the response according to our interviews with the logisticians. We performed the sensitivity analysis on the Nepal problem and the results are explained in the following. The derived managerial insights are discussed in Section 5.2.

4.4.1. Sensitivity to demands

The impacts of varying demands − 60%, −40%, −20%, +20%, +40% and + 60% on the total logistics cost and total response time objectives are presented in Fig. 7. Our analysis showed that although both objectives are sensitive to changes in the demands, the configuration of the proposed relief distribution network (e.g., number of located and the place of suggested SAs) did not change in 66.6% of scenarios. For instance, despite the increase of demands by 40% there is no need for additional SA to deliver relief items in 40 days if we compare it to the original value. The number and location of established SAs are same when the demands decrease by 40% and 60%. However, as Fig. 7 depicts, the suggested earliest time for efficiently delivering relief items increases when the demand is raised.

4.4.2. Sensitivity to recurring and human resource costs

Every established MSU imposes recurring costs. Similarly, each located SA needs sufficient number of human resources for

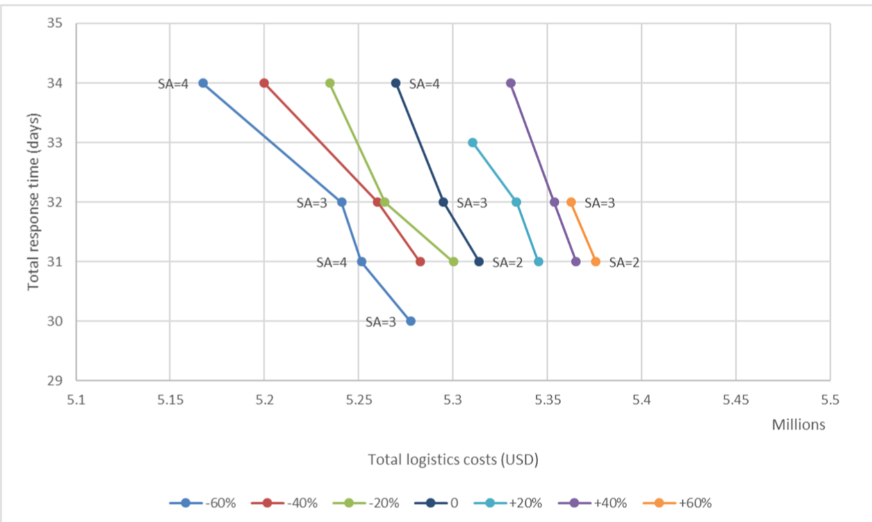

Fig. 8. Impact of changing recurring and human resource costs.

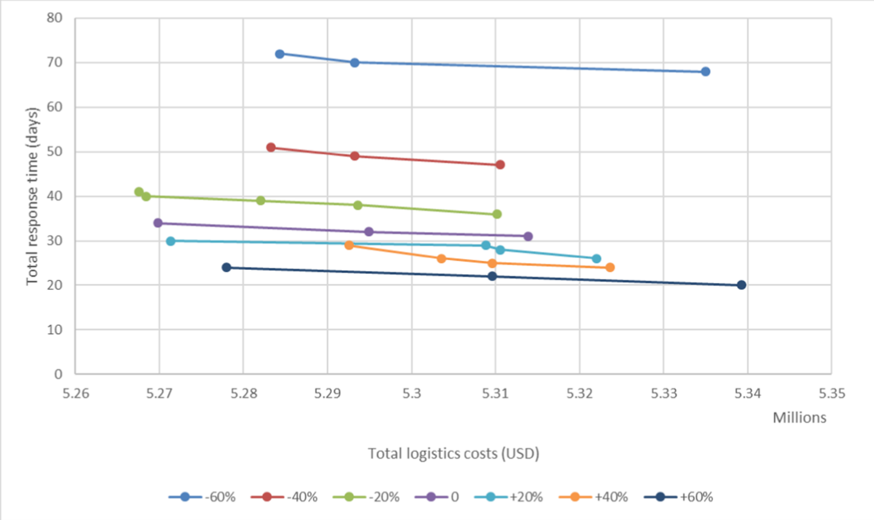

Fig. 9. Impact of changing the number of available ground transportation fleets.

duration of operation. Fig. 8 illustrates the changes in the objectives if we vary the recurring and human resource associated costs parameters simultaneously by − 60%, −40%, −20%, +20%, +40%, and + 60%. Interestingly, our analysis showed that the maximum and minimum number of established SAs and MSUs do not change while varying the recurring and human resource cost parameters from − 60% to + 60% of the original values. However, it could be predicted that the decrease and increase in the abovementioned cost parameters would affect the total logistics costs. Interestingly, decreasing recurring and human resource costs by − 60% enables allocating more air fleets for transportation and eventually can result in quicker response. However, increasing these costs do not change the shortest response time.

4.4.3. Sensitivity to numbers of available ground and air transportation fleets

Fig. 9 represents the impacts of varying available ground transportation means by − 60%, −40%, −20%, +20%, +40% and + 60% on the logistics costs and response time objective functions. This figure shows that having access to more ground fleets enables quicker relief distribution for a lower total logistics costs compared to the original values. For instance, by comparing the impact of + 40% change in the number of available ground transportation with original values we note that our model suggests quicker relief distribution with fewer logistics costs. However, the decrease of the available number of ground fleets increases both response time and logistics costs. With − 40% change in the available ground fleets, the earliest response time raises up to 50%.

Moreover, Fig. 10 illustrates the results of varying available air transportation means. As this figure shows, marginal decrease/increase in the number of air fleets does not affect the objective values considerably. However, − 40% and − 60% changes increase the

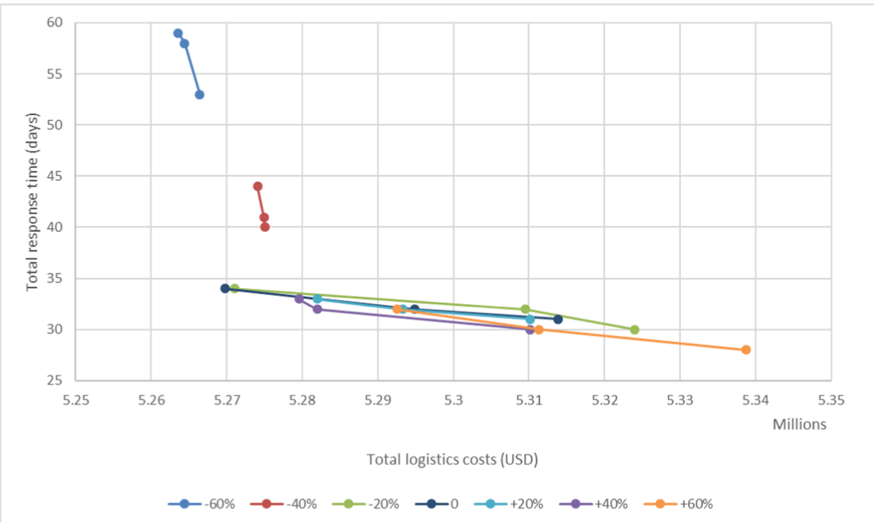

Fig. 10. Impact of changing the number of available air transportation fleets.

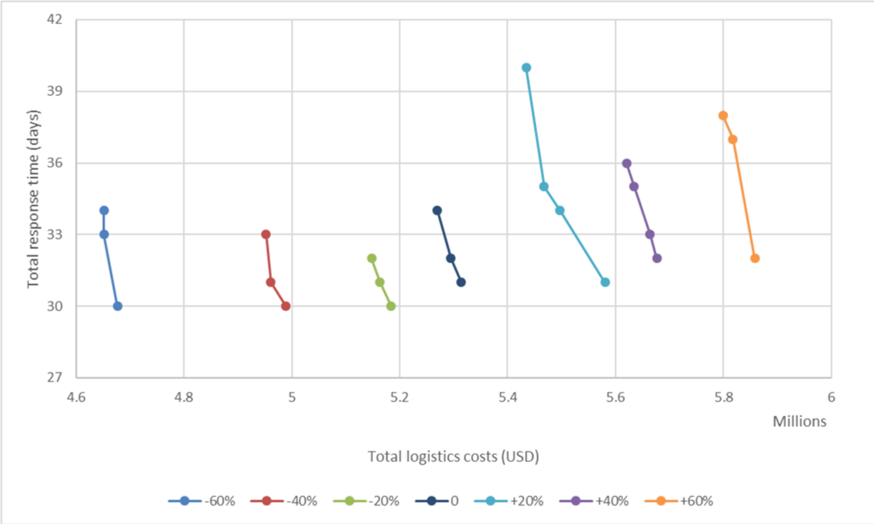

Fig. 11. Impact of changing ground transportation costs.

response time drastically as more ground fleets have to be used to deliver relief items. This also justifies the decrease in the logistics costs, as ground transportation is way much cheaper than its air counterpart for the same distance.

4.4.4. Sensitivity to costs of ground and air transportation means

Transportation costs have been often referred to as one of the main uncertain factors in the response contexts (Baharmand et al., 2017a; Loree and Aros-Vera, 2018). Figs. 11 and 12 present the outcome of analyzing the sensitivity of objective functions to varying ground and air transportation costs. These figures are the outcome of investigating the impacts of changing related cost factors by − 60%, −40%, −20%, +20%, +40% and + 60%. In fact, this could be predicted that any increase or decrease in the transportation cost factors affects the logistics costs directly. However, the impact of air transportation cost on the cost objective is much larger than the impact of ground transportation cost. For instance, + 20% increase in the ground transportation costs moves the curve of total logistics costs to the right side (overally more expensive) by 5% while similar increase in air transportation costs moves the curve to the same direction by roughly 17%. The effect of changing cost factors on the response time is also noteworthy. For instance, + 20% change of ground transportation cost does not impact the earliest response time while similar change in air transportation cost increases the response time.

4.4.5. Sensitivity to weight of relief items and setup days

The impacts of varying relief package weight − 60%, −40%, −20%, +20%, +40% and + 60% on the total logistics cost and total

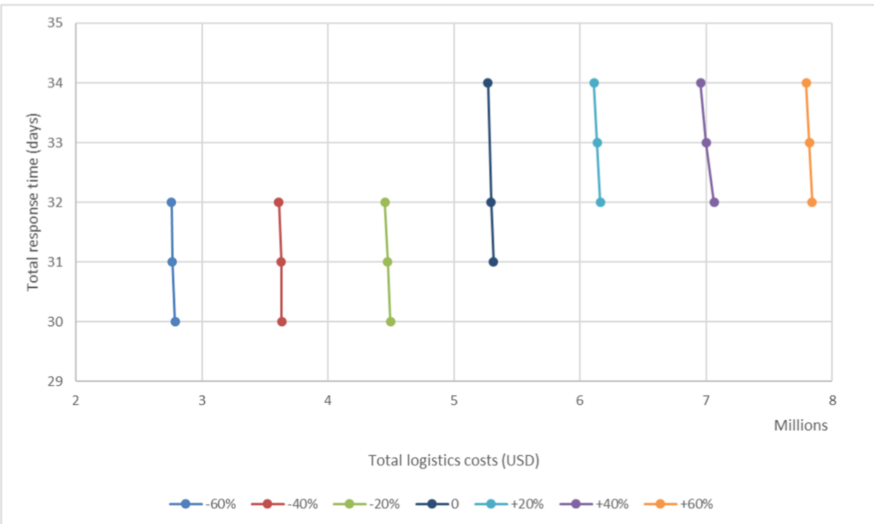

Fig. 12. Impact of changing air transportation costs.

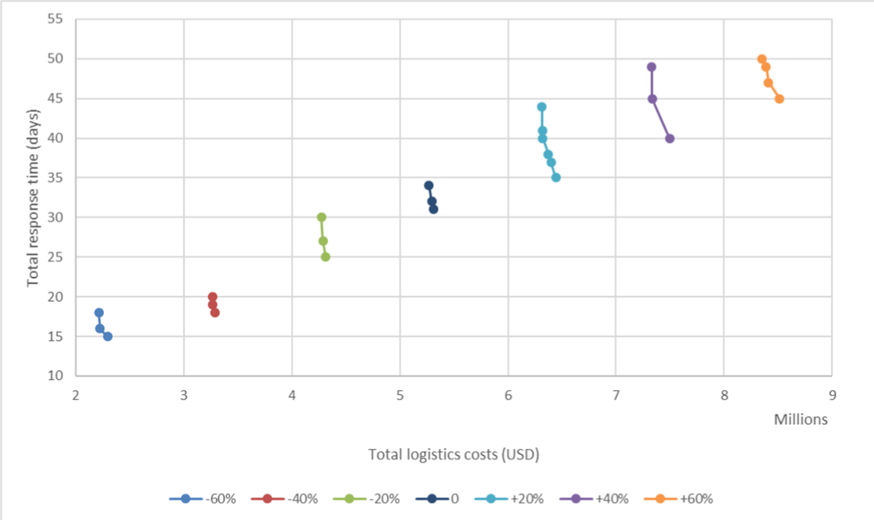

Fig. 13. Impact of changing relief items weights.

response time objectives are presented in Fig. 13. Such changes mean running the model for packages with 2, 3, 4, 6, 7 and 8 kg of weight respectively while capacity constraints have not been changed. Interestingly, the impact of changing every 1 kg is approximately 20% on both logistics costs and response time which is significant. These results suggest that DMs face one important decision with significant outcomes in the immediate response; how much weight should be considered for the relief package.

In addition, we investigated a + 100% change in the assumed number of setup days (by considering four days instead of two days); however, we do not observe any change in the logistics costs and the structure of previously suggested networks although the operations time increases considerably (approximately + 15% for all solutions).

5. Discussion

In this section, we discuss our findings with respect to five aspects: scalability, runtime, the potential impact of uncertainty, stability of results, and interplay between immediate response and relief. Then, we explore the difference between our results and the choices of the practitioners for the Nepal case. Finally, we elaborate on the managerial implications and insights.

Scale In our study, we used a data set related to a real world operation which included 1 MEP, 8 SAs, 24 (accumulated) PODs, 2 transportation modes, and a 45-days timeline. We ran the same model for a scenario with 4 MEPs, 18 SAs, 105 (accumulated) PODs and relaxed transportation/time constraints. Since the solution time for the latter was approximately 2 h on a personal laptop, we argue that this model can be run and used by operational responders equipped with a notebook. Since parallel computation is supported by CPLEX, we used this approach within our laptop (from 1 core to 2 cores). This approach reduced the solution time in all the runs (cf. Table 6) by approximately %31.

Nepal is relatively a small country with only in-land access, and the studied case may not be counted as a “large–scale problem” (given that large–scale problems in the commercial settings often have more than 100,000 PODs (Cebecauer and Buzna, 2018)), though there is no consensus in the literature regarding the characteristics of a large–scale problem in the context of a humanitarian response. To investigate how the model scales with different network configurations and sizes more validation or application to further cases and different networks is required to ensure the performance of the solution algorithm remains relevant for the immediate response.

Runtime Decreasing the solution time is highly favorable also owing to the time constraints and possible need for re-running the model with the newly available information. In this regard, one solution can be to use high-performance processing approaches (parallel processing, computer clusters, or super computers). Although we only checked runtime reduction with 2 cores, Carle (2012) showed that using 8 cores (instead of 1) can decrease the solution time of the mixed-integer problem instances by %65.

Another solution can be to change the employed methodology for solving the model. For instance, other approaches having maybe a lower quality of results (e.g., from transforming a multi-objective model to a single-objective model with weights) but with a higher solution speed, can be used. Further examination of the approaches for decreasing the solution time will be conducted in a future research direction.

Uncertainty We explained in Section 2.2.2 that stochastic and robust approaches have a limited applicability due to data and computational resource requirements (Maier et al., 2016; Charles et al., 2016; Manopiniwes and Irohara, 2017). However, there are other approaches in the literature, such as time period planning horizon and rolling planning horizon, to address uncertainty with deterministic data (Huang et al., 2015). The deterministic approaches are normally used in disaster settings (with the help of pre-disaster information, such as census reports) because there is no information that allows for using other paradigms. We adapted the two aforementioned approaches in our proposal. Literature suggests to divide the response phase into the immediate response and relief phases to better understand differences between these contexts (for instance Kovács and Spens (2007) or Huang et al. (2015)). We combined this approach with breaking down the immediate response phase into multiple timesteps (Maharjan and Hanaoka, 2018; Loree and Aros-Vera, 2018). This combination enables the opportunity to reflect the differences between the two phases into the corresponding models, plus it helps to quickly re-run the proposed models with latest reliable data during the immediate response phase. This approach can also improve the capacity to address sudden changes in the relief network, i.e., improving network flexibility, and helps DMs to avoid disruptions in the relief distribution (Prasad et al., 2017).

Stability of results We highlight the importance of checking the stability of results given that some key parameters of the affected region, like demands, may change rapidly (Holguín-Veras et al., 2012; Fereiduni and Shahanaghi, 2017). To address this, we analyzed the effect of changing some individual parameters on the suggested networks. The reason for running single parameter tests is the lack in the sufficient information regarding the changes in these parameters with respect to each other. In this regard, we consider an effective multi-dimensional sensitivity analysis approach that can be used in the field (given the time and data constraints of the logisticians) as a future research direction.

Interplay between the two phases As our proposed model only addresses the location–allocation problem in the immediate response, we also have to discuss the interplay between the solution of this phase and the relief phase. Because the contextual characteristics, e.g., data availability, objectives, and constraints, vary between these two phases (Kovács and Spens, 2007; Gralla et al., 2014, 2016), we propose considering two separate location models, which to the best of our knowledge, has not been addressed in the literature. An alternate model is needed for investigating the performance of located temporary distribution centers with respect to the new data for the parameters and constraints in the relief phase, and then suggests adding or closing locations to customize the network accordingly. This is another future research direction of our study.

5.1. Divergence between results and practice

Our results for the 2015 Nepal earthquake are different from the measures taken by the UN WFP in reality. This can be discussed in two directions.

i The deviation occurs owing to the lack in the application of a formal and transparent approach to model and solve the related decision problem;
ii Our model misses numerous objectives or constraints and therefore does not adequately represent the decision situation or the real circumstances of the DMs.

To further investigate the extant of compliance of these explanations with reality, we reviewed the reports of the UN WFP that were published during the Nepal response. Moreover, we consulted with a UN WFP representative who participated in our field research to validate our findings.

In the Logistics Cluster reports, there were some critical considerations for opening the SAs. For instance, one consideration referred to road access whereas another one related to decreasing the capacity issues in the SAs.

"Staging areas and logistics hubs have been established at strategic locations in the affected areas where the road infrastructure still allows access by larger trucks, and which can also support local air operations to hard-to-access locations: Chautara (Sindhupalchock district) – 4 MSUs; Deurali (Ghorka district) – 5 MSUs; Bharatpur – 4 MSUs. (Logistics Cluster situation update, May 18, 2015)"

"A storage facility in Dhulikhel (Kavre district) will be established to increase the HSA capacity, to help de-congest KTM and to offer storage capacity for international air shipments before onward movement. (Logistics Cluster situation update, May 5, 2015)"

We note that we already considered the access to highways and main roads as the main concern for selecting the candidate locations (as our interviewees in the field has highlighted). However, as confirmed subsequently by the UN WFP representative, they only considered those locations that could be accessed through highways on the very first day of the immediate response.

Thus, if we modify our "candidate locations set" to include only the highway accessible locations, we should be able to obtain results with validated parameters. Unexpectedly, our model suggests a solution (Chautara and Dhulikhel) that can cover 100% demands in 31 days with 4% less costs compared to the network of the UN WFP (Chautara and Deurali). Although the SA in Dhulikhel was opened some days later than the SA in Deurali (May 10, 2015 vs. April 26, 2015), we think that the UN WFP could revise their decision (use Dhulikhel when it was opened instead of Deurali). Therefore, we believe that HOs could enhance the performance of their relief distribution network with the support of a model similar to ours.

However, although we validated the time and cost objectives with the humanitarians, there might be some other criteria or constraints that our model misses. This can have a significant impact on the results obtained from our model. For instance, we did not consider the fairness criterion in our model (Chapman and Mitchell, 2018). Practitioners referred to fairness (and equity) in our interviews; however, their approach to consider this criterion was not clear and lacked transparency. Some referred to the priority of regions and targeted groups whereas others mentioned the timeliness of the deliveries (Anaya-Arenas et al., 2016). Thus, defining an appropriate objective function for fairness requires further investigation and validation with practitioners, which will be performed in another future research direction.

5.2. Managerial insights

The need for more efficient humanitarian response has been noted in the literature several times (Van Wassenhove, 2006; Kovács and Spens, 2007; GHA, 2018). In addition, it has been proven that delays and late relief deliveries often add to the sufferings of the affected people (Paul et al., 2017) which highlights the importance of timely operations. We note that balancing response time and logistics costs entails careful trade-off analysis between the two conflicting objectives. In our study, the decision regarding which objective would be more critical than the other is left to the decision maker through a posteriori analysis approach. Our investigations implied that considering the same response time, logistics costs could be reduced by selecting SA locations that have shorter transit distances to densely populated PODs.

Moreover, the divergence between the UN WFP network and our model partly means that without using formal and transparent DSSs, efficiency cannot be guaranteed. Our study also reveals that the weight of relief packages and the number of available ground/air transportation fleets affect the total logistics costs and response time more significantly than other parameters.

Our findings partly mean that more attention has to be paid to the varieties and costs of transportation means because the heterogeneous capacitated transportation means can speed up the delivery process significantly. The lack of sufficient air transportation fleets, e.g., cargo helicopters, at the early stages of disaster response has been reported several times (Lum and Margesson, 2014; Baharmand et al., 2016). Unfortunately, this shortage often increases the response time significantly. Our analysis shows that having access to more ground transportation fleets decreases the response time while the logistics costs are not affected significantly. A field study depicts that transportation costs could be better controlled by effective use of logistics service providers to take care of transportation (Baharmand et al., 2017a). Another solution can be to use more ground fleets as a result of setting up several MSUs at multiple SAs (e.g., in every district in the Nepal case) which often increases the access to local fleet resources. This approach has proven to solve resource issues in several relief operations such as the 2015 Nepal earthquake response (Wijeyewickrema et al., 2015). As our model suggests the number/type of transportation means required for shipping relief items, it can contribute to mitigate the major delays through proper transportation planning and coordination between different nodes of the network.

As the next important finding of our paper, the parameter with the most impact on the values of our model is the weight of relief packages. This parameter is directly connected to the humanitarian daily ratio, the vulnerability level of the affected people and the resilience of the affected country (Baharmand et al., 2016). Decision regarding selecting and providing a relief item often relies on the availability of resources, the needs assessments results, the official regulations of the affected country and the inclusion of HOs in different clusters. Our analysis shows every 1 kg variation in the weight of relief package can change the objective values drastically. Despite such potential impact, to the best of our knowledge, there is very limited research in the literature (e.g., van Kempen et al. (2017)) to support selecting and determining the weight of relief packages for sudden-onset disasters response.

Given the above explanations, if the necessary input estimates could be provided, our model could be used as a DSS for future relief operations to locate SAs and potentially increase time and cost efficiency. However, the insights of our study can be beneficial not only for humanitarian operations, but also for other contexts where time and cost efficiency are of high importance such as food supply chains. The appropriate location of temporary warehouses (for instance grain silos) and allocation of heterogeneous transportation means can contribute to reducing the delays in food grain shipments significantly, as noted by Mogale et al. (2018).

6. Conclusions

In this study, a multi-commodity multi-layer bi-objective location–allocation model for the immediate aftermath of sudden-onset disasters was proposed. The model was designed to consider the constraints and requirements of field-based decision makers, and it fits the humanitarian work process. The features of the proposed model and its assumptions were challenged and validated with the help of practitioners. The model was solved using the AUGMECON2 algorithm, given its efficiency for dealing with multi-objective mixed-integer models. We applied our model to the data of the UN WFP for the 2015 Nepal earthquake case and compared our results with their relief operations in the Nepal response. We also used some randomly generated numerical instances based on the Nepal case to check the performance of our model further. In addition, the sensitivities of objectives on some critical parameters were checked.

Our results showed that the proposed model can assist HOs to establish a stable time and cost-efficient network in constrained contexts, as the immediate response phase. With respect to the time efficiency, the proposed model could satisfy the targeted timeframe for delivering a ten-day humanitarian food ratio to the beneficiaries. However, the main outcome of using the suggested model was that it could decrease the logistics costs by up to %8, which could contribute significantly to reaching more beneficiaries and potentially saving more lives. Investigating the model with some changes in the demand (up to ± 60%), number of air/ground transportation fleets (up to ± 60%), distinct costs parameters (up to ± 60%), relief weight (up to ± 60%) and setup days (+ 100%) showed that our model can propose stable results against major fluctuations.

Our study has implications for research and practice. We characterized the specific context of immediate response and provided information about critical requirements that OR models have not yet addressed for this environment. While this information helped us to highlight the methodological contribution of our model, they can be used in future studies to propose relevant analytical models to address different logistics problems in disasters contexts. Furthermore, our model could complement other models for the transportation and scheduling decisions in such contexts.

For practice, our study stressed that while the location decision can have a great impact on the efficiency and timeliness of response, balancing response time and logistics costs entails careful trade-off analysis due to the conflicting natures of these objectives. We showed that without using a formal and transparent DSSs, the time and cost efficiency cannot be guaranteed. However, our investigations implied that considering the same response time, logistics costs could be reduced by selecting locations that have shorter transit distances to densely populated demand points. In this regard, we note the potential of our model for applications in the immediate response given the positive feedback that we have received from practitioners. Our model could be used as a DSS for future operations if the necessary input estimates could be provided. It could also be used to examine the performance of previous operations to capture the insights regarding what has been done and what could be improved. Furthermore, we noted that the weight of relief packages and the number of available ground/air transportation fleets could affect the total logistics costs and response time significantly. This information partly reveals that the heterogeneous capacitated transportation means can speed up the delivery process significantly.

For a future study, several future research directions have been identified. First, our model addressed the immediate aftermath of sudden onset disasters; however, its impact on the next phase of the response, i.e., the relief phase, has not been investigated. Second, working on a multi-dimensional sensitivity analysis approach that can be used by logisticians in the field helps to ensure the stability of the solutions of the model. Third, more validation with practitioners is required to ensure the usability of the model for operations in the field. Fourth, the use of high-performance processing approaches and heuristics to decrease the solution time needs further investigation. Fifth, the objectives for the location–allocation decision can be expanded to consider, for instance, fairness or social costs, as suggested by Loree and Aros-Vera (2018).

Acknowledgements

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Appendix A. Input data

A summary of the input data for our model is presented in Tables A.7 and A.8.

Table A.7
Definition of parameters.

Parameter description	Input data	Source
Candidate locations for establishing staging areas (and their capacity to erect MSUs)	13 nodes: Chautara (6); DhadingBesi (6); Dhunche (6); Bidur (6); Charikot (6); Deurali (6); Bharatpur (6); Dhulikhel (6)	UN WFP reports
Demand information, 2,169,087 people, and 370 village development committees (VDCs) in seven districts require a ten-day food ratio.	2011 GoN census report and UN WFP project plan	
Available transportation means in nodes	25 trucks and 25 tractors with 15 mT and 3 mT weight capacity, respectively, and 3 helicopters with 2.5 mT weight capacity (maximum 4 tours) which can be dispatched every day.	Logistics Officer at UN WFP
Commodity characteristics	Each person's 0.5-kg food portion per day for each person including rice or High Energy Biscuits (HEBs) for ten days (5 k g each for the duration of 10 days). 1-mT rice occupies 1.5-m3 volume and 0.4 m2 surface space, whereas 1-mT HEC occupies 2.5-m3 volume and 0.67m2 surface space.	Logistics Officer at UN WFP
Available MSU type (total available number)	32 m 10 m (32); 20% of each MSU surface should be left empty for indoor movements (layout design). Setup days = 2	Logistics Officer at the UN WFP
Number of MSUs that can be erected simultaneously	Due to constrained number of human resources in the immediate response who were trained to setup MSUs, this parameter is assumed to be 1 in our case	Logistics Officer at the UN WFP

Table A.8
Travel time and distances

No.	Candidate location	HSA	Gorkha	Dhading	Rasuwa	Nuwakot	Sindhup.	Dolkha	Ramechhap
1	Deurali	110 (190)	104 (170)	173 (280)	235 (422)	190 (300)	286 (495)	395 (650)	343 (550)
2	Bharatpur	155 (300)	77 (175)	125 (250)	202 (420)	145 (270)	249 (497)	350 (630)	321 (420)
3	Chautara	82 (143)	217 (375)	191 (355)	233 (440)	165 (310)	55 (90)	144 (270)	155 (224)
4	Dhulikhel	31 (70)	170 (305)	143 (285)	166 (310)	120 (240)	68 (127)	156 (310)	124 (185)
5	Charikot	133 (260)	273 (490)	246 (475)	269 (560)	220 (430)	72 (150)	54 (120)	83 (145)
6	Dhunche	118 (280)	171 (290)	114 (212)	45 (120)	117 (265)	187 (372)	330 (590)	244 (430)
7	Bidur	65 (157)	118 (190)	92 (167)	68 (165)	20 (40)	165 (147)	274 (485)	222 (385)
8	DhadingBesi	89 (175)	77 (140)	32 (60)	130 (280)	81 (150)	179 (349)	290 (505)	236 (406)

Appendix B. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.tre.2019.05.002.

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