Models and metrics to assess humanitarian response capacity

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ABSTRACT

The race to meet vital needs following sudden onset disasters leads response organizations to establish stockpiles of inventory that can be deployed immediately. These government or non-government organizations dynamically make stockpile decisions independently. Even though the value of one organization’s stock deployment is contingent on others’ decisions, decision makers lack evidence regarding sector capacity to assess the marginal contribution (positive or negative) of their action. To our knowledge, there exist no metrics describing the system capacity across many agents to respond to disasters. To address this gap, our analytical approach yields new humanitarian logistics metrics based on stochastic optimization models. Our study incorporates empirical data on inventory stored by various organizations in United Nations facilities and in their own warehouses to offer practical insights regarding the current humanitarian response capabilities and strategies. By repositioning inventory already deployed, the system could respond to disasters in the same expected time with a range of 7.4%–20.0% lower cost for the items in our sample.

1. Introduction

Capability to rapidly deploy life-saving commodities in response to natural disasters is vital. The humanitarian response capacity spans various actors and activities, which are often not coordinated. A common strategy government and non-government organizations use to improve humanitarian response is to pre-position stockpiles of critical commodities in various locations prior to disaster events. While increased inventory certainly improves response capacity, the incremental impact of continual stockpile deployments by various organizations is difficult to assess.

The reason is a complex system: dozens of organizations manage hundreds of distinct items in dozens of warehouses globally in order to respond to events that vary in location, type, and size. Thus, there are no sector metrics for humanitarian stockpile capacity, even though combined efforts across organizations determine the extent to which needs are met following a disaster. Moreover, there is no mechanism to influence numerous organizations’ stockpile decisions toward system-wide improvement given inherent coordination challenges in the sector.

To more easily assess this complex landscape and guide decisions toward system improvement we propose new humanitarian logistics metrics based on stochastic optimization models. The metrics assess the quality of the humanitarian system according to various objectives (e.g., cost, time, need met, etc.). These numerical values help organizations understand how their isolated inventory decisions affect the response capacity for the system as a whole. Such evidence enables decisions that effectively weigh internal objectives (e.g., procurement and warehousing costs, organizational mission, etc.) with contribution to system capacity.

We evaluate our approach with a combination of proprietary data from the United Nations (UN), publicly available data from various sources, and expert opinion on parameter values. We show that the current allocation of inventory among the warehouses for which we have data can be improved significantly. By repositioning inventory already deployed, the system could respond to disasters in the same expected time with a range of 7.4%–20.0% lower cost for the items in our sample. Such efficiency gains translate directly into more humanitarian services for the same donation budget.

We show that coordination is increasingly important as the number of organizations deploying stockpiles grows. Organizations acting in isolation might optimally place inventory in the same location rather than deploy stock to serve more regions in a coordinated system. Fortunately our approach does not require explicit coordination, which is challenging to implement, since incremental
decisions based on sector-wide metrics would improve system performance even if made independently.

We conduct sensitivity analysis to consider robustness to empirical data quality and to parameter value assumptions. Metrics and optimal decisions are robust for most parameter value assumptions. They are moderately sensitive to the empirical data used for the risk portfolio. The sensitivity analysis guides further efforts to collect data and calibrate the model for sector use.

The approach proposed in this paper addresses important gaps in the growing literature on performance measurement for humanitarian logistics. It summarizes dynamic empirical data from a complex system with a few intuitive metrics. The metrics are based on accepted modeling approaches yet extend beyond myopic outcomes of independent organizations to measure and improve sector-wide capacity. And most importantly, they guide system improvement without the need for explicit coordination.

2. Research design

This section characterizes the practical context of disaster response that motivates our analytical approach, described in section 3, and outlines the empirical research design we use to assess its potential. The section closes by positioning the research as an extension of established modeling approaches that fills a gap in the humanitarian metrics literature.

2.1. Context and motivation

Immediately following a disaster that outpaces community coping mechanisms, various outside organizations rush to provide life-saving commodities to meet health, water, food, shelter, or other needs for the affected population. The response is expedited by inventory prepositioned by these organizations, which could include government (local, regional, national, or foreign), non-government (NGO), military, or private sectors. The stock for this initial deployment could be centralized or deployed across several locations. For large-scale and/or urgent crises, organizations may choose to utilize stock in several locations and incur the additional cost of shipping farther to meet needs. In most cases, this initial push is intended to meet human needs within the first few days, followed by replenishment from strategic suppliers based on assessments of need in the affected community. Hence, the initial push is typically transported by air unless ground transportation offers better transit time from a nearby stocking point; sea shipping is rarely used for initial deployment. Our model considers both air and land modes to optimize distribution cost and/or time for the initial response to a sudden onset disaster.

Poor response to a widely publicized event pushes organizations to take tangible actions. Such actions often include increasing the size and/or number of locations for critical commodity stockpiles (typically skewed toward the nature of a recent event and not a broader risk portfolio). On the other hand, constrained fundraising and/or expiration of stockpiled items pushes organizations to reduce stock. As a result, numerous organizations are continually adjusting stockpile deployment.

These dynamic decisions are made independently for the same population of potential beneficiaries. Organizations do not have explicit incentives to coordinate; this can be exacerbated by lack of centralized data and visibility into needs and roles of the actors (Tomasini and Van Wassenhove, 2005). The result is a potentially chaotic response (Van Wassenhove, 2006). Furthermore, there is no central authority to enforce compliance to coordinated solutions, such as optimization of sector-wide stock.

Fragmented decision-making and limited transparency about response capacity make it difficult to assess, much less optimize, the combined level of preparedness for a region. As one manager at a large organization told us, a key unanswered question is “If we had one million dollars from a donor, what would we buy and where would we put it?”

2.2. Research questions and empirical study

To overcome coordination issues and improve system performance, we propose sector-wide metrics based on analytical models for disaster response capacity to inform and evaluate the dynamic, independent decisions of numerous organizations. The scope of these metrics and our analysis includes stockpile capacity for rapid response to sudden-onset disasters. We do not consider slow-onset disasters or ‘steady-state’ response. Items in these situations are more likely to be shipped by slower, less expensive transportation modes and/or from suppliers directly instead of being shipped rapidly from stockpiles.

We suggest that metrics could fill two gaps limiting coordinated decisions on stockpile capacity: (1) organizations lack evidence to evaluate system capacity, and (2) organizations lack guidance to operationalize system improvement. To close these gaps, our approach seeks to address two research questions:

1. What is the quality of current inventory positions across stockpile depots? (system assessment)
2. What is the value, positive or negative, of incremental change to the combined system? (decision support)

Dynamic answers to the first question provide effective evidence to motivate systemic actions by an individual organization and/or a coordinated group of decision makers. They also form the basis for more general insights regarding the value of stockpile capacity. Actions taken primarily focus on three decisions: (i) which items to buy; (ii) where to put these items; and (iii) stock transfers between depots. Proper application of answers to the second question will guide incremental change resulting from such decisions toward system improvement without the need for explicit coordination.

We use empirical data to assess the potential for these metrics to answer the questions posed. Despite the challenges of coordination, we found two data sources for stockpile inventory spanning multiple organizations in the humanitarian sector. First, inventory quantities and owners for the six United Nations Humanitarian Response Depots (UNHRDs) around the world, which offer space for organizations at no-cost or on a cost-recovery basis, are published dynamically online (United Nations, 2014). Second, several years ago the UN Office for the Coordination of Humanitarian Affairs (OCHA) conducted a “Global Mapping of Emergency Stockpiles” to track stock levels in various organizations’ warehouses; participation was voluntary and each organization provided its own data (UN Office for the Coordination of Humanitarian Affairs, 2014)). To our knowledge, our study is the only analytical assessment of those data. We analyze the combined sector capacity in these datasets across a broad portfolio of risk scenarios. As our research does not focus on disaster forecasting, we leverage a widely used historical database for our scenarios.

2.3. Relevant literature

Our work is mainly related to two streams of literature. The first stream utilizes mathematical optimization to pre-position disaster stockpiles. Our analytical approach is based on two-stage stochastic linear programs. Several authors have used such models to determine where to place inventory in the first stage in order to optimize the response in the second stage. The second stage of these
stochastic linear programs is often represented by a set of disaster scenarios. The paper most related to our work is the straightforward and effective model of Duran et al. (2011). The authors work with CARE International to decide which depots to open and how much to store in each, with the objective of minimizing average time-to-respond to a disaster with a C-130 aircraft. The authors consider factors such as multiple disasters within a replenishment period and need for items based on disaster type, but omit factors such as transportation by truck and transportation costs in general. Other papers in this stream take into account more sophisticated aspects of disaster response. Several authors include the effect of potential damage to supply depots or network arcs (Barbarosoglu and Arda, 2004; Mete and Zabinsky, 2010; Rawls and Turnquist, 2010; Kilbi et al., 2013). Other researchers consider unique aspects of specific disaster contexts: de Brito Junior et al. (2013) develop a model that takes into account donations based on media response; Salmeron and Apte (2010) propose a stochastic optimization problem that dictates how best to allocate a budget before a random disaster strikes in order to minimize casualties afterwards. Hong et al. (2015) and Rawls and Turnquist (2011) take into account reliability; these authors include constraints to ensure a minimum probability of meeting demand. Jahre et al. (2016) use a detailed case study to show that optimal warehouse locations should consider the political and security situation and that jointly prepositioning for emergency response and ongoing operations reduces cost and response time. We utilize similar two-stage stochastic linear programs as found in these papers as well as the existing stochastic optimization body of literature (Shapiro et al., 2014). Our contribution is not to develop more sophisticated stochastic linear programs but rather to use such models to develop new metrics for the humanitarian sector, in a similar manner as Acimovic and Graves (2015) use a normalized (non-stochastic) linear program to develop an inventory balance metric for an online retailer. Preliminary versions of the models used in this paper were first introduced in master’s theses advised by the authors of this paper (Nishimura and Wang, 2013; Seelbach, 2015). This paper extends those works by adding aspects to the model, developing additional metrics, and evaluating both with a more detailed and robust data set.

The other relevant stream of literature consists of papers that define metrics for humanitarian logistics. Abidi et al. (2014) provide a thorough review of this literature, most of which emerged after the 2004 Indian Ocean tsunami. They conclude that the literature focuses on theory and models, with limited application to actual humanitarian supply chains, and that further work is needed in applying mathematical and stochastic programming for performance measurement. Haavisto and Goentzel (2015) offer a more recent review and identify the challenges of aligning goals within an organization. The difficulty of aligning goals is one reason that the humanitarian logistics literature focuses on performance measurement within an organization rather than across the sector. Our effort applying stochastic programming to develop sector-wide metrics fills a gap in the humanitarian logistics measurement literature.

3. Analytical approach

Our approach to developing sector metrics is grounded in analytical assessment of response capacity for the humanitarian system. A natural way to do this is to compare outputs of the current system with an optimal system; the metrics then measure normalized distance between the current and optimal state. We use a stochastic linear program (SLP) to determine the optimal state, which is the technique adopted by much of the pre-positioning community as outlined in the literature review.

In applying optimization to humanitarian logistics, authors utilize different methods and optimize different objectives: maximize throughput, minimize time-to-respond, minimize cost with penalty for unmet demand, minimize casualties, optimize a mix of objectives, and so on (Gralla et al., 2014). Our objective value considers time and cost, assuming that organizations will want to deliver goods as fast as possible while still being fiscally responsible. Implicitly, the model maximizes the amount of commodities delivered, since unmet demand is served by a dummy node with a significant cost penalty. We also find the efficient frontier between time and cost, so that organizations can make pareto optimal decisions according to their particular balance of speed and cost in their objectives (Tomasini and Van Wassenhove, 2009).

The context and our objectives motivate a slightly different application of stochastic optimization models than previous work, which focused on optimal facility location and capacity for one organization. First, we do not emphasize the facility location decision. We study stockpile humanitarian warehouse facilities that are already established, and any potential sites not yet established would be in prescribed locations. Second, we do not seek to prescribe strategic, optimal capacity (e.g. warehouse space, inventory) for an organization to implement, but rather to dynamically measure the quality of combined tactical capacity across organizations. We list modeling assumptions/decisions as well as assumptions related to input parameters below:

1. The warehouse locations are given. We are focusing on tactical decisions, not strategic decisions such as where to place new buildings. Often, warehouse location must also consider the political and security situation (Jahre et al., 2016), which is beyond the scope of our analysis.
2. There are no warehouse capacity constraints. If a warehouse reaches capacity, then we assume organizations can acquire additional warehouse space in the vicinity. Our model provides the marginal value of inventory changes, which could be compared with the variable cost of temporary leased space or incorporated into analysis to justify the fixed costs of deploying new warehouse space.
3. There are no transportation capacity constraints. We assume sufficient carriers are available for hire. While transportation may be difficult to procure depending on the market and context at the time, the fixed time parameter could be configured to characterize origins with transportation procurement challenges.
4. The model considers a single commodity at a time. With no bundle constraints across commodities, single commodity results are easily combined for analysis. Multicommodity models would unnecessarily complicate the analysis.
5. Each country has some level of internal capacity. A country can meet the needs for a certain number of affected people, beyond which outside assistance provides support. This number varies by country. The model itself is flexible enough to accept any value for a country’s capacity to respond to a domestic disaster. Thus, when calibrated, the model will analyze capacity of the international community to respond to disasters only for amounts that exceed a country’s own ability to satisfy the needs of the beneficiaries.
6. All inventory is available for any global disaster. We assume that any stock earmarked for a specific region or purpose would not be included in the master inventory database. If stock count data are included, then we assume the owning organization is willing to use the items for an international response. Inventory earmarked for a specific region could be incorporated as an adjustment to a country’s internal capacity.
7. The SLP is scenario based. Each scenario is an equally likely disaster from the past. We assume a good proxy for a forecast of future disasters consists of selecting a disaster that actually occurred after 1989 with probability 1/|K|, where K is the set of all disasters. In consultation with experts, the insurance sector uses a similar “equally likely scenario” approach, albeit with more sophisticated scenario generation. Potential weaknesses of this assumption are that probability distribution of disasters may change over time and that very large anomalous disasters may skew results.

8. True demand for items is linear in persons affected. There is room to develop more sophisticated models that translate attributes of a given disaster into the amount of an item required by the outside aid community. However, creating such models is beyond the scope of this paper. A direct relationship effectively translates between persons affected and items needed. We note that the model does not require the relationship to be linear. Item need could be calculated off-line and fed into the SLP.

9. Relief stock is transported to the country’s capital. The practical reason is that the historical data we use aggregates events at the country level. The capital is a good proxy since it is often the primary port of entry to a country for air transport. Inland capacity for final distribution is often a bottleneck in humanitarian response, but this is very contextual by event and cannot be generalized for our model. Customs is a common decoupling point for international humanitarian response supply chains.

10. Transportation cost depends on the weight of a given item. Further, the total cost for a specific item is linear in the number of units being shipped and in distance. This is a common assumption in supply chain literature.

11. The model focuses on transportation cost or time. Like warehouse capacity, procurement cost for stockpile capacity would be considered in follow-on investment analysis, informed by our response metrics. Warehouse processing cost or time could easily be incorporated in arc costs, though our study considers it negligible compared with transportation.

3.1. Model

The analytical foundation for our metrics is a scenario-based SLP with two stages. The first stage uses the current inventory allocation for capacity measurement; it determines where to place inventory for the optimal capacity benchmark. The second stage is a transportation problem that allocates supply to demand, where the demand occurs at a single disaster node for each scenario in the risk portfolio. The SLP minimizes total expected time or cost to deliver the items from supply nodes to disaster nodes in the portfolio.

We first define parameters and variables for the SLP. A dummy supply node is employed in order to satisfy demand for disasters when the need exceeds combined stockpile inventory.

\( I \equiv \{i \} \) — Set of all depots and warehouses except the dummy node.

\( W \equiv I \cup W^D \) — Set of all depots including dummy node.

\( K \equiv \{ k \} \) — Set of possible disaster scenarios.

\( J \equiv \{ j \} \) — Set of possible disaster locations.

\( M \equiv \{ m \} \) — Set of disaster types (e.g., storm, earthquake, etc.)

\( R \equiv \{ r \} \) — Set of transportation modes.

\( c_{ir} \) — Cost in dollars to transport a single item from \( i \) to a location \( j \) via mode \( r \).

\( \tau_{ir} \) — Time to ship a single item from \( i \) to a location \( j \) via mode \( r \) (item independent).

\( c_{W}(\tau_{W}) \) — The cost (time) from the dummy supply node to a disaster.

\( j^k \) — Location of disaster in scenario \( k \) (Note that \( \tau_{j^k r} \) and \( c_{j^k r} \) are the respective time and cost to ship an item to specific location \( j^k \) where the disaster in scenario \( k \) occurred.)

\( p^k \) — Probability of scenario \( k \) occurring. \( \sum p^k = 1 \)

\( S_{mt} \) — Domestic capacity to respond to a disaster in location \( j \) of type \( m \) at period \( t \).

\( \chi \in \mathbb{N} \) — Starting inventory in the system as a whole, not including the dummy node.

\( \text{TAP}^k \) — Total Affected Population in scenario \( k \).

\( \beta_{mt}^k \) — Units of item demanded per person at location \( j \) at time \( t \) for disaster type \( m \).

\( d^k \equiv \max \{ \text{TAP}^k \beta_{p^k,m,t} - S_{p^k,m,t} \} \) — Actual demand for an item for scenario \( k \).

\( y^i_k \) — Decision variable: how much to send from \( i \) to the scenario \( k \) via mode \( r \).

\( X \) — The \(|I| \times |W| \) dimensional vector of starting inventory in each supply node. Its elements are \( X_i \) (May be decision variable or parameter.)

Note that several of the parameters may differ among line items: a bar of soap is much cheaper to ship than an entire kitchen set; a latrine plate can serve dozens of people while a blanket may serve only one or a fraction of a person. The SLP formulation for minimizing time is (note: the SLP that minimizes cost is analogous):

\[
V^W(X) = \min_{y} \sum_{k} p^k \sum_{i \in I, r} \tau_{j^k r} y^k_{ir} \tag{1a}
\]

s.t. \[
\sum_{i \in I, r} y^k_{ir} = d^k \quad \forall k \tag{1b}
\]

\[
\sum_{r} y^k_{ir} \leq X_i \quad \forall i \in I, k \tag{1c}
\]

\[
y^k_{ir} \geq 0 \quad \forall i, k, r \tag{1d}
\]

The objective function (1a) minimizes the expected time-to-respond: the time-to-respond to any specific scenario is weighted by the probability of that scenario occurring. Constraints (1b) ensure that in each scenario, the demand is met. The model enforces the fact that the supply being shipped from any single depot must not be greater than the supply at that depot (1c) and be non-negative (1d). This is a simplified version of the model in Duran et al. (2011). We did test a more complicated model with delivery deadline cutoff times but do not present those results here, in part because the optimal allocation of inventory is very sensitive to the choice of cutoff time.

An SLP is not required to calculate these metrics for current inventory. Additionally, some of the metrics we propose below do not require an SLP. However, using a linear program allows us to calculate dual variables and maintains similar structure as the model for our optimal benchmark. The formulation that optimizes inventory allocation makes \( X \) a decision variable and adds a constraint to ensure the sum of the supply is equal to \( \chi \).

\[
V^{OPT,w}(\chi) = \min_{X} \left\{ V^W(X) : \sum_{i \in I} X_i = \chi, X_i \geq 0 \quad \forall i \in I \right\} \tag{2}
\]

We define the objective values with the dummy costs subtracted as \( V^{w}() = V^W() - \sum_{k} p^k \sum_{r} \tau_{j^k r} y^k_{ir} \), where the \( y^k_{ir} \)'s are fixed as the respective solutions to the above SLPs.
3.2. Metrics

By solving this SLP and manipulating the output, we create metrics aimed to answer the questions we posed in section 2. We list the metrics, describe each one in detail, and then consider how they align with our research questions.

\[ \Delta = \frac{\sum \text{current capacity}}{\sum \text{target capacity}} \]

Balance metric

\[ \mu = \sum_k p_k d_k \] Weighted average of demand

\[ \bar{\mu} = \sum_k p_k \min(d_k, \chi) \] Average demand met

\[ \gamma = \sum_k p_k \delta_k \] Fraction of demand served

\[ \delta_k = \sum_{k \in \chi} p_k \] Weighted fraction of disasters completely served

\[ \phi = \frac{\sum \text{current capacity}}{\sum \text{target capacity}} \] Average time(cost)

\[ \pi_i = \sum_k \pi_i^k + (1 - \delta)\tau_W \] Adjusted dual variable for depot i over all scenarios

3.2.1. The balance metric \( \Delta \)

The balance metric \( \Delta \) assesses the allocation of current capacity. More specifically, it estimates how far out of balance the actual allocation of inventory is relative to the optimal. This metric is similar to the deterministic version reported in Acimovic and Graves (2015), which used data from an online retailer to show that an item’s balance metric was highly correlated with the item’s future actual incurred shipping costs.

We note a few properties of this balance metric:

1. It approximates the proportional increase in cost (time) to serve beneficiaries given that one’s inventory is allocated as it actually is as opposed to being allocated optimally. Thus, it measures the value of change through reallocation.
2. The optimal value is 1. Anything greater than 1 is considered out-of-balance.
3. The metric is affected by which depots are considered. If a new depot is opened in a disaster hotspot and no inventory is placed there, then the balance metric will increase (because \( \text{VOPT} (\chi, n) \) will decrease). In this sense, operational managers can be alerted to the fact that the inventory is out-of-balance given the new depot.

3.2.2. Fraction served (\( \gamma \)) and weighted fraction of disasters covered (\( \delta \))

The fractions served \( \gamma \) represents the average weighted fraction of demand met, where the weights are derived from the risk portfolio probabilities. It does not depend on how the items are allocated among the depots. We note that it can be influenced by very large disasters. For example, including a disaster scenario affecting tens or hundreds of millions of people in the risk portfolio will have a significant impact on \( \mu \), the denominator in the fraction that defines \( \gamma \). Thus, these values may appear low, and must be interpreted with this in mind.

The weighted fraction of disasters covered \( \delta \), on the other hand, is relatively robust to outliers. If system stock contains only 1000 items, then an unserved disaster affecting 1001 or 10,000,000 people have the same impact on the calculation of \( \delta \). This robustness comes at the cost of not conveying a sense of the magnitude of the disasters that go unserved. \( \delta \) provides different information from \( \gamma \), and the two together can help operational managers understand the adequacy of the total inventory level.

3.2.3. Time and cost per unit delivered

The average time (cost) to deliver one unit to a beneficiary from a depot is represented by \( \phi \). Even though this number should not be used to predict supply arrival times for operational planning in a real situation, where the context may not match model parameters, it can provide objective approximations of the relative time to deliver items.

3.2.4. Dual variables

The marginal increase in total expected time (cost) to serve more beneficiaries by adding a unit to depot \( i \) can be estimated by the adjusted dual variables \( (\pi_i) \) for the SLP that utilizes actual inventory allocations (corresponding to constraints (1c)). We adjust the sum of the original dual variables \( \sum_k \pi_i^k \); otherwise they would be dependent on the choice of the dummy value \( \tau_W (c_{W}) \), which is rather arbitrary.

The value of \( \pi_i \) may be positive or negative. In general, an organization adding a unit of inventory to the system might expect total costs to increase: if a disaster strikes, it might ship more items at a higher total cost, with the benefit of serving more beneficiaries. However, if the current stock allocation is particularly imbalanced, then adding inventory to the right place could actually decrease the expected cost, while also serving more beneficiaries.

This set of metrics offers multiple dimensions for system assessment to address the research design questions: to assess the quality of the current inventory positions and to quantify the value of incremental change to the combined system stock. More specifically, the metrics’ relationship to key decisions is such: (i) which items to buy \( [\gamma, \delta] \); (ii) where to put these items \([\pi_i] \); and (iii) should we transfer inventory \( [\Delta] \).
4. Data

We use empirical data from several sources to assess how the proposed metrics address the issues raised and research questions posed. While we discuss assumptions and overall details in subsections 4.1 to 4.4, more specific details regarding how we collected the data can be found in appendix A.

4.1. Disaster data

As mentioned earlier, we leverage historical data for our risk portfolio. Specifically, we assume that each disaster recorded between January 1990 and the summer of 2013 has an equal chance of occurring again, utilizing data from EM-DAT (Centre for Research on the Epidemiology of Disasters, 2014). EM-DAT tracks the following: the month and year of the disaster, total affected population (TAP), the country, the type of disaster, and other fields we do not utilize. We include only sudden onset disasters: earthquakes, epidemics, floods, mass movement dry and wet, storm, volcano, and wildfire. We assume stockpiles are used for unexpected events rather than those that organizations could foresee (e.g., drought) and use procurement capacity or less expensive transportation modes. Of the records in this database for these disasters, 22% of the values for TAP are null: we exclude these from our analysis. Despite the limitations of any database with the objective of recording details related to every disaster that occurs (Guha-Sapir and Below, 2006), this database is recognized as the best of its kind and has been utilized by many other researchers working in similar domains (Peduzzi et al., 2009; Duran et al., 2011, 2013). We examine the potential bias of the null values in section 5.3.1.

4.2. Depot and inventory data

Governmental and non-governmental organizations that choose to stockpile disaster relief supplies may utilize their own depot or those offered by the government or other organizations. As mentioned earlier, we utilize two sources of data capturing depot information and inventory. The UNHRD website hosts a real-time stock report that details which organizations are housing which items where within the UNHRD network (United Nations, 2014). The OCHA “Global Mapping of Emergency Stockpiles” database holds data voluntarily submitted by organizations regarding items in their stockpile: organization name, name of the city for the stockpile location, item name, and quantity, among some other fields (UN Office for the Coordination of Humanitarian Affairs, 2014). This database is proprietary and not open to the public. We combine the data from the UNHRD and OCHA databases to determine an overall estimate of organizations’ inventory levels around the world. We merge duplicate records when one organization appears in both databases for the same item in the same city. For simplicity, we also merge the inventory of stockpiles within near areas, such as Kuala Lumpur and Subang that are about a 30 min drive from each other, without minimal impact on overall cost. In this case, we put all of Malaysia’s inventory in Subang when we run the model. This is one of seven similar instances. In the end, we consider 25 locations in our analysis.

4.3. Time and cost data

We assume two modes of transportation are available: air and truck. We do not consider sea transportation as the study focuses on immediate deployment of the stockpile. We assume the cost of transporting goods is linear in the number of units being transported. Thus, for each warehouse-disaster-mode triplet, we calculate the time and the cost-per-metric-ton-km for the route. This, paired with information on the weights of each item, allows us to calculate the cost of shipping a single unit on a specific route.

For air, we assume the time and cost are based solely on distance along an arc of a great circle around the earth. For trucks we utilize Google’s “Distance Matrix” API (application programming interface) to calculate the road distance and driving time between a warehouse and a disaster (Google, 2014). If there is no way to drive on land between two points, the API may return results including a ferry trip over water. We believe this is reasonable because organizations may use a route where a ferry option exists in lieu of air.

If no land driving route exists, then trucks cannot be used on a particular route. Additionally, we assume trucks would not be used if the driving time is more than 100 hours. Of the 7175 warehouse-disaster arcs we consider, about 31% are drivable according to the Google API. Of this 31% subset of drivable routes, 71% take 100 or fewer hours to traverse.

The time to move an item by air (truck) has a fixed component and a variable component dependent on the distance (driving time). We approximate the time and cost parameters as such:

\[
\text{cost per kilometer per metric ton} = \begin{cases} 25 \text{ USD} & \text{truck} \\ 0.1 \text{ USD} & \text{air} \end{cases} \\
\text{fixed component} = \begin{cases} 10 \text{ USD} & \text{truck} \\ 50 \text{ USD} & \text{air} \end{cases} \]

\[
\text{variable component} = \begin{cases} 0.1 \text{ USD} & \text{truck} \\ 5 \text{ USD} & \text{air} \end{cases}
\]

\[
\text{time to move an item} = \begin{cases} 1 \text{ hour} & \text{truck} \\ 6 \text{ hours} & \text{air} \end{cases}
\]

The time to move a trucked item is approximately constant (driving time). We approximate the time and cost parameters as such:

\[
\text{cost per kilometer per metric ton} = \begin{cases} 25 \text{ USD} & \text{truck} \\ 0.1 \text{ USD} & \text{air} \end{cases} \\
\text{fixed component} = \begin{cases} 10 \text{ USD} & \text{truck} \\ 50 \text{ USD} & \text{air} \end{cases} \]

\[
\text{variable component} = \begin{cases} 0.1 \text{ USD} & \text{truck} \\ 5 \text{ USD} & \text{air} \end{cases}
\]

\[
\text{time to move a trucked item} = \begin{cases} 1 \text{ hour} & \text{truck} \\ 6 \text{ hours} & \text{air} \end{cases}
\]

\[
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\text{time to move a trucked item} = \begin{cases} 1 \text{ hour} & \text{truck} \\ 6 \text{ hours} & \text{air} \end{cases}
\]

Item weights were retrieved from International Federation of the Red Cross and Red Crescent Societies (2009). These weights are utilized to calculate transport cost, which is measured in cost per kilometer per metric ton. In section 3.1 we defined a parameter \(\beta\) that dictates for an item how many units are required per person affected. For the non-country and non-weather related items we assume the following: a bucket serves a family of five; two jerry cans serve a family of five; a kitchen set serves a family of five; a latrine plate serves 50 people; two mosquito nets serve a family of five, in countries where malaria is present; a bar of soap serves one person. We consulted the Sphere handbook (The Sphere Project, 2014), historical appeals for funding that specify commodity requirements, the UNHRD website (United Nations, 2014), and humanitarian experts (Bauman, 2014) in order to estimate the items needed per person. To determine whether a country was at risk for malaria, we consulted the CDC website (Centers for Disease Control and Prevention, 2014).

Blankets are more complicated because demand depends on the
Table 1
Summary metrics for items in actual depots (Ability to meet demand).

<table>
<thead>
<tr>
<th>Item</th>
<th>Units</th>
<th>Demand (μ)</th>
<th>Demand met (μ)</th>
<th>Fraction of demand served (γ)</th>
<th>Fraction of disasters served (δ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blanket</td>
<td>852,563</td>
<td>561,746</td>
<td>75,150</td>
<td>0.13</td>
<td>0.96</td>
</tr>
<tr>
<td>Bucket</td>
<td>106,844</td>
<td>185,926</td>
<td>21,206</td>
<td>0.11</td>
<td>0.90</td>
</tr>
<tr>
<td>Jerry can</td>
<td>437,530</td>
<td>371,852</td>
<td>61,300</td>
<td>0.16</td>
<td>0.93</td>
</tr>
<tr>
<td>Kitchen set</td>
<td>126,143</td>
<td>185,926</td>
<td>23,105</td>
<td>0.12</td>
<td>0.91</td>
</tr>
<tr>
<td>Latrine plate</td>
<td>4,650</td>
<td>18,593</td>
<td>1,321</td>
<td>0.07</td>
<td>0.83</td>
</tr>
<tr>
<td>Mosquito net</td>
<td>395,588</td>
<td>428,591</td>
<td>46,386</td>
<td>0.15</td>
<td>0.91</td>
</tr>
<tr>
<td>Soap bar</td>
<td>111,595</td>
<td>929,631</td>
<td>41,289</td>
<td>0.04</td>
<td>0.76</td>
</tr>
</tbody>
</table>

In order to assess the quality of system inventory allocation we consider the values of the $\Delta$ (balance) and $\phi$ (average time/cost to ship) metrics. Table 2 (Table 3) shows the results when time (cost) is minimized in the SLP. This table also lists the corresponding cost (time), average distance traveled, and fraction of units by air.

Results can be used to assess the quality of a given item deployment. For instance, blankets are the best allocated item for both time and cost and jerry cans are the worst allocated. Across the board, items are more out of balance with respect to cost than time. The balance metric also quantifies the potential value of changing allocation. For these items, reallocation could improve response time between 7% and 17% or reduce costs between 15% and 37%. Quality is also defined by absolute time (cost) to respond. Note that soap bars are better balanced than jerry cans with respect to time, but that it takes longer on average to deliver soap bars. This is in part due to the small number of soap bars in stock. This highlights the fact that an additional unit of inventory not only allows the system to serve more beneficiaries, but also may reduce the overall time or cost to respond.

Additionally, we can use the model to assess the right balance of cost and time by plotting the efficient frontier of these competing objectives. Fig. 1 plots the efficient frontier for jerry cans. The curve is constructed from ten points, each of which minimizes cost for a given constraint on average time-to-respond. Points above the curve are suboptimal: either the cost can be lower while keeping the time-to-respond the same or vice versa. We note that the slope of the efficient frontier is very gradual, which indicates significant time savings can be achieved with minimal increase in costs. For instance, when cost is minimized and time is ignored, the optimal cost is about $0.65USD and the resulting time-to-respond is about 28 h. If cost is allowed to increase by 8% (from $0.65USD to $0.70USD), then the resulting average time-to-respond decreases by 36% (from 28 to 18 h). Thus, for a small increase in monetary budget, a much quicker response time can be realized.

To gain further insight from the efficient frontier, we can calculate how much cost savings are achievable while maintaining the current expected time-to-respond through inventory reallocation. In graphical terms, this is equivalent to bringing the single point in Fig. 1 straight down onto the efficient frontier. In the jerry can example, the cost-to-respond would drop by 20.0%, from $0.89USD to $0.71USD, while maintaining the same current expected time-to-respond of 16.4 h. For all seven items, the achievable cost savings subject to no change in current time-to-respond are as follows: blankets (7.4%); buckets (19.6%); jerry cans (20.0%); kitchen sets (14.3%); latrine plates (14.9%); mosquito nets (18.4%); soap bars (18.9%). While these cost savings are less than those suggested by the balance metric column in Table 3, they are attainable without any degradation of time-to-respond on average.

It is also interesting to consider how the degradation of time-to-respond changes. Fig. 2 shows how the actual allocation of 852,563 blankets.

Table 2
Time optimization for actual inventory allocation: summary metrics (the value being optimized, average time to ship an item, is in bold).

<table>
<thead>
<tr>
<th>Item</th>
<th>Balance metric (Δ) (time)</th>
<th>Average time to ship an item (hrs) (ϕ)</th>
<th>Average cost to ship an item (USD) (ϕ)</th>
<th>Average distance traveled (km)</th>
<th>Fraction of units moved by air</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blanket</td>
<td>1.07</td>
<td>15.6</td>
<td>5.13</td>
<td>5,810</td>
<td>98%</td>
</tr>
<tr>
<td>Bucket</td>
<td>1.15</td>
<td>16.9</td>
<td>2.66</td>
<td>6,530</td>
<td>99%</td>
</tr>
<tr>
<td>Jerry can</td>
<td>1.17</td>
<td>16.4</td>
<td>0.94</td>
<td>6,250</td>
<td>99%</td>
</tr>
<tr>
<td>Kitchen set</td>
<td>1.13</td>
<td>16.3</td>
<td>15.60</td>
<td>6,190</td>
<td>99%</td>
</tr>
<tr>
<td>Latrine plate</td>
<td>1.13</td>
<td>17.5</td>
<td>9.35</td>
<td>6,880</td>
<td>100%</td>
</tr>
<tr>
<td>Mosquito net</td>
<td>1.14</td>
<td>16.0</td>
<td>1.34</td>
<td>5,990</td>
<td>100%</td>
</tr>
<tr>
<td>Soap bar</td>
<td>1.16</td>
<td>18.6</td>
<td>0.39</td>
<td>7,580</td>
<td>99%</td>
</tr>
</tbody>
</table>
comparing to the optimal allocation of blankets when both time and cost are optimized. This figure suggests that much more inventory should be allocated to Subang in order to serve the significant demand in Asia. It is also better to have items in Ankara when minimizing time and in Warsaw when minimizing cost. Ankara is nearer to potential disaster locations via air transportation, while Warsaw is better connected to potential disaster locations via truck.

5.2. Decision support results

While charts reporting on the actual and optimal inventory allocation for various scenarios can provide insights, practitioners may need more specific evidence to support a decision. This is particularly the case when they may not be able to reallocate stock to the optimal site since their depots are in other locations. The dual variables provide an estimate of the value of an additional unit of inventory in each location. From this, one can estimate the value of transshipping between locations, or the cost of replenishing to a different depot.

Fig. 3 shows the adjusted dual variables ($p_i^0$) returned by the optimization software. We do not consider or address degeneracy, multiple optimal dual variables, or the validity of the duals beyond infinitesimal perturbations. The adjusted duals are estimates of the increase in the time or cost objective function if an additional unit is placed at the specific depot. They are often positive because the total time or cost to serve increases when a unit is added to the system; this is the cost for the benefit of serving more people. Subang and Jakarta stand out because adding an item and serving more people actually reduces the average cost and time, respectively. This is a product of significantly suboptimal actual inventory allocations.

5.3. Sensitivity analysis and discussion

Our model is based on data and assumptions that may be incomplete or inaccurate. We analyze the sensitivity of the model to data integrity, our choices of parameter values, and disaster risk profiles we utilized.

5.3.1. Data integrity

In appendix B we analyze the distribution of null values in the disaster TAP data. We find that it is not entirely uniform: some countries and disaster types have propensity for null values that are much higher or lower than the average (e.g., Pakistan has 47% null, while the Philippines has 7% null). We anticipate that skewness of missing values may impact the optimal allocation of inventory, although we have not run any tests. For instance, if many values in Pakistan are null and if we ignore these corresponding disasters, it is possible the model may place too little inventory near Pakistan and too much inventory in Asia. Filling in these missing values using a model based on total killed and other attributes can be an avenue of future research.
5.3.2. Parameter values

For many of our input parameters, the true values either lie in a range or are unknown. To explore how robust our study results are to these input data, we perform sensitivity analysis on several parameters, specifically reporting how varying input parameters within a range affects the balance metric and the optimal allocation of inventory. The detailed results of this sensitivity analysis can be found in appendix B. We summarize our findings here in Table 4. For each parameter, we multiply the base case value by 2 (or by 10 for countries' abilities to respond) and observe the impact on the balance metric. If the balance metric went from 1.2 in the base case to 1.1 when we doubled the parameter value in question, we record this as a (negative) proportional increase of \(\left(\frac{1.1}{1.2}\right) \times 100 = -8.3\%\). The parameter values tested are in decreasing order of the absolute value of the impact on the proportional increase in the average value of the balance metric over the seven items. While the model's outputs change with the choice of these input parameters, the output varies in a way that can be easily explained. We believe the fact that the outputs change in explicable ways lends validity and credibility to our underlying assumptions. However, improvements can still be made and a next step is to calibrate the model with more accurate input parameter values using data from organizations themselves.

5.3.3 Disaster risk profile:

![Fig. 3. Blankets: Dual variables for depots for actual allocation while minimizing time and cost.](image-url)

**Table 4** Summary of sensitivity analysis to parameter values.

<table>
<thead>
<tr>
<th>Parameter (objective type, multiplicative increase in parameter value)</th>
<th>Corresponding average proportional change in balance metric</th>
<th>Behavior of balance metric</th>
<th>Behavior of optimal allocation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed time to acquire airplane (objective: time, increase: (\times 2))</td>
<td>-3.3%</td>
<td>Decreases: as fixed time dominates total time, optimal and actual objective values are equally bad. Ratio converges to 1.</td>
<td>As air fixed time increases, allocation to Dubai and Subang (Ankara and Warsaw) decreases (increases). Ankara and Warsaw are more truck-friendly locations in our data. As airspeed increases, allocation to Dubai and Subang (Ankara and Jakarta) decreases (increases). As long as air cost is more than truck, then allocation to Dubai (Warsaw) increases (decreases) with cost of air. As air cost dominates truck cost, allocation is decided by air cost alone, even though trucking is used slightly more often.</td>
</tr>
<tr>
<td>Airspeed (objective: time, increase: (\times 2))</td>
<td>-3.3%</td>
<td>Decreases: see “fixed time.”</td>
<td>As capacities increase, more should be placed in Subang and less in Dubai and Ankara.</td>
</tr>
<tr>
<td>Cost of air (objective: cost, increase: (\times 2))</td>
<td>1.3%</td>
<td>Increases: as air cost increases, penalty of not stocking enough in truck-friendly locations increases.</td>
<td>Increases: as capacities increase, much of residual demand would b disasters in Asia, which is not where inventory is now.</td>
</tr>
<tr>
<td>Capacity (number of beneficiaries) of countries' to respond to domestic disasters (objective: time, increase: (\times 10))</td>
<td>1.1%</td>
<td>Increases: as capacities increase, much of residual demand would b disasters in Asia, which is not where inventory is now.</td>
<td>Increases: as capacities increase, much of residual demand would b disasters in Asia, which is not where inventory is now.</td>
</tr>
</tbody>
</table>
The results of our model are based on the disaster risk profile we built utilizing historical data from the EM-DAT database. In order to understand the model's sensitivity to the specific disaster risk profile employed, we perform two experiments: one is on a subset of the data over various 10 year rolling horizons and the other is on a dataset with outliers removed.

We first calculate each item's balance metric over a ten-year rolling horizon, beginning in 1980—1990 and ending in 2003—2013. Over these 10-year blocks, different disasters are included or excluded. We include details and figures in appendix B. The balance metric for different items changes depending on the subset of disasters being considered. The absolute value of the balance metric does change over time. For instance, the balance metric for blankets (optimizing time) is about 1.04 in 1980, rises to 1.09 in 1986, and then stays at about 1.06 from 1991 onwards. In order to isolate how much of the variation is due to disaster scenarios affecting all items, and how much is due to disaster profiles that affect items differently, we normalize each item by the balance metric for buckets, which we set to 1.0. For the most part, blankets are the most balanced items — consistently at about 0.92 the normalized value of the buckets balance metric — while soap bars and jerry cans are some of the most imbalanced — mostly at about 1.02 the normalized value of buckets. Rank order is often preserved, which suggests that the model is moderately robust: the value of the balance metric may change depending on the risk scenario, but if an item is imbalanced in one risk scenario, it will likely remain imbalanced for other risk scenarios. The most salient exception is that of mosquito nets. Mosquito nets’ balance metric consistently declines from 1982 onwards. This reflects the trend that — based on the recorded disasters in the EM-DAT database — the optimal allocation of mosquito nets to African warehouses grew over the past few decades. Additionally, soap bars' and jerry cans' balance metrics — while consistent from 1980 until about 1997 — dropped in value after that and fell below the buckets' balance metric. This suggests the model is fairly useful in highlighting which items need special attention and further investigation. However, it can be somewhat sensitive to the disaster profile in certain situations.

We also investigate the model’s sensitivity to outliers: disaster scenarios with extremely large numbers of people affected. In our dataset, the largest 1% of all scenarios (corresponding to 24 disasters in China, 10 in India, and 1 in Pakistan) account for 66% of the total affected population. The five largest disasters affect an average of 178,000,000 people per disaster. To understand the impact of these disasters, we run some of our experiments with these top 1% of disasters removed from the risk portfolio.

Table 5 shows the balance metric (optimizing cost) and fraction of demand served for the base case (from Tables 1 and 3) and for the risk portfolio without the top 1% of disasters. As expected, the fraction of demand served increases significantly with outliers removed. However, changes in the balance metric values are only slight and rank order of items is preserved: blankets are still the best balanced and jerry cans are still the worst.

In addition, the inventory deployment is similar, as indicated by Fig. 4 for jerry cans, an item which shifts more than other items. With the outliers removed, slightly less is deployed to Subang, which is near to the outlier locations in Asia, but the allocation is generally the same. Even though only 34% of demand remains when we remove the extremely large disasters, the resulting decisions are robust.

As with any supply chain model, results for our approach can be improved with better forecasts. This analysis indicates where to focus such efforts. Given its robustness to outliers, there is little need to precisely forecast the size of super disasters. Rather, it is better to develop the right mix of risk scenarios in the portfolio to reflect trends in likelihood and location of disasters.

6. Discussion

Working back from our research questions, we now consider the context that motivated our approach. We noted two challenges that can lead to suboptimal system capacity. First, numerous humanitarian organizations are continually making adjustments to their stockpile inventory. Second, these organizations typically make these adjustments independently of others’ actions. Metrics from the empirical study demonstrate that over time the system can easily become suboptimal for meeting disaster needs. For instance, Fig. 3 suggests that blankets should be moved from Panama to Subang to save money and time. However, the inventory in Panama is owned not only by several organizations but also by organizations different from those that own inventory in Subang. To overcome these challenges, we proposed that sector-wide metrics based on analytical models could fill two gaps that limit coordination on stockpile capacity: (1) lack of evidence to understand the value of systemic rather than independent decision making, and (2) lack of guidance to operationalize system improvement.

Our metrics for system assessment help to close the first gap by quantifying the quality of the current system and the potential for improvement. The managerial use of metrics for decision support helps to close the second gap. We show that models and metrics outlined in this paper can help organizations explicitly estimate the time or dollar value of specific tactical decisions. Our approach provides information in a timely manner — in a real-time dashboard we describe below, for example — as evidence to guide decisions that improve system performance.

In addition, the metrics can frame productive discussions among organizations and donors regarding further investments in capacity. Organizations have new evidence to demonstrate the systemic impact of their actions, and donors have evidence to determine where investment is most needed.

In this section, we discuss how the results can be used for system assessment, how the results can be used for decision support, and broader insights that can be derived from our model.

6.1. System assessment discussion

The fundamental system assessment questions focus on the quality of the current capacity and the value of incremental change. Regarding overall capacity, the γ and δ offer complementary metrics for quality assessment. While system stock serves a small fraction of the potential affected population, it is sufficient to meet needs for most disasters in the risk portfolio. The model offers the potential to refine the metric for fraction of disasters served with better data for domestic internal capacity.

Combined with φ, which considers how quickly system stock can be deployed, wecan simultaneously quantify the impact on needs met and timeliness from changes in overall stock level. Organizations as well as donors can use this marginal analysis to prioritize investments.

<table>
<thead>
<tr>
<th>Table 5</th>
<th>Metrics with outliers (top 1% of disasters) removed.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Item</td>
<td>Balance metric (cost)</td>
</tr>
<tr>
<td></td>
<td>Base case</td>
</tr>
<tr>
<td>Blanket</td>
<td>1.15</td>
</tr>
<tr>
<td>Bucket</td>
<td>1.35</td>
</tr>
<tr>
<td>Jerry can</td>
<td>1.37</td>
</tr>
<tr>
<td>Kitchen set</td>
<td>1.27</td>
</tr>
<tr>
<td>Latrine plate</td>
<td>1.25</td>
</tr>
<tr>
<td>Mosquito net</td>
<td>1.36</td>
</tr>
<tr>
<td>Soap bar</td>
<td>1.29</td>
</tr>
</tbody>
</table>
The allocation of given system stock also has significant impact on system performance. The balance metric, $\Delta$, succinctly addresses both research questions by assessing how well each item is allocated and by quantifying the potential for performance improvement through reallocation.

One useful tool we provide is to normalize the inventory data using our metrics. In Table 1 we see that there are significantly more blankets than any other item. However, if we normalize the inventory by the number of people each unit is able to serve, we see that jerry cans actually have the highest capacity to serve beneficiaries in the “Fraction of demand served” column. We provide value by measuring inventory levels in terms of items’ abilities to meet demand as opposed to absolute numbers of units in warehouses.

We want to reemphasize that the numerical values derived from the model should not be taken literally. The model is already useful in allowing users to better understand the system and how well it is functioning. However, it still needs to be calibrated using input from the humanitarian logistics community. Even when calibrated and based on better data, however, care must still be taken when interpreting the results. The model is most useful for making relative comparisons. For instance, if the model shows that average time to ship blankets is 15.6 h and for buckets the time is 16.9 h, in reality, buckets may not show up exactly 1 h and 18 min later than blankets on average. Rather, for some reason that warrants further investigation, buckets are allocated less effectively than blankets. If buckets are a critical item, then perhaps more buckets should be added or they should be transferred.

This leads to a related question: does improvement of a few hours in response time really make a difference for humanitarian outcomes? First, recall that the savings are on average. If an item can be reallocated to be shipped on average in 14 h instead of 16 h, then this is a 12.5% reduction in system time-to-respond, and a 20% reduction in variable time, considering the 6 h fixed time assumption. Second, a few hours of time could make a big difference within the 72 h window commonly used to benchmark initial response efforts. For example, arriving a few hours earlier could result in a parking space at the airport that may not be available later. Finally, reducing flight times by a few hours could have important implications on transport capacity: being better positioned means that more round trips with a single airplane are possible within the 72 h window. The UN and/or military can quickly mobilize an “air bridge” to take advantage of well positioned stock in this manner.

To complement the empirical study using historical data, we present a small case study using real time data to explore how a manager or coordinated group might actively monitor sector capacity. By compressing a lot of information into a simple dashboard, these metrics can alert managers or coordinated groups to changes that may have otherwise gone unnoticed. For this case, we monitor the publicly available UNHRD stockpile data daily and calculate relevant metrics. We also post our prototype dashboard publicly: http://stockpile.humanitarian.acimovic.com/. We do not post this analysis, which is limited to sector inventory stored in UNHRDs, as definitive evidence for action. Rather, we hope it can facilitate valuable conversation among academics and practitioners as to the best way to implement, interpret, utilize, and validate such metrics.

We show in Fig. 5 one part of the web dashboard: detail of the balance metric. We also describe the actions behind some metrics’ changes. Note that “Organization A” added blankets and jerry cans
to Accra, which — according to our analysis — is not the optimal location due to the corresponding increase in the balance metric. On the other hand, the actions of “Organization B” adding kitchen sets to Dubai and “Organization A” deploying kitchen sets from Accra both helped to bring that line item into better balance.

6.2. Decision support discussion

To consider how the metrics enable decision support, we walk through the decisions mentioned in the research design and consider how a manager or coordinated group could use the results from section 5 as evidence. While we focus on managerial decision-making, the discussion is equally relevant for donors who want their contributions to have the most impact on the system.

One strength of our approach is that a manager or coordinated group does not need to reoptimize the entire system frequently in response to every system change. The data will always have integrity issues; perfectly optimizing the system is a futile task anyway. In fact, we provide tools that allow managers to avoid running an optimization model at all, as long as some central entity calculates and publicizes the metrics regularly. Managers can monitor items’ metrics, be alerted when the situation needs attention, and then make good (not necessarily perfect) incremental changes using the dual variables as a guide. The dual variables allow managers to understand the impact of taking an action that is not optimal, but that may be necessary due to context and which might capture much of the optimal solution’s value.

6.2.1. Which items to buy

Imagine a manager (or coordinated group) is deciding whether or not to procure an item, and if so, which one. She may sort the items by δ and by γ using the data in Table 1. From a system-wide perspective, soap is the item that serves the smallest fraction of demand and the smallest fraction of disasters covered. An additional soap bar will alleviate a unit of unserved demand (1 − δ) = 0.24 of the time a disaster strikes.

The manager could further place a value on each unit inversely proportional to its importance in a typical disaster, say v. Then, the manager may sort items by v·γ or v·δ. Those items with the smallest values would be targeted for procurement. Determining values for v’s is an avenue for future research as part of a dialogue with input from the humanitarian logistics community.

6.2.2. Where to put these items

Assume now that a donor provides funding for blanket procurement and a manager or coordinated group must decide where to place them. The manager can use the dual variables to determine which depot results in the smallest increase (or biggest decrease) in total time or cost to serve beneficiaries. Thus, she would add it to the depot with the smallest π_f^i. According to Fig. 3, Subang would be the best place to minimize cost, and Jakarta would be the best place to minimize time. Adding a unit to Subang would decrease the expected total cost, even though the system is also serving more people. This is because the current inventory position is imbalanced. One can rank preferable warehouses by the dual values. If certain non-quantifiable factors prevented the manager from placing items in Subang, she might choose Nairobi instead, the location with the second lowest dual value. Thus, dual variables offer an objective assessment of the value of a location to consider with other factors such as the political climate, incentives, and risks in making decisions.

6.2.3. Stock transfers between depots

One way a manager or coordinated group can prioritize items that are out of balance is to sort items by balance metric Δ. Looking at Tables 2 and 3, we see that jerry cans are the most imbalanced item with respect to cost and time. With this item prioritized, the manager could decide among a few alternatives to improve the situation:

1. Investigate potential systematic issues that could cause the imbalance. Is there one dominant organization that is not optimizing inventory or coordinating with others? Were jerry cans delivered to a suboptimal location due to vendor error or cheaper procurement costs? Are there location risks that outweigh cost or time advantages? Acimovic and Graves (2015) showed that one large online retailer addressed previously undetected systematic errors by implementing a version of this balance metric.

2. Transfer jerry cans from one warehouse to another. The operations manager could move a unit of inventory from the depot with the largest π_f^i to the depot with the smallest π_f^j. The estimated value of doing this is π_f^i − π_f^j. If the value of real-location exceeds the shipment cost, then the manager might shift inventory from depot i to depot j. For instance, in examining data similar to Fig. 3, but for jerry cans instead of blankets, we estimate the value of moving a jerry can from Panama (dual variable of 0.139) to Subang (dual variable of −0.011) would net about 0.139 − (−0.011) = $0.15 USD in cost savings.

3. Procure new jerry cans into the warehouse with the smallest π_f^i.

4. In a non-emergency phase of a disaster, ship items to beneficiaries from the warehouse with the lowest true cost, defined as min_{c_i} − π_f^i, in an attempt to rebalance the system.

6.3. Deriving broader insights

Beyond the research questions posed, our model and metrics can be used to answer broader questions for the humanitarian logistics community. The examples below are illustrative of ways in which these model-based metrics can be used and also offer evidence that, when considered with the assumptions and sensitivity analysis, could already guide strategies in the humanitarian community.

6.3.1. Cost structure for rapid response

The results in Tables 2 and 3 provide insights regarding the potential to optimize cost or time in global disaster response. These objectives depend greatly on the transportation mod mix, since air is very fast but very expensive compared with truck. Global organizations focused on cost may attempt to strategically deploy stock in order to more effectively use ground transportation. Our results show this is not easy. Given the current network structure, trucks are only useful for up to 2% of the stock when time is the objective, whereas they carry around 20% when cost is being minimized. We show in appendix C that for a wide range of inventory levels, trucks carry only between 15% and 25% of the freight when minimizing cost. Since the global road network is fairly disconnected (and often too long to drive when it is connected) organizations must still rely heavily on air, even when 25 depots around the world are considered. Since trucks cannot effectively reach many disasters from current depot locations, the potential to significantly reduce cost by shifting modes from air to truck is limited. Transportation for the immediate response is going to be costly.

However, given the stock allocation in our data, there is significant potential to reduce the high cost of transporting 80% of freight by air through more effective distributed location of stock. The balance metric, Δ, indicates that proper allocation can reduce transportation cost by 15–37% for these items. The value of a global footprint for stockpile deployment is not only to respond quickly in
saving lives but, perhaps as important, to lower the inherently high
cost of transporting critical items within 72 h of a disaster in order
to leverage limited funding to reach more people.

6.3.2. Allocation strategies according to system inventory

Fig. 2 showed the optimal allocation given the current inventory level for blankets of 852,563. Fig. 6 extends this to show the optimal allocation of blankets when time is minimized for several levels of system inventory.

From Fig. 6 we see that Dubai and Ankara are good locations if there is little inventory in the system. As inventory is added to the system, Subang becomes increasingly important because of the larger disasters that occur in Asia. The dotted line on this figure corresponds to the current total inventory level; as such the allocation along this dotted line matches the middle stacked bar in Fig. 2. We note in Fig. 6 that one is not necessarily decreasing the proportion of inventory kept in Ankara reduces, even if the actual inventory stays constant or increases. It is interesting to note that placing all 852,563 blankets optimally among only Dubai, Ankara, and Subang (the warehouses with the largest allocations of inventory) and forcing all other warehouses to hold zero units results in 3.6% additional expected deployment cost as opposed to using all warehouses as shown in Fig. 6.

It is surprising that Stockholm is a useful location to store blankets. This is due to the fact that flight paths on the spherical earth position Stockholm closer to certain disaster locations like China than other possible depots in the dataset. In the scenario when one million blankets are kept in the system, it is optimal to keep about 3% of these blankets in Stockholm, which serves disasters in China most often, followed by Mexico (as backup to China than other possible depots in the dataset) and then Russia.

6.3.3. The value of coordination

In addition to providing evidence for supply chain strategies, the model-based metrics also help us understand the value of sector coordination. To isolate the value of coordination, we compare optimal supply chain strategies for different numbers of organizations under extreme coordination scenarios. Assume that the current inventory of 852,563 blankets is evenly distributed among \( N \) identical organizations where \( N \in \{5, 50, 500\} \). First, we calculate system cost-to-respond when each organization optimizes the placement of its share of the inventory \((852,563/N)\) in isolation, but with the benefit of the SLP model. Next, we calculate the system cost-to-respond when organizations fully coordinate to optimize the placement of all inventory using a sector-wide SLP model. The increase in system cost-to-respond when organizations work in isolation is 1.0% when \( N = 5 \), 6.3% when \( N = 50 \), and 17.8% when \( N = 500 \). As the number of organizations grows, it is increasingly important to optimize decisions considering the system capacity. This experiment demonstrates the potential value in developing and sharing sector metrics to guide decisions toward system improvement, even if individual organizations are optimally deploying their own capacity.

7. Conclusion

Numerous humanitarian organizations deploy resources to increase logistics capacity in responding to natural disasters. Often these efforts are not coordinated and the combined capacity to meet needs is difficult to assess. Focusing on stockpile inventory, we propose new humanitarian logistics metrics that enable assessment and evaluation of response capacity while also providing evidence to guide dynamic, independent decisions toward system improvement.

Empirical studies using data from the United Nations demonstrate the potential for this approach. Results show that the combination of metrics, each focused on a distinct dimension of capacity, paints a new and effective common operating picture for the humanitarian sector. At the same time, we outline how the system metrics that quantify marginal change can facilitate decision support. Finally, the metrics offer quantifiable evidence to develop insights that inform strategies and shape policies.

There are limitations to our approach that provide avenues for future work. First, we utilize past disaster data to forecast future needs. Our results are only moderately robust to the scenario selection from these historical data. The metrics should be based on better forecasting methods, such as those used by the insurance sector to assess future risk to property. Second, we make several assumptions about parameters that can be improved by further engaging the humanitarian community for more extensive and more current data. These data might include: broader and more current inventory levels; better estimates of each country’s internal capacity to respond; and better estimates of delivery costs and times. Third, the model does not incorporate potential constraints for individual organizations, such as warehouse space or procurement budget. Further consideration and expert opinion would be required to mix strategic and tactical decisions, fixed and variable costs, and the priority and importance of each commodity in a multi-commodity model. Fourth, response capacity incorporates more than stockpile inventory. The structure of the SLP is easily
extended to include supplier capacity to replenish depots and/or to deliver directly to the affected community. For instance, the model would highlight if several NGOs have contracts with a single supplier whose capacity is below the sum of the contracted amounts of the NGOs. Finally, we hypothesize that the value of information provides incentive for further information sharing. Empirical study regarding the interest and use of the proposed metrics could confirm or deny this virtuous cycle.

After circulating initial drafts of this research, the authors were invited to join a newly formed Working Group on Emergency Supply Pre-positioning Strategies (ESUPS). This group is facilitated by the emergency services branch of the United Nations Office for the Coordination of Humanitarian Affairs (UN-OCHA) and involves representatives from various UN and non-governmental organizations (NGOs).

Furthermore, the Inter-Agency Standing Committee (IASC) for inter-agency coordination of humanitarian assistance task force on preparedness and resilience recently developed the emergency response preparedness (ERP) framework, which aims to “optimize the speed and volume of critical assistance delivered immediately after the onset of a humanitarian emergency.” (Inter-Agency Standing Committee secretariat, 2015). Together with UN-OCHA, we defined a process to incorporate our analytical approach along with the newly updated Global Mapping of Emergency Stockpiles database in support the ERP efforts. We presented this combined process at the annual Humanitarian Networks and Partnership Week in February 2016. Through engagement with the ESUPS working group and positioning our approach within the ERP framework, we have begun the process to calibrate, validate, and implement the ideas outlined in this paper. In publicly sharing our research and our metrics, we hope to provide practical contribution while encouraging discourse to improve the methods.

Acknowledgments

The open data shared by the United Nations Humanitarian Response Depot (UNHRD) and the Centre for Research on the Epidemiology of Disasters (CRED) were essential for this research. We also thank the Emergency Services Branch of the United Nations Office for the Coordination of Humanitarian Affairs for sharing information on the Global Mapping of Emergency Stockpiles database. Pierre Honnorat and Virginie Bohl were very helpful refining the assumptions and describing the decision-making landscape. We also thank Nicholas Hood, Kathryn Kimie Nishimura, Jian Wang, and Lauren Seelbach for their contributions.

Appendix

A Data details

A.1 Disaster data details

As mentioned in the main text, we utilize EM-DAT data to describe the disaster scenarios. We make several adjustments to and assumptions about these data for our analysis of disasters:

1. We use the capital city as the location for any disaster that occurred in a country. The EM-DAT database does include some data indicating a more precise location, but this is a text description of where the disaster took place that might be blank or might be a partial list of provinces, for example. Instead of resorting to judgment to decipher locations from the few records with such descriptions, we used the geographic coordinates of country capitals for all historical disasters. From a logistical perspective, this assumption actually represents a more accurate network for many countries where the capital is a primary port of entry and/or regulatory hub (e.g. central medical stores) for imported supplies.

2. We use the “Total Affected” field to measure the number of people affected by a disaster. According to the EM-DAT database’s website description, “Total Affected” is defined as the sum of “People suffering from physical injuries, trauma or an illness requiring medical treatment as a direct result of a disaster”, “People needing immediate assistance for shelter”, and “People requiring immediate assistance during a period of emergency; it can also include displaced or evacuated people.” (Centre for Research on the Epidemiology of Disasters, 2014). Although it can be argued that this field may be subject to more bias than “Number Killed,” for instance (Peduzzi et al., 2009), we use it because it is a more accurate representation of the number of people that need supplies such as blankets, buckets, jerry cans, soap, kitchen kits, latrine plates, and mosquito nets (the items we evaluate). Additionally, only 22% of the records have null values for “Total Affected” as opposed to about 23% of null values in “Number Killed.” We exclude records with null values for “Total Affected” in our study. Breakdown of null values are explored in appendix B.1.

3. If a disaster affected more than one country, we include only one of the countries affected. However, the model itself is flexible enough to incorporate multiple locations per disaster.

4. We examine only sudden onset disasters and epidemics. Specifically, we include: earthquakes, epidemics, floods, mass movement dry, mass movement wet, storm, volcano, and wildfire. We exclude: complex disasters, droughts, extreme temperature disasters, industrial accidents, insect infestations, miscellaneous accidents, and transport accidents.

5. We utilize post-1990 data due to completeness and homogeneity (Peduzzi et al. (2009) utilize post-1980 data for a similar reason.).

6. Some disasters have a value of 0 for the month-of-year field (as opposed to a number between 1 and 12). If we are examining disasters and needs year-by-year, we include these disasters (and for blankets, set the need equal to the average for that country over the course of the year). If we are analyzing the data month-by-month, we exclude these disasters.

For countries’ abilities to respond, we assume that the following countries would not require any outside assistance: Austria, Belgium, Bulgaria, Canada, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Nicosia, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, The Netherlands, United Kingdom, United States. We assume all other countries require assistance for disasters affecting more than 1000 people.

A.2 Depot and warehouse data details

If an organization houses an item in a UNHRD, it may show up in both databases. Thus, we merged them as follows. For each item an organization holds in a particular city, we assume that the following

1. Jerry can, collapsible, w/screw cap, 1.Lt, “Jerry can, collapsible, 10 L with Tap cap,” “Jerry can 20 Lt,” among other descriptions. We considered for jerry cans and buckets that they were all the same regardless of description or size. We performed similar data-
cleaning on the other items that we examine. Thus, a record consists of the organization, city, item name, and quantity. Additional data cleaning was required to match the names of the organizations among the two databases as well.

Finally, we took steps to “merge” similar depots. For instance, a depot is listed in Kuala Lumpur as well as Subang. These locations are about a 30 min drive from each other. Including both locations in our model resulted in different inventory allocations in Kuala Lumpur and Subang, even though the inventory in Malaysia stayed constant. Therefore, to make the model and results easier to interpret, we picked only one depot for each of the countries in our database, and reallocated all the inventory from the other depots in that country to the one warehouse. Specifically, we reallocated inventory from:

- Ottawa, Canada, to Toronto, Canada
- Saint-Brieul, France, to Roissy-en-France, France
- Kuala Lumpur to Subang
- Molde, Kapp, Kolbotn, and Trollasen, Norway, to Oslo, Norway
- Lae, Papua New Guinea, to Port Moresby, Papua New Guinea
- Madrid, Spain, to Barcelona, Spain
- Gloucestershire, UK, to Oxfordshire, UK

A.3 Time and cost data

Although we can select an option to prefer to not use ferries with the Google API, if a ferry route exists, it will return the distance using a ferry. If there is no way to drive between two points and no ferry exists, no result will be returned, and we assume air must be used.

A.4 Item specific data

A.4.1 Items needed per person. To determine whether a country was at risk for malaria, we consulted the CDC website (Centers for Disease Control and Prevention, 2014) to determine which countries had any risk for malaria at all. We assume that if a country has at least a partial (or localized) risk, then mosquito nets are needed for any disaster that strikes in that country. Otherwise, no mosquito nets are needed for that country. We do not attempt to track each country’s disaster month relative to the rainy/malaria season. We assume that the impact of any disaster is great enough and long-lasting enough that families will need mosquito nets at some point over the next year following a disaster, which will include the rainy season.

A.4.2 Blankets. Implicit in the method we use to calculate blankets needed per person is the assumption that we can serve a fractional number of blankets to beneficiaries on average. That is, if at a low temperature we serve two blankets per person, and at a high temperature we serve one blanket per person, then we assume between these temperatures we serve 1.5 blankets on average per person: half the people require one blanket and half require two.

As mentioned in the main text, we calculate the blanket needs per person by first calculating the thermal insulation needs per person according to temperature. According to guidelines set by the United Nations High Commissioner for Refugees (2012), thermal insulation requirements per person are 4 TOG at 10 °C, 6 TOG at 0 °C, 8 TOG at −10 °C, and 9 TOG at −20 °C. The guidelines also suggest that someone resting indoors at 20 °C requires 1.5 TOG.

When we regress number of medium blankets required in addition to basic clothing against temperature Fahrenheit, the relationship (using the five data points of TOG versus temperature Celsius from United Nations High Commissioner for Refugees (2012) and converting Celsius to Fahrenheit) is essentially perfectly linear ($R^2 = 0.993$), which is confirmed by visual inspection. In this way we obtain the blanket equation mentioned in the main text:

$$\text{NumBlanketsPerPerson} = (3.34 - 0.044(\text{NightlyLowTempInF}))^+,$$

where $(a)^+ \equiv \max(a,0)$. As mentioned earlier in the main text, to obtain $\text{PeopleServedPerBlanket}$ (the $\beta$ parameter in our model), we take the inverse of $\text{NumBlanketsPerPerson}$. Note that $\text{PeopleServedPerBlanket}$ is not linear in temperature. If $\text{NumBlanketsPerPerson} = 0$, we assume that no blankets are needed, and set the demand to zero.

The above equation is a function of the nightly low temperature. Because we are defining demand at the country level, due to paucity of more specific location data, we assume that the nightly low temperature is the same across an entire country for the entire month. We captured the average low temperature by month for each country in our database by querying the website World Weather Online (2014). This website averages all the cities within a country for which it has data across all the years for which it has data. Thus, between the temperature data and equation A.4.2, we can estimate the number of people served per blanket for any country for each month.

To determine how many blankets are available in the stockpile warehouses, we first need to determine the TOG of the different types of blankets that are stored. We concentrate only on thermal blankets, ignoring cotton blankets (which are sometimes deployed to warm weather disasters). Table 6 below lists all the different descriptions of blankets that we found, and our estimate of the TOG based on UN High Commissioner for Refugees (2013) and International Federation of the Red Cross and Red Crescent Societies (2009) guidelines.

This is a list of all the fields in the databases that mention the word blanket. We have converted the text to TOG per Table A1:

<table>
<thead>
<tr>
<th>Table A1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Insulation (TOG) of blankets of different descriptions</td>
</tr>
<tr>
<td>Description</td>
</tr>
<tr>
<td>blanket cotton 100%</td>
</tr>
<tr>
<td>Blanket cotton 50%</td>
</tr>
<tr>
<td>Blanket, 150 × 200 cm, polyester</td>
</tr>
<tr>
<td>Blanket, woven, 80% COTTON, 20% POLYESTER, 1.2 × 1.8 m, light</td>
</tr>
<tr>
<td>Light weight Blankets 1.2 × 1.8 m 80%cotton,20%polyester</td>
</tr>
<tr>
<td>Blanket (normal season) 30% wool + 70% synthetic fiber Thickness 4 mm Water and months proof impregnated, whipped ends Grey or other dark colors</td>
</tr>
<tr>
<td>Blanket, 150 × 250 cm, Fleece</td>
</tr>
<tr>
<td>Blanket, 30% wool</td>
</tr>
<tr>
<td>Blanket, UNHCR, 30% wool</td>
</tr>
<tr>
<td>Blanket</td>
</tr>
<tr>
<td>Blanket (Medium thermal resistance) 150 × 200 cm 50% wool Woven</td>
</tr>
<tr>
<td>Blanket (medium thermal) 150 × 200 cm 50% wool 50% Woven</td>
</tr>
</tbody>
</table>

(continued on next page)
null value percentages differ significantly: floods have 13% null values while storms have 30%. Floods are dispersed across many countries, with the top five countries (China, India, Indonesia, Philippines, and Brazil) involved in only 25% of all floods. Storms are most prevalent in Philippines, China, Bangladesh, Vietnam, and India, which together involve 40% of all storms in our dataset. By drilling into countries themselves, we see that China, India, and the Philippines report a higher fraction of null values for storms than for floods. Because — in India for example — flood season and storm season do not coincide, the model could then put too many items near India during flood season and not enough during storm season. The existence of null values is a shortcoming of the data. However, we do not believe the heterogeneity of the distribution of null values is severe enough to invalidate the results. We note that one could build a model to fill in the missing TAP values. In fact, for 74% of the null TAP values, there is a non-null ‘NumberKilled.’ Thus one might predict TAP based on attributes such as ‘NumberKilled,’ country, season, disaster type, and so on. Building such a model is beyond the scope of this paper.

### B. Sensitivity analysis

#### B.1 Data integrity: total affected population null values

Here, we examine those disasters within the subset we consider, but also include those with null TAP values. Namely, we include disasters between 1990 and 2013 which were sudden onset in countries with limited capacity to respond. We exclude disasters in the USA, Canada, and most of Europe. Within this subset of disasters, 994 of the 4586 disasters had null TAP values, or 21.7%. Table A2 shows the subset of countries with 50 or more disasters between 1990 and 2013, and their respective fraction of null values. Some countries have null TAP values as prevalent as 41% (Pakistan) and as low as 7% (Philippines). This may cause the model to place too little inventory in the Middle East and put too much in Asia. Table A3 shows the prevalence of null values by disaster type. Some disaster types have null TAP values as high as 74% (MassMovementDry) and as low as 10% (Earthquakes). Because all of our items are disaster independent, this would affect the model only through the locations of these disasters. Two disaster types stand out because they occur often and because their null value percentages differ significantly: floods have 13% null values while storms have 30%. Floods are dispersed across many countries, with the top five countries (China, India, Indonesia, Philippines, and Brazil) involved in only 25% of all floods. Storms are most prevalent in Philippines, China, Bangladesh, Vietnam, and India, which together involve 40% of all storms in our dataset. By drilling into countries themselves, we see

<table>
<thead>
<tr>
<th>Description</th>
<th>TOG</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blanket 150 × 200 cm 50% wool (virgin) or recycled wool, and 50% of other synthetic fibers such as cotton or cotton/synthetic mix</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket 150 × 200 cm 50% wool</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket 50% wool</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket 50% wool + 50% synthetic fibers</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket 50% wool 50% synthetic fibers</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket IFRC spec50% wool (Raised)</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket INTERSOS</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket woven dry raised (type AI/LTR)</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket, 50% wool</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket, fleece, 1.5 × 2 mt</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket, fleece, synthetic, 1.5 × 2 mt, medium thermal – UNHCR item 05787</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket, medium thermal 50%wool1.5 × 2 m</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket, polyester 100%, w/logo</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket, Synthetic 1.5 × 2 m, medium thermal</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket, woven acrylic450 g/m2 With AECID logo</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket, woven Without logo</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket, woven, 50% wool, 1.5 × 2 m, medium thermal resistance</td>
<td>2.5</td>
</tr>
<tr>
<td>Blankets (composite material)</td>
<td>2.5</td>
</tr>
<tr>
<td>Blankets Woven Dry Raised (type AI/LTR)</td>
<td>2.5</td>
</tr>
<tr>
<td>Blankets, 150 × 200</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket, 50% wool, 50% Fabric, 210 × 120 cm</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket, polyester 100%, w/logo</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket, fleece, 1.5 × 2 mt</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket, fleece, 200 × 140 cm, JICA logo</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket, Wool, 210 × 160 cm, Bundle of 30</td>
<td>2.5</td>
</tr>
<tr>
<td>Blanket (cold season) 70% wool + 30% acrylic Thickness: 5 mm Water and months proof impregnated, whipped ends Grey or other dark colors</td>
<td>3.5</td>
</tr>
<tr>
<td>Blanket (cold season), 203 × 152 cm,70% wool +30% synthetic, Thickness 5 mm, Wool blend</td>
<td>3.5</td>
</tr>
<tr>
<td>Blanket, quilted</td>
<td>5</td>
</tr>
<tr>
<td>Blanket, quilts, various size</td>
<td>5</td>
</tr>
</tbody>
</table>

#### Table A2

| Prevalence of null values in TAP countries with 50 or more disasters. |
|------------------------|-----------------|-----------------|-----------------|
| **Country** | **Number of disasters with TAP = Null** | **Number of disasters total** | **Percentage null** |
| Pakistan | 32 | 79 | 41% |
| Afghanistan | 35 | 90 | 39% |
| Russia | 41 | 109 | 38% |
| India | 78 | 239 | 33% |
| Australia | 24 | 76 | 32% |
| Nigeria | 16 | 55 | 29% |
| Mexico | 28 | 115 | 24% |
| Iran | 19 | 85 | 22% |
| Japan | 17 | 80 | 21% |
| China | 83 | 409 | 20% |
| Colombia | 14 | 78 | 18% |
| Peru | 11 | 62 | 18% |
| Indonesia | 34 | 203 | 17% |
| Thailand | 12 | 79 | 15% |
| Vietnam | 18 | 119 | 15% |
| Bangladesh | 17 | 123 | 14% |
| Democratic Republic of the Congo | 6 | 51 | 12% |
| Brazil | 7 | 83 | 8% |
| Philippines | 19 | 263 | 7% |
B.2 Sensitivity of our choice of parameter values

As we mentioned earlier, we made several assumptions and approximations when choosing transportation and other parameter values. Here, we investigate how the balance metric as well as the optimal inventory allocation changes if we were to vary some of those input parameters.

B.2.1 Cost of air. Figs. A1 and A2 show how the balance metric and optimal inventory allocation change if the cost of air varies. We adjust both the fixed and variable portion of the air cost by the factor listed in the x-axes of the figures.

B.2.2 Fixed time to acquire an airplane. We assume that the fixed time to acquire an airplane is 6 h. In Figs. A3 and A4 we show how the balance metric and optimal inventory allocation change as the fixed time to acquire an airplane varies from 0 h to 24 h.

B.2.3 Speed of aircraft. Figs. A5 and A6 show how the balance metric and optimal inventory allocation change as average airspeed varies from 75 kph to 2400 kph (with the realistic case being in the middle, around 600 kph).

---

<table>
<thead>
<tr>
<th>Disaster type</th>
<th>Number of disasters with TAP = Null</th>
<th>Number of disasters total</th>
<th>Percentage null</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mass movement dry</td>
<td>14</td>
<td>19</td>
<td>74%</td>
</tr>
<tr>
<td>Wildfire</td>
<td>68</td>
<td>106</td>
<td>64%</td>
</tr>
<tr>
<td>Mass movement wet</td>
<td>143</td>
<td>231</td>
<td>62%</td>
</tr>
<tr>
<td>Storm</td>
<td>331</td>
<td>1089</td>
<td>30%</td>
</tr>
<tr>
<td>Epidemic</td>
<td>104</td>
<td>502</td>
<td>21%</td>
</tr>
<tr>
<td>Flood</td>
<td>283</td>
<td>2145</td>
<td>13%</td>
</tr>
<tr>
<td>Volcano</td>
<td>11</td>
<td>99</td>
<td>11%</td>
</tr>
<tr>
<td>Earthquake (seismic activity)</td>
<td>40</td>
<td>395</td>
<td>10%</td>
</tr>
</tbody>
</table>

---

Table A3: Prevalence of null values in TAP disaster types.

However, we do perform sensitivity analysis on the uniform number of beneficiaries the countries can serve. We vary the number from 100 to 10 million. Fig. A7 shows how the balance metric changes with countries’ abilities to respond. Fig. A8 shows the optimal inventory for blankets. We notice in the first figure that items become more imbalanced, and in the second that Subang becomes the optimal location to put blankets as countries’ abilities to respond increase. These are related, and both phenomena reflect that fact that many of the very large disasters occur in Asia.

One interesting thing we note is that the percent of items moved by truck and the optimal inventory for some of the warehouses are not monotonic. We might naively expect that as airspeed decreases (increases), more (fewer) items will be moved by truck, and thus inventory will be optimally allocated to truck-friendly (truck-hostile) warehouses. What we see instead is that truck costs drive inventory allocation within a specific range. When the airspeed is very slow, many items are moved by truck, but the optimal allocation of inventory is driven by the air option, since it dominates the objective value. In the limit where airspeed is infinite, the optimal allocation of inventory would not depend on air at all. All warehouse locations would have equal air time to every disaster. Thus, the optimal inventory allocation would be driven purely by what is good for the truck option. Thus, more inventory would be able to be moved by truck because in these truck-friendly warehouses, the time to transport by truck to some disaster regions would be less than the fixed time to transport by air to the same locations. This is why the optimal inventory allocation for Stockholm increases then decreases with airspeed. At the macro-level, as airspeed increases, inventory is shifted to more truck-friendly locations because the variable air time becomes less and less relevant.

B.2.4 Sensitivity to countries’ abilities to respond. We made an assumption that countries requiring international assistance could serve 1000 beneficiaries affected by themselves, but would require aid for any affected population above 1000. We assume that countries such as the USA, most of those in Europe, and Canada would not require any aid. Our model has the flexibility to accept custom values for each country to reflect the fact that each nation may have a different number of beneficiaries they can serve for a given disaster type and item. Developing and finding these country-specific custom values is beyond the scope of this paper.

| Countries’ abilities to respond | 1 & 2 & 3 & 4 & 5 & 6 |
|-------------------------------|---|---|---|---|---|
| Countries requiring international assistance | 4,282 | 3,246 | 1,904 | 794 | 221 | 44 |

Fig. A8. How the optimal allocation of blankets to warehouses (with respect to time) changes depending on countries’ capacity to serve a number of beneficiaries in a sudden-onset disaster.

B.3 Disaster risk profile

B.3.1 Ten year rolling horizons: The results presented in this paper rely on a dataset including disasters from 1990 to 2013. This set of disasters corresponds to one risk scenario: each disaster between 1990 and 2013 has equal chance of occurring again. We can investigate how the results may change based on different risk profiles. We examine 10-year consecutive blocks of disasters between 1980 and 2013. Thus, disasters between 1980 and 1990 would constitute one scenario (identified by its starting year), while disasters from 1981 to 1991 would constitute another. Fig. A9 shows how the balance metric for different items changes depending on the subset of disasters being considered. In order to isolate how much of the variation is due to disaster scenarios affecting all items, and how much is due to disaster profiles that affect items differently, we show in Fig. A10 each item’s balance metric normalized by the balance metric for buckets. (We chose a normalizing item that was not affected by weather, time-of-year, or malarial prevalence within a country.)
The balance metric for a given risk scenario is normalized by the bucket’s balance metric in the database, and will need to be used about 80% of the time no matter how large the range of inventory levels, the percentage moved by truck decreases. This is mainly due to very large disasters occurring in China, which (according to our assumptions and data) have a large impact on the percentage moved by truck. As more units of inventory are stored in the warehouses, the balance metric changes depending on the risk scenario, as shown in Fig. A10. In Fig. A11, we show how the percentage moved by truck versus number of units in inventory (blankets, mosquito nets, latrine plates, kitchen sets, blankets) changes depending on the risk scenario, as defined by a 10-year subset of disasters identified by the starting year. Each item’s balance metric for a given risk scenario is normalized by the bucket’s balance metric for that same scenario.

C percentage of items moved by truck

In Fig. A11, we show how the percentage moved by truck changes as more units of inventory are stored in the warehouses. The percentage goes up initially because as more items are stocked, more of these items can be placed in truck-friendly locations. As the number of items being stockpiled grows above one million, the percentage decreases. This is mainly due to very large disasters occurring in China, which (according to our assumptions and data) are reachable only by airplane. What is interesting to note is that for a very large range of inventory levels, the percentage moved by truck is within 15% and 25%. Even with the 35 warehouses in our database, air will need to be used about 80% of the time no matter how many units are in inventory.

Fig. A10. How the balance metric (time) changes depending on the risk scenario, as defined by a 10-year subset of disasters identified by the starting year. Each item’s balance metric for a given risk scenario is normalized by the bucket’s balance metric for that same scenario.

Fig. A11. Percent moved by truck versus number of units in inventory (blankets, minimizing cost).

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