# EVP Terminal Report:
# Operations research for disaster preparedness and response

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**Abstract**

This terminal report describes the project conducted by the above-named exchange visitor with the objective of developing operations research models for disaster preparedness and response. The report describes the objectives of the project, the activities undertaken, the findings based on field visits, the development of the mathematical model, and conclusions based on the model. This terminal report is submitted in partial fulfillment of the requirements for the Exchange Visitor Program alternative arrangement for technical knowledge transfer.

## 1 Review of activities undertaken

The objective of this project are as follows:

1. Utilization of quantitative models in Operations Research to make recommendations for improving the efficiency and effectiveness of the Philippine disaster response.
2. Development of a mathematical model for disaster management that:
   (a) would be used as the basis of the decision-support tool for coordinating relief operations in the aftermath of a disaster,
   (b) can be used to simulate and estimate the benefit of coordinated operations,
   (c) can quantify the benefits of particular investments in infrastructure that would improve the Philippines resilience to disasters

This project consisted broadly of four phases, namely:

- Data gathering
- Mathematical modeling
- Evaluation of the model
- Development of a decision-support tool

A brief description of each phase and the summary of activities undertaken in each phase follows.

| Phase | Description |
|---|---|
| Data gathering | This phase consisted of compiling data on the affected population from Typhoon Yolanda, data of Visayas municipalities, and data of Visayas' transportation network (sea routes, air routes, road networks connecting municipalities and cities, and air).<br><br>Data on the municipality-level affected population from Typhoon Yolanda was compiled from Situational Reports generated by the National Disaster Risk Reduction Management Council (NDRRMC) released on November 2013. I gathered data on geographical coordinates of municipalities from the Philippine GIS Data Clearinghouse (PhilGIS, 2013). A major stumbling block was that a text file-based Visayas road network data was unavailable in any public domains. I overcame this challenge by manually entering data on national highway arc distances between pairs of municipalities queried from Google Maps. Data on sea routes between ports in Visayas was compiled from Ports.com. All data was compiled in csv files. A more detailed description of the data-gathering phase is found in Section 5.<br><br>We also gathered data on the process of disaster preparation and disaster response in the Philippines. This information was gathered from interviews conducted with Mr. Dragoslav Djuraskovic (the Head of Logistics of the UN World Food Program in the Philippines) and Dir. Thelsa Biolena (Director of the DSWD Disaster Risk Reduction and Response Operations Office, DRRROO), and from a field visit of the DSWD National Resource Operations Center in Pasay City. More details on the Philippine humanitarian logistics are found in Section 3.<br><br>*Data sources:*<br>NDRRMC (http://www.ndrrmc.gov.ph/) |

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|---|---|
| | PhilGis (http://www.philgis.org/freegisdata.htm)<br>Google Maps (https://www.google.com/maps)<br>Ports.com (http://ports.com/) |
| Mathematical modeling | Based on the description of the Philippine humanitarian supply chain, I developed a mathematical model for pre-positioning of relief aid in temporary storage areas close to a projected typhoon path, and its deployment after the typhoon strikes. A description of this mathematical model and its derivation is found in Section 4.<br><br>To gather feedback on the models, I also gave a two talks in universities in the Philippines, one first talk part of the IBM Analytics Lecture Series (on December 10, 2014 held at the University of Asia and the Pacific), and the second talk was hosted by the Ateneo de Manila Institute of Sustainability (on December 12, 2014 at AdMU). There was favorable feedback and we received constructive criticisms to improve the model. |
| Evaluation of the model | We evaluate the decision support tool based on data from Typhoon Yolanda that we gathered in the data-gathering phase of this project. We simulate the effect of using our decision-support tool for disaster preparedness and response during Typhoon Yolanda. The results of this computational experiment are found in Section 5. |
| Development of a decision-support tool | Based on the mathematical models, I developed a decision support tool that: (i) prescribes quantities of emergency relief aid items to be pre-positioned in temporary storage locations before a typhoon, and (ii) prescribes allocation of emergency relief aid and transportation vehicles to affected locations after a typhoon. This decision support tool was programmed in Python and uses the CPLEX Python API for solving the optimization models that I developed. The input to this tool are csv files on an uncertainty model for a projected disaster, the transportation network in the projected affected regions, locations of regional warehouses and candidate temporary storage facilities, and the list of transportation vehicles available for disaster response. The solution is outputted onto a csv file. The description of the decision support tool is found in Section 6. |

## 2 Introduction humanitarian logistics

Humanitarian logistics is defined by Thomas and Mizushima (2011) as "the process of planning, implementing and controlling the efficient, cost-effective flow and storage of goods and materials, as well as related information, from the point of origin to the point of consumption for the purpose of meeting the end beneficiaries' requirements."

There are several differences between a humanitarian supply chain and a commercial supply chain, which we summarize below:

| | Commercial Supply Chain | Humanitarian Supply Chain |
|---|---|---|
| Objective | Cost or profit | Fairness, demand coverage or timeliness |
| Supply | Standard | Non-standard (e.g. in-kind donations) |
| Transportation network | Fixed | Subject to uncertainty (e.g., disruptions) |
| Demand | Existing forecasting techniques | Difficult to forecast |

A commercial supply chain transforms raw materials and components into a finished product that is delivered to the end customer. The objective in planning a commercial supply chain involves either minimizing cost or maximizing profit. Supply is standardized in the sense that all units in a particular node (i.e., supplier, manufacturer, customer) are the same. The network configuration in a commercial supply chain are generally fixed. The demand in a commercial supply chain are products, and it is relatively stable and predictable. In contrast, in the humanitarian supply chain, the objective involves either maximizing fairness, maximizing demand coverage, or maximizing timeliness. Supply in a humanitarian supply chain is non-standard, since a large part of it comes from in-kind donations (e.g., blankets, clothes, canned foods, etc.). The network configuration is subject to uncertainty due to disruptions. For example, after Typhoon Haiyan (local name: Yolanda) struck the Visayas islands, the Tacloban airport was inoperational due to the damange from the typhoon. Demand is also difficult to predict, since it is generated from random events that are unpredictable in terms of timing, type, and size.

Disaster management has four distinct phases of activities, varying depending on the timeline and the objective of the activity. These four phases are mitigation, preparedness, response, and recovery.

1. **Disaster mitigation.** The activities in this phase serve two purposes: to prevent a hazard from becoming a disaster, or to reduce the possible effects of a disaster by proactive measures. A critical activity in the mitigation phase is risk assessment, which analyzes the potential for hazards (e.g. creating flood hazard maps).

2. **Disaster preparedness.** In this phase, the goal is to decide on the actions to perform pre-disaster to most effectively support the response to minimize the damage to affected communities. Examples of activities in this phase include facility location, prepositioning of assets, resource allocation, transportation planning, and the design of partnerships and contracts for responding to a disaster.

3. **Disaster response.** The response phase starts while the disaster is in progress. The objective in this phase is to manage the available resources to minimize the suffering of the impacted

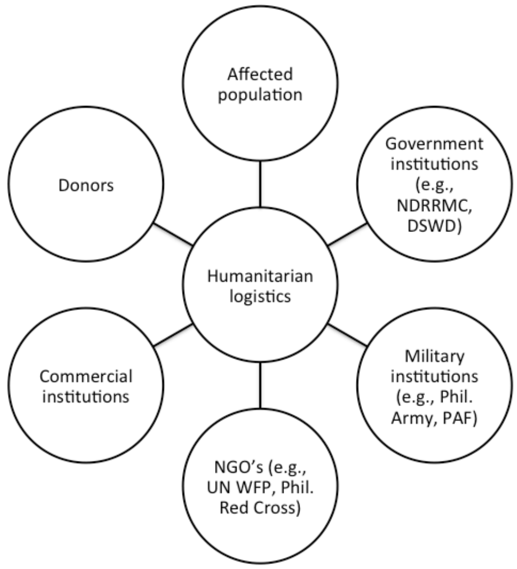



Figure 1: Stakeholders in a humanitarian supply chain.

community. In this phase, timeliness is essential because the impacted community might be without food, water, or medical supplies. The main activities in this phase include "last mile distribution", which aims to distribute the supply (prepositioned stocks, irregular donations, and other procured supply) as fast as possible to the affected areas.

4. **Disaster recovery.** Activities in this phase span long-term developmental actions that are taken following the response phase. The objective in this phase is to restore the system to the greatest extent possible and to stabilize the impacted community.

Figure 1 illustrates the stakeholders of a humanitarian supply chain. The affected population correspond to the demand side of a humanitarian supply chain. Government institutions, such as the National Disaster Risk Reduction Management Council (NDRRMC) and the Department of Social Welfare and Development (DSWD) are responsible for carrying out mitigation activities, such as strengthening infrastructure, or coordinating preparedness, response and recovery activities. The military, such as the Philippine Army and the Philippine Air Force, are responsible for providing manpower and logistics during preparedness and response phases. Non-governmental organizations (NGOs) are involved in all four phases of disaster operations. Sometimes the government has contractual agreements with commercial institutions to provide logistics or additional supply during the response phase. Donors are the supply side of the humanitarian supply chain.

# 3 Humanitarian logistics in the Philippines

The following section describes the current processes for disaster preparedness and disaster response in the Philippines. This information has been gathered from news articles, from interviews with field experts, and from field visits to DSWD warehouses.

The Philippines is a disaster-prone country. It ranks first globally for exposure to natural hazards in the 2013 OCHA Global Focus Model. An average of 20 typhoons enter the Philippine Area of Responsibility (PAR) annually, although not all make landfall. Unfortunately, the geographic landscape of the Philippines cause coordinating disaster operations is very difficult. The country is composed of 7,107 islands. It has a population of roughly 100 million spread across some 2,000 islands. It has been observed by Apte (2009) that the difficulty of humanitarian logistics is the highest for sudden and dispersed disasters, which is certainly the case in the Philippines. Therefore, even though humanitarian logistics is a necessary operation in the Philippines, the government faces a lot of challenges in its implementation.

Currently, there exists an agency for preparing for and responding to natural calamities in the Philippines, like typhoons and earthquakes (Bueza, 2013). This agency is the National Disaster Risk Reduction Management Council (NDRRMC). NDRRMC is a working group of various governmental and non-governmental organizations involved in disaster management. It utilizes the UN Cluster Approach for coordination, where a cluster is a group of humanitarian organizations working in the same sector (e.g., food and non-food items), and one organization is assigned as the cluster leader. Clusters provide a clear point of contact and create partnership among different organizations. The following table shows the clusters and cluster leaders in Philippine disaster management:

| Cluster | Cluster leader |
|---|---|
| Food and Non-food items | Department of Social Welfare and Development (DSWD) |
| Camp coordination and management | Office of Civil Defense (OCD), Local DRRMCs |
| Protection | Department of Social Welfare and Development (DSWD) |
| Livelihood | Department of Social Welfare and Development (DSWD) |
| WASH, Health, Nutrition and Psychosocial Services | Department of Health (DOH) |
| Logistics and emergency telecommunications | Office of Civil Defense (OCD), NDRRMC Operations Center |
| Education | Department of Education (DepEd) |
| Agriculture | Department of Agriculture (DA) |
| Early Recovery | Office of Civil Defense (OCD) |

In disasters affecting more than two regions, as with Typhoon Yolanda, the NDRRMC takes the lead in disaster response operations. If there are two or more provinces affected, regional DRRMCs take lead. For smaller disasters, the local government units (LGU) take the lead.

In this project, we focus on the problem of pre-positioning and post-disaster allocation of 'family

(a) Military volunteers providing manpower (b) Pallets of food packs ready to be shipped

Figure 2: Repacking of family food packs in a DSWD warehouse before Typhoon Ruby (international name Hagupit).

food packs' (FFPs). The family food pack is a core response modality applied by the government during emergencies. A food pack consists of 6 kilos of rice, 6 pieces of cereal, 4 cans of sardines, 4 cans of corned beef. As from the table above, the supply chain of family food packs is managed by DSWD. The last mile distribution of FFPs is not under the scope of this project, since it falls under the jurisdiction of OCD (logistics). FFPs have an expiration date, of usually one year after it is packed. There have been few reports in the past of expired FFPs being delivered to aid beneficiaries (DSWD, 2014).

Each Philippine region has at most one DSWD regional warehouse where stockpiles of family food packs are stored. The main DSWD warehouses are at the National Resource Operations Center (NROC) located in Pasay City. Each week, the inventory level of family food packs in each regional warehouse is managed and monitored by the DSWD Disaster Response Operations Monitoring and Information Center (DSWD-DROMIC). The warehouses implement a basestock policy, where inventory levels in each warehouse must meet predetermined targets, and an order for additional FFPs is triggered whenever they are not met. The order is placed with NROC, which uses military personnel and volunteers to process FFPs. The targets pre-Yolanda are 3,000 FFPs for regional warehouses and 10,000 FFPs for NROC. The targets post-Yolanda were modified to 30,000 FFPs for regional warehouses and 100,000 FFPs for NROC. The volunteers assemble the family food packs into individual plastic bags. Figure 2a shows military volunteers repacking family food packs in a DSWD warehouse in preparation for Typhoon Ruby on December 2014. After the family food packs are assembled, warehouse personnel put them inside straw sacks, then load the sacks onto pallets. Each pallet contains 25 sacks, each of which containing 6 family food packs. Figure 2b shows the final product in the form of pallets of family food packs ready to be shipped to regional warehouses.

NDRRMC practices both Rapid Damage and Needs Assessment (RDNA), to provide quick and accurate information on the effect post-disaster to determine whether additional assistance is needed, as well as Post-Disaster Needs Assessment (PDNA), to determine whether assistance


(a) Operations planning board at NROC

(b) Visayas logistics map

Figure 3: Ad-hoc tools used for planning disaster operations.

is needed for rehabilitation. Only recently has NDRRMC started practicing Pre-Disaster Risk Assessment (PDRA). PDRA is held at the NDRRMC headquarters and is attended by core agencies of NDRRMC, including DSWD-DRRROO, where they are briefed on the typhoon track and the projected list of affected municipalities. Before PDRA was implemented, DSWD waits for LGU's to request assistance before responding. Under PDRA, relief items are pre-positioned strategically based on the type of calamity and hazard.

Also located at NROC is an operations planning room, which serves as headquarters for DSWD to plan disaster operations once a major typhoon projected to affect multiple regions. Some relief organizations use inventory management systems such as Sahana Eden and Aidmatrix's SCM4Hunger to provide easy access to information about inventory of relief goods. DSWD utilizes the Relief Goods Inventory and Monitoring System (RGIMS), developed by DSWD and UN WFP by customizing Sahana Eden. RGIMS helps managing warehouse inventory by providing information on the acquisition, receiving, processing, and release of relief goods.

The current incarnation of IT systems in humanitarian organizations provide easy access to information to help managers make planning decisions. However, despite the ease of access to information, making planning decisions is difficult due to the complex nature of the relief environment. Many international relief agencies rely on using ad-hoc methods for decision-making (Beamon and Kotleba, 2006; Balcik and Beamon, 2008). This is also true in the case of Philippine disaster operations. For example, when planning for prepositioning stockpiles of FFPs days before a typhoon, NROC planners compile information by region (number of projected affected families, number of families in evacuation centers, percentage of displaced families assisted, available FFPs, FFPs distributed) in a large board for a visual snapshot of the current system state (see Figure 3a). Based on this information, they then plan how much FFPs to augment to each regional warehouse. Once the typhoon strikes, the allocation plan of FFPs to affected municipalities is made by drawing

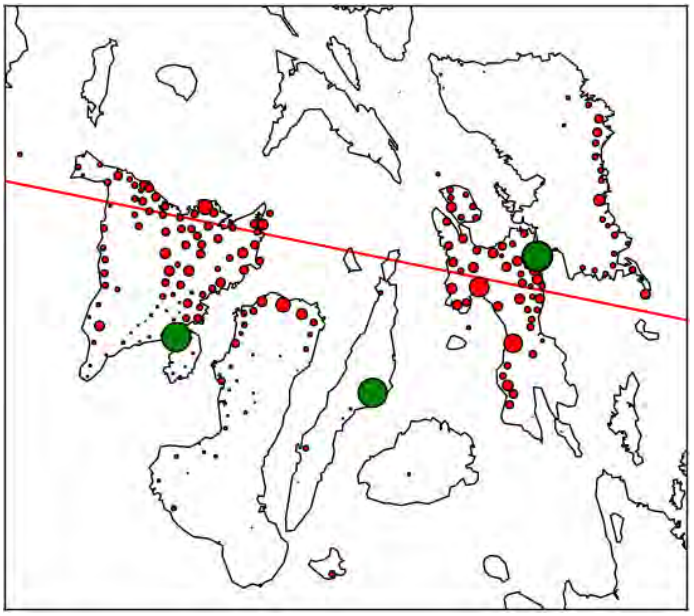


Figure 4: Pre-disaster supply and post-disaster demand during Typhoon Yolanda. The green nodes represent levels of pre-disaster supply in regional warehouses (Cebu City, Iloilo City and Tacloban City). The red nodes represent levels of post-disaster demand per municipality.

routes on maps of the affected region. Figure 3b shows the map of available Visayas routes that was released by the UN Logistics Cluster a few days after Typhoon Yolanda to help organizations plan their response operations.

Due to the inherently high uncertainty and complexity in the relief environment, using ad-hoc methods to coordinate disaster operations may lead to an inefficient (high costs, duplication of efforts, and waste of resources) and ineffective (slow response and unsatisfied demand) response. In the next section, we develop optimization models to quantitatively determine the optimized disaster plan. These models can be used to develop decision support tools that can prescribe plans for disaster managers, in lieu of the ad-hoc methods used today.

# 4 The mathematical models

As discussed in the previous section, family food packs are stockpiled in regional warehouses. Figure 4 illustrates pre-disaster supply and post-disaster demand during Typhoon Yolanda. We will now develop mathematical optimization models for the efficient delivery of relief aid from regional warehouses to the intended aid beneficiaries. In particular, we develop: (i) an optimization model for pre-positioning family food packs to temporary storage areas pre-disaster, and (ii) an optimization model for fair and efficient allocation of family food packs post-disaster. To aid in visualizing the models, we present figures illustrating the solutions of the models. Details of the computational results are presented in Section 5.

## 4.1 Pre-positioning FFPs in temporary storage pre-disaster

Regional warehouses are strategically located in major transportation hubs. However, depending on the path of the typhoon, the regional warehouses may be located far from the projected demand,

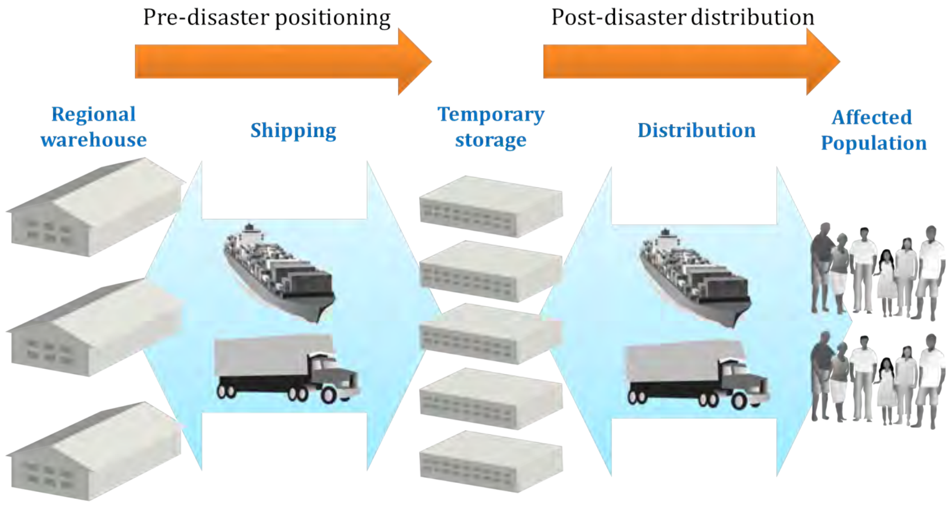



Figure 5: Pre-positioning relief aid in temporary storage facilities.

hence resulting in an inefficient post-disaster response (see Figure 4). A few days before a typhoon strikes, the government has a forecast of the regions and municipalities that will be affected by the disaster. For example, typhoons can be predicted several days in advance and can be tracked with the aid of satellites and computer models. The government can use these few days pre-disaster to pre-position supply in temporary storage facilities (e.g., school gymnasiums) that are geographically closer to the projected demand, resulting in a decreased post-disaster response time. Figure 5 illustrates this concept.

Pre-positioning relief items is recently being implemented by DSWD under the PDRA system. However, there are many challenges that make pre-positioning difficult to implement. The first major challenge is that the path of the typhoon (and hence, demand) is uncertain when relief items have to be pre-positioned. On December 3, 2014, DSWD has started pre-positioning relief goods in preparation for Typhoon Ruby (international name, Hagupit) which then was expected to make landfall on December 6 (Francisco, 2014). However, on December 3, there was still a lot of uncertainty in the potential track the typhoon could take (Fritz, 2014). Figure 6 shows the predicted typhoon track of two forecast models on December 3. The Joint Typhoon Warning Center predicted that the typhoon's path will avoid making landfall in the Philippines. But the European ECMWF model, which agrees with PAGASA's forecasts, predicted a direct landfall in the Philippines .

The second major challenge in pre-positioning is that some parts of the transportation network can be disabled post-disaster. Hence, pre-positioning decisions have to take into account the potential unavailability of some transportation arcs. As an example, the Tacloban airport was effectively destroyed by strong winds and a 13 foot storm surge from Typhoon Yolanda. The airport terminal and control tower were demolished, and the airport was rendered unusable. Hence, relief aid was unable to arrive by air for the first four days to Tacloban City, the worst-hit city by Typhoon Yolanda.

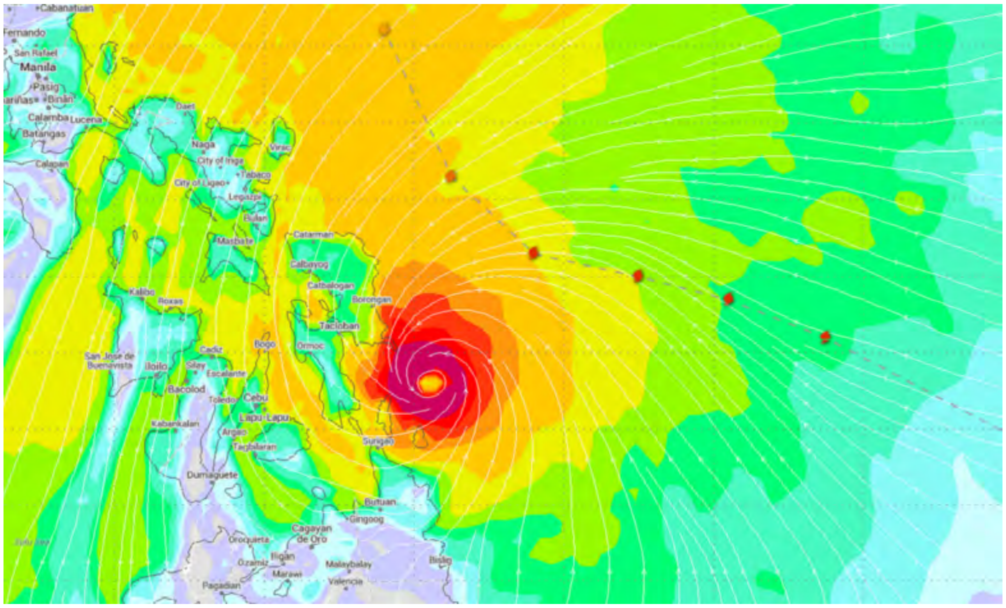
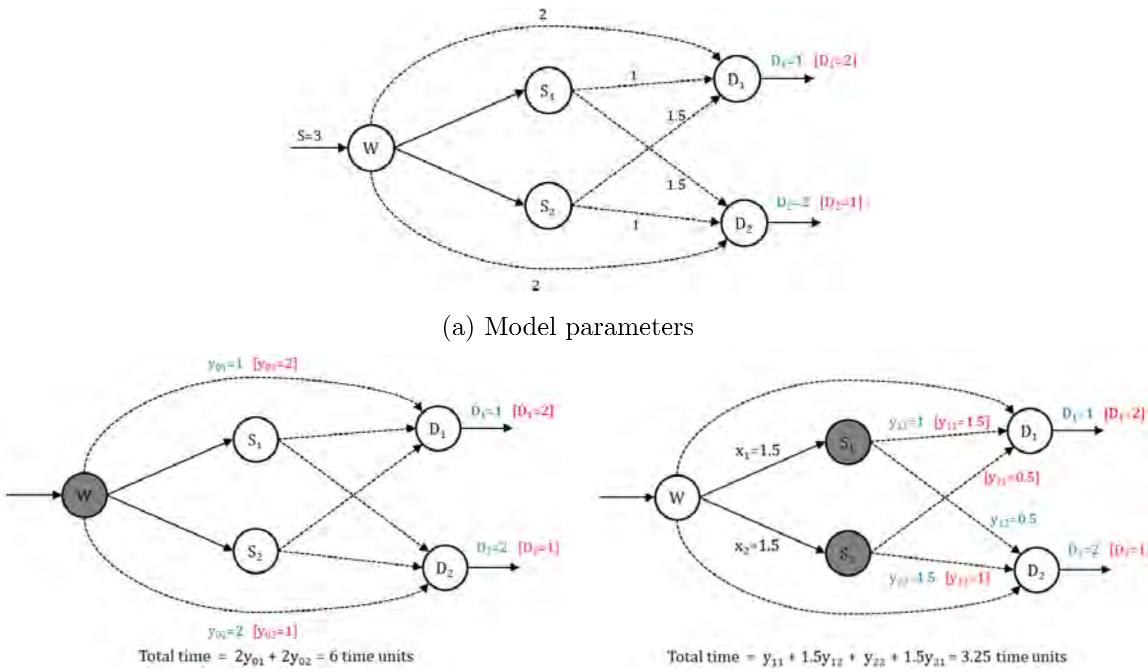



Figure 6: The track forecasts for Typhoon Hagupit on December 3, 2014. The Joint Typhoon Warning Center (hurricane markers with dashed lines) predicted Typhoon Hagupit will avoid landfall in the Philippines. However, the European model solution (color contours) had the typhoon making landfall.

We will develop an optimization model that determines the optimal locations for pre-positioning and the optimal pre-positioned quantities given the demand and transportation arc uncertainties. Let us first introduce the model on a small relief supply chain network shown in Figure 7a. There is a single regional warehouse $W$ with 3 units of supply. There are two candidate temporary storage facilities $S_1$ and $S_2$. The social enterprise has to plan to respond to two demand sites $D_1$ and $D_2$. The demand in each site is unknown, however, with a probability of $\frac{1}{2}$ that $d_1 = 1$ and $d_2 = 2$, and a probability of $\frac{1}{2}$ that $d_1 = 2$ and $d_2 = 1$. The numbers on each arc corresponds to the time it takes to send a unit of flow through the arc. From the figure, $S_1$ ($S_2$) is closest to demand site $D_1$ ($D_2$). The warehouse is the furthest away from both demand sites. Before the disaster, the social planner can decide to store units at $S_1$ and $S_2$ (using the solid arcs). After the disaster, the social planner can utilize any of the dotted arcs to send flow through to the demand sites. Assume that the arcs are uncapacitated. Figure 7 illustrates two solutions to the problem. In Figure 7b, the planner keeps its relief items in the regional warehouse, and ships directly to the demand sites after the disaster strikes. In this solution, the total time to respond to the disaster is 6 units (in both demand scenarios). Now consider the solution in Figure 7c, where the planner sends its supply to the temporary storage. In this solution, the total response time is 3.25 units under both demand scenarios. Therefore, by positioning relief items in temporary storage, the planner is able to respond to either disaster in almost half the response time as when keeping all the relief items in the regional warehouse.

The above is a simple example to introduce the setting of our model. Next we introduce our general optimization model for pre-disaster positioning of relief goods in the face of demand




(a) Model parameters

(b) No temporary storage

(c) With temporary storage

Figure 7: Motivating example and two network flow solutions.

uncertainty. First, we introduce some notation. Let $V_w$ be the set of regional warehouses. Let $S_i$ be the inventory level at warehouse $i \in V_w$, which is a parameter of the model. We denote the set of candidate temporary storage facilities as $V_s$. Let us denote by $V_d$ the set of the demand sites. Demand site $i$ is projected to require $d_i$ units of relief goods after the disaster. The actual demand required in site $i$ is unknown upon the time of making decisions about temporary storage. The following table summarizes the notation that we will use for the model:

**Vertices:**

$V_w$ the set of regional warehouses

$V_s$ the set of candidate temporary storage facilities

$V_d$ the set of demand sites

**Edges:**

$E_s$ the set of arcs from a regional warehouse to a temporary storage facility

$E_d$ the set of arcs from a temporary storage facility to a demand site

**Parameters:**

$S_i$ inventory level of relief item in regional warehouse $i \in V_w$

$d_j$ demand in site $j \in V_d$

$c_{ij}$ cost (or time) incurred by each flow unit in arc $(i, j)$

$c_{0j}$ cost (or time) incurred by each flow unit from private supplier to node $j$

$u_{ij}$ capacity of arc $(i, j)$

**Decision Variables:**

$x_{ij}$ flow from warehouse $i$ to temporary storage $j$, where $(i, j) \in E_s$

$y_{ij}$ flow from temporary storage $i$ to demand site $j$, where $(i, j) \in E_d$

$y_{0j}$ flow from private supplier to demand site $j$, where $(0, j) \in E_d$

We need a few more notations before we introduce our model. Let $\delta^+(S)$ be the set of directed arcs into the node set $S$. Let $\delta^-(S)$ be the set of directed arcs out of the node set $S$. With a slight abuse of notation, we will denote the set of a single node $\{i\}$ as $i$.

Now we are ready to discuss our model. Consider a social enterprise that needs to determine, a few days before a disaster is predicted to arrive, how to position its supply located in regional warehouses to temporary storage areas to best respond to the disaster victims' needs. The demand of relief goods is unknown to the social enterprise. If the demand is a random variable with a known probability distribution, then the problem can be formulated as a two-stage stochastic optimization problem. That is, the flow variables from the regional warehouses to the temporary storage areas (which we denote as $\mathbf{x} \in \mathbb{R}_+^{V_s}$) are the first-stage variables that need to be determined before the realization of the random demand vector $\mathbf{d} \in \mathbb{R}_+^{V_d}$. The optimal first-stage flow is found by solving the following optimization problem:

$$\begin{aligned} \underset{\mathbf{x}}{\text{minimize}} \quad & E_{\mathbf{d}}\left(C(\mathbf{x}, \mathbf{d})\right) \\ \text{subject to} \quad & \sum_{e \in \delta^-(i)} x_e \leq S_i, \quad \forall i \in V_w, \\ & x_e \geq 0, \qquad\qquad \forall e \in E_s, \end{aligned} \tag{4.1}$$

where $C(\mathbf{x}, \mathbf{d})$ is the minimal post-disaster response time after the demand $\mathbf{d}$ is realized and the supply is pre-positioned according to $\mathbf{x}$. The first constraint states that the total flow out of any warehouse must not exceed the inventory level in that warehouse. The second constraint specifies that flows must be nonnegative.

$C(\mathbf{x}, \mathbf{d})$ is determined by solving the recourse problem of determining the optimal second-stage flow $\mathbf{y} \in \mathbb{R}_+^{E_d}$ from the temporary storage areas to the demand sites. Mathematically, the recourse problem is given by

$$\begin{aligned} C(\mathbf{x}, \mathbf{d}) \quad := \quad \underset{\mathbf{y}}{\text{minimize}} \quad & \sum_{e \in E_d} c_e y_e \\ \text{subject to} \quad & \sum_{e \in \delta^+(j)} y_e \geq d_j, \qquad \forall j \in V_d, \\ & \sum_{e \in \delta^-(i)} y_e \leq \sum_{e \in \delta^+(i)} x_e, \quad \forall i \in V_s, \\ & y_e \geq 0, \qquad\qquad \forall e \in E_d. \end{aligned} \tag{4.2}$$

The first set of constraints implies that the demand in each demand site must be met by the flow from temporary storage sites. The second set of constraints implies that the outflow from temporary storage sites cannot exceed the amount of pre-positioned inventory in that site.

Without loss of generality, we can assume that there is no demand in temporary storage $i$. If a temporary storage $i$ has demand $d$, one can just introduce a new node $j$ with a cost $c_{ij} = 0$ and with demand $d$. We can also assume that the recourse problem is always feasible by adding a node corresponding to a private sector supplier that can send flow to nodes that need additional supply at a longer response time.

The key in the recourse problem is that the optimal value of the recourse variables $\mathbf{y}$ depend on the particular realization of the demand vector $\mathbf{d}$. Note that the recourse problem is simply a linear program (which can be solved efficiently with commercial off-the-shelf solvers such as CPLEX or Gurobi). However, to solve for the optimal flow to temporary storage areas, one has to solve the two-stage stochastic optimization problem (4.1). Solving a two-stage stochastic optimization problem is typically impractical except for the special case of $\mathbf{d}$ having a discrete probability distribution. (Methods proposed for solving a two-stage stochastic network problem approximate the expected recourse function with a sequence of weighted averages of stochastic subgradients that are linear (Powell and Cheung, 1994; Cheung and Chen, 1998).) Moreover, it is unrealistic to assume that the social enterprise has knowledge of the probability distribution of the demand vector $\mathbf{d}$. In fact, if the social enterprise mis-specifies the demand distribution, the resulting solution might be suboptimal under the true demand distribution.

For the reasons outlined above, we instead propose a robust optimization formulation. In this formulation, the only information known about the random demand vector $\mathbf{d}$ is that it lies in a nonempty convex and compact uncertainty set $\mathcal{U}$. An example of an uncertainty set is

$$\mathcal{U} = \left\{ \mathbf{d} \in \mathbb{R}^{V_d} : \exists \sigma \in \mathbb{R}_+^{V_d} \text{ such that } \bar{d}_j \left(1 - \sigma_j\right) \leq d_j \leq \bar{d}_j \left(1 + \sigma_j\right), \forall j \in V_d, \sum_{j \in V_d} \sigma_j \leq \Gamma \left|V_d\right| \right\}. \tag{4.3}$$

In this uncertainty set, the demand in each site $j$ is allowed to deviate from the nominal demand $\bar{d}_j$. However, there is an upper bound $\Gamma$ on the system-average deviation. The smaller values for $\Gamma$ imply a more restrictive uncertainty set.

One method for determining the first-stage variables is to determine it assuming that the random demand vector will take a nominal value, say $\bar{\mathbf{d}}$. However, this does not ensure that the resulting allocation will have a low cost against all possible demand realizations in $\mathcal{U}$. Instead, the first-stage variable can be chosen to protect against the worst-case demand realization in $\mathcal{U}$, which is the core idea in robust optimization. In the robust framework, we assume that nature is against us, and after the social enterprise determines the first-stage decision, nature chooses the demand vector $\mathbf{d}$

that results in the highest second-stage cost. Hence, the robust optimization problem solves

$$\begin{aligned} \underset{\mathbf{x}}{\text{minimize}} \quad & \sup_{\mathbf{d}\in\mathcal{U}} \{C(\mathbf{x},\mathbf{d})\} \\ \text{subject to} \quad & \sum_{e\in\delta^-(i)} x_e \le S_i, \quad \forall i \in V_w, \\ & x_e \ge 0, \qquad\qquad \forall e \in E_s, \end{aligned} \tag{4.4}$$

Note that the problem is a min-max-min optimization problem. By taking the dual of the innermost minimization problem (4.2), the resulting maximization problem combined with the $\mathbf{d}$ variables results in a bilinear optimization problem, which is known to be NP-hard. In the remainder of this section, we will describe a method to approximately solve (4.4) that can be tractably implemented using off-the-shelf commercial solvers such as CPLEX and Gurobi.

It is possible to instead solve a tractable linear program upper bound to the NP-hard problem (4.4) using the method described in Atamtürk and Zhang (2007) that finds a certificate of feasibility for the innermost recourse problem by Farkas' Lemma. The idea behind this is that we can introduce auxiliary decision variables $\mathbf{z} \in \mathbb{R}_+^{E_d}$ where $y_{ij} \le z_{ij}$. (Recall that $\mathbf{y}$ depended on the realization of $\mathbf{d}$. Later we'll see that this is not going to be the case for $\mathbf{z}$.) Then we find a certificate of feasibility for the innermost recourse problem. Consider now the following system of inequalities:

$$y_e \le z_e, \quad \forall e \in E_d, \tag{4.5}$$

$$\sum_{e\in\delta^+(j)} y_e \ge d_j, \quad \forall j \in V_d, \tag{4.6}$$

$$\sum_{e\in\delta^-(i)} y_e \le \sum_{e\in\delta^+(i)} x_e, \quad \forall i \in V_s, \tag{4.7}$$

$$y_e \ge 0, \quad \forall e \in E_d. \tag{4.8}$$

For a given $\mathbf{z} \in \mathbb{R}^{E_d}$ and $\mathbf{d} \in \mathbb{R}^{V_d}$, we would like to know under which conditions would there exist a feasible first-stage solution $\mathbf{x}$ that satisfies the system of inequalities. Note that by Farkas' lemma, this is the case if for all feasible values $(\mathbf{v},\mathbf{w})$ of the dual recession cone, i.e.,

$$v_j - v_i \le w_{ij}, \quad \forall (i,j) \in E_d, \tag{4.9}$$

$$\mathbf{v},\mathbf{w} \ge \mathbf{0} \tag{4.10}$$

satisfy the following condition

$$\sum_{j\in V_d} v_j d_j - \sum_{i\in V_s} v_i \left( \sum_{e\in\delta^+(i)} x_e \right) \le \sum_{e\in E_d} z_e w_e. \tag{4.11}$$

Following Atamtürk and Zhang (2007), we observe that (4.9)–(4.10) is the dual recession cone of a subgraph $G(V, E_d)$, where $V = V_s \cup V_d$. The extreme rays of the dual recession cone correspond to cuts of the subgraph. In other words, $(\mathbf{v},\mathbf{w})$ is an extreme ray if there exists a node set $S \subseteq V$ where $v_j = 1$ if $j \in S$, $v_j = 0$ if $j \notin S$, $w_{ij} = 1$ if $i \notin S, j \in S$, and $w_{ij} = 0$ otherwise. Therefore,

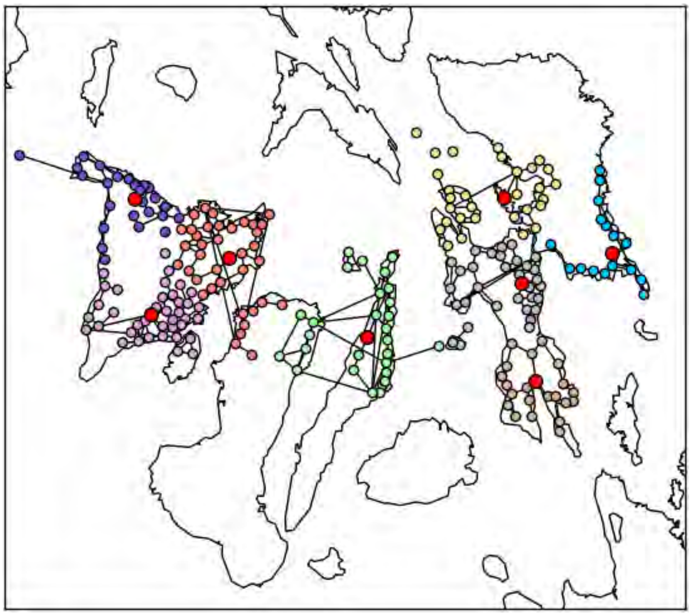


Figure 8: Graph partitioning using k-means with 8 clusters. Nodes with the same color belong to the same cluster. The red nodes correspond to cluster centers. Lines connecting nodes refer to a direct connection between the two nodes.

it is sufficient to check (4.11) for all extreme rays in the dual recession cone. Hence, for a given $\mathbf{z} \in \mathbb{R}^{E_d}$ and $\mathbf{d} \in \mathbb{R}^{V_d}$, $x$ is a feasible first-stage flow if and only if

$$\sum_{i \in S_s} \sum_{e \in \delta^+(i)} x_e + \sum_{i \notin S_s} \sum_{j \in S_d} z_{ij} \geq \sum_{j \in S_d} d_j, \quad \forall S_s \subseteq V_s, S_d \subseteq V_d$$

Hence, consider the following optimization problem with an exponential number of constraints:

$$\begin{aligned}
\underset{\mathbf{x},\mathbf{z}}{\text{minimize}} \quad & \sum_{e \in E_d} c_e z_e \\
\text{subject to} \quad & \sum_{e \in \delta^-(i)} x_e \leq S_i, && \forall i \in V_w, \\
& \sum_{i \in S_s} \sum_{e \in \delta^+(i)} x_e + \sum_{i \notin S_s} \sum_{j \in S_d} z_{ij} \geq \max_{d \in \mathcal{U}} \left\{ \sum_{j \in S_d} d_j \right\}, && \forall S_s \subseteq V_s, S_d \subseteq V_d, \\
& x_e \geq 0, && \forall e \in E_s, \\
& z_e \geq 0, && \forall e \in E_d.
\end{aligned} \tag{4.12}$$

Note that the optimal cost of (4.12) is an upper bound for the cost of the original min-max-min robust optimization model (4.4). Intuitively, this is because it is a more restrictive problem since $z_e \geq y_e(d)$ for all $\mathbf{d}$ [Note that $y_e$ depends on the particular realization of $\mathbf{d}$ due to its being a recourse decision variable].

Note that this optimization model has an exponential number of constraints. For example, if there are 10 temporary storage areas and 10 demand sites, the order of magnitude of the number of constraints is $2^{10} \times 2^{10} \simeq 10^6$. If there are 30 temporary storage areas and 30 demand sites, then the number of constraints is roughly $10^{18}$!

We make the optimization model more tractable in a three-phased approximation, which we describe next. We illustrate the phases in computational experiments with data from Typhoon Haiyan. For interested readers, we describe in Appendix A how the model parameters are determined from raw data.

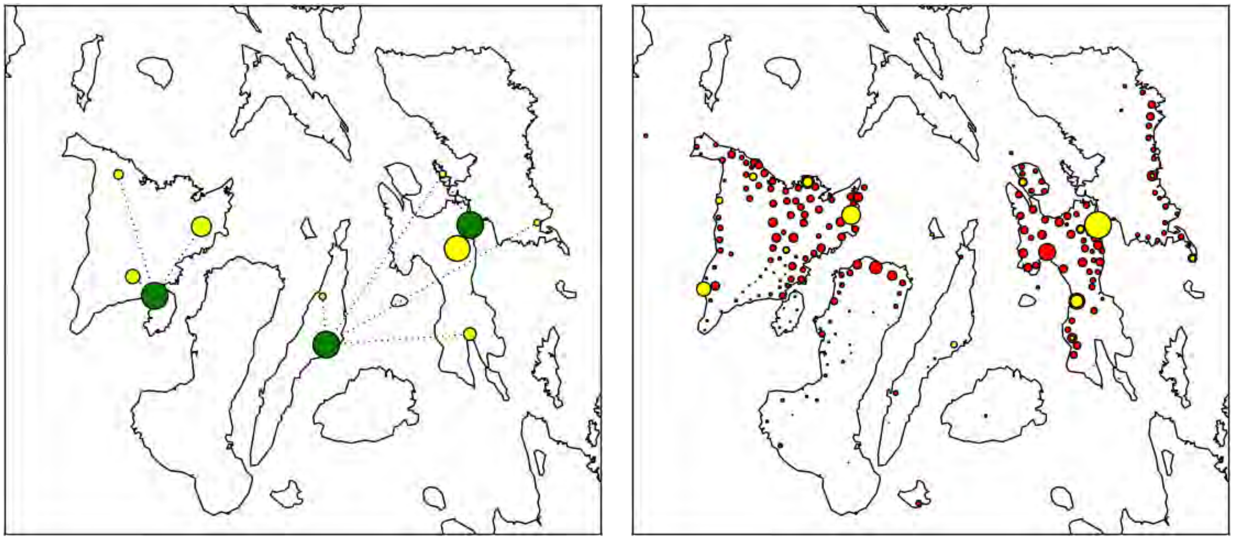
#### 4.1.1 Phase I: Geo-location clustering of municipalities

In the first phase, we reduce the number of nodes by clustering the transportation graph by location into $k$ clusters. For example, Figure 8 shows a partition with 8 clusters. The partitioning can be calculated by solving the $k$-center problem. That is, given $n$ cities with specified distances, one wants to build $k$ warehouses in different cities and minimize the maximum distance of a city to a warehouse. In graph theory, this means finding a set of $k$ vertices for which the largest distance of any point to its closest vertex in the $k$-set is the smallest. The graph must be a complete graph with distances satisfying the triangle inequality. In our setting, these conditions can be fulfilled by adding missing edges with distance equal to the shortest distance between the two endpoints. This problem is NP-hard. However, simple greedy approximation algorithms can build a $k$-set with an approximation factor of 2. See Vazirani (2001) for more information on the $k$-center problem. However, another simpler method for generate reasonable partitions is through $k$-means clustering, popular in data-mining, where each city is an observation represented by its longitude and latitude. The goal of $k$-means clustering is to partition the $n$ observations into sets so as to minimize the within-cluster sum of squares. Note that the difference with the $k$-means clustering is that it ignores the edge information (actual distances) and bases its clustering on the Manhattan distance. For example, $k$-means will put two cities "close" to each other in the same cluster, even if the road between them must go around a mountain. However, based on applying $k$-means clustering to actual data, we believe that clustering using $k$-means results in good partitions (see Figure 8).

#### 4.1.2 Phase II: Solve the inter-cluster problem

We assume that there is a single demand site and a single temporary storage site in each cluster located at the cluster center. Instead of solving the original problem with $|V_d|$ demand nodes and $|V_s|$ storage nodes, we can solve the much smaller problem instance of (4.12) with $k$ demand sites and $k$ temporary storage locations. The first stage solution will prescribe storage quantities for each cluster.

Figure 9a plots the solution of the inter-cluster problem (4.12) with 8 clusters. The green nodes correspond to locations of stockpiled relief items in regional warehouses (Cebu City, Iloilo City and Tacloban City). The yellow nodes correspond to the 8 cluster centers, and the size of the node is proportional to the supply to be pre-positioned in the cluster. The Iloilo City warehouse ships family food packs for pre-positioning in three clusters in Western Visayas. The Cebu City warehouse ships FFPs to serve four small clusters in Central and Eastern Visayas. The Tacloban City warehouse ships FFPs to serve two clusters in Eastern Visayas.



(a) Inter-cluster allocation (b) Intra-cluster pre-positioning

Figure 9: The solutions of inter-cluster allocation and intra-cluster pre-positioning on Typhoon Haiyan data. In (a), the green nodes correspond to supply in regional warehouses. The yellow nodes correspond to supply allocated to clusters. The dotted line between a regional warehouse and cluster center imply that the warehouse ships supply to that cluster. In (b), the yellow nodes correspond to pre-positioned supply in temporary storage facilities. The red nodes are municipalities with demand.

#### 4.1.3 Phase III: Solve the intra-cluster pre-positioning problem

After Phase II, we have determined the *quantities* of relief items to pre-position in a given cluster. However, we still have not determined the *location* of where to pre-position the relief items. To do this, we solve an intra-cluster pre-positioning problem, which determines where and how much relief items to pre-position in a set of candidate temporary storage facilities. Let $C$ be the cluster, and $V_s(C)$ be the set of candidate temporary storage facilities. We can assume that the within the cluster, demand is deterministic (since there's less demand variation within a cluster). Suppose $S$ is the supply to be pre-positioned in a cluster (from the solution of Phase II). Given that we want to set up at most $M$ temporary storage facilities in the cluster, the intra-cluster pre-positioning problem solves the deterministic problem:

$$
\begin{aligned}
\underset{\mathbf{s},\mathbf{y},\mathbf{z}}{\text{minimize}} \quad & \sum_{e \in E_d(C)} c_e y_e \\
\text{subject to} \quad & \sum_{e \in \delta^+(j)} y_e + s_j \geq d_j + \sum_{e \in \delta^-(j)} y_e, && \forall j \in V_s(C), \\
& \sum_{e \in \delta^+(j)} y_e \geq d_j, && \forall j \in C \setminus V_s(C), \\
& \sum_{j \in V_s(C)} s_j = S, \\
& s_j \leq S z_j, && \forall j \in V_s(C), \\
& \sum_{j \in V_s(C)} z_j \leq M, \\
& y_e \geq 0, && \forall e \in E_d(C), \\
& z_j \in \{0, 1\}, && \forall j \in V_s(C).
\end{aligned}
\tag{4.13}
$$

The problem solves for the optimal pre-positioned supply at a municipality $j$, denoted by $s_j$. Note that $z_j$ is a binary decision variable that takes a value of 1 if temporary storage facility $j$ is used for pre-positioning relief items, and takes a value of 0 otherwise. The first set of constraints specify that flow into a municipality plus pre-positioned supply should cover both demand and outflows for municipalities that are candidate storage areas. The second set of constraints specify that non-storage municipalities must have enough inflows to meet the demand. The third constraint says that the sum of pre-positioned supply in all municipalities must equal $S$. Because of the fourth constraint, a municipality can only have pre-positioned supply if $z_j = 1$. The fifth constraint specifies that there can be at most $M$ temporary storage locations in the cluster.

A challenge in the intra-cluster problem is the which values for the demand to use in parameterizing the model (4.13). One solution is to simply use the nominal demands $\bar{\mathbf{d}}$. However, the problem with this is that there might not be enough supply $S$ planned for the cluster to meet the nominal demand (since it was allowed to deviate from nominal in the intra-cluster phase). Instead, one can scale the nominal demand to achieve a feasible problem (4.13). Alternatively, one can set $y = z$ in the recourse problem, where $z$ is the optimal value of the variables in (4.12) (i.e., assume that regardless of the demand realization, the recourse is the same), and determine the minimum feasible cluster demands. Then scale the municipality demands based on the minimum feasible cluster demands.

Solving (4.13) on Typhoon Haiyan data, with a maximum of two temporary storage facilities per cluster, we get the solution illustrated in Figure 9a. The yellow nodes correspond to the temporary storage facilities with pre-positioned relief items. The size of the nodes is proportional to the pre-positioned quantity. There are a total number of 16 pre-positioning facilities utilized. The red nodes correspond to municipalities with post-disaster demand. The size of the red nodes is proportional to the demand. Tacloban City has the largest quantity of pre-positioned supply.

### 4.2 Fair and efficient distribution of FFPs post-disaster

Rapid damage and needs assessment (RDNA) is done post-disaster to determine affected areas and populations with the greatest unmet needs. Once needs have been assessed, disaster managers have to decide on how to allocate the available emergency relief items to the affected population. A tool that has increasingly been employed in such assessments is a "prioritization matrix" which ranks municipalities in priority for receiving aid (Benini and Chataigner, 2014). This matrix contains indicators which are aggregated into a composite index that determines the rank of the municipality. Prioritization matrices were used in disaster response for Yolanda. These matrices combine indicators for magnitude (e.g. number of affected persons), intensity (e.g. percentage of destroyed dwellings, wind speed), and pre-existing conditions (e.g. poverty rate). Prioritization matrices are useful visual guides for disaster managers to make post-disaster distribution decisions.

However, despite having this information, post-disaster distribution remains a difficult task especially with a large-scale disaster such as Yolanda since multiple facilities have to be coordinated for a timely distribution. Much of the focus of post-disaster operations after Typhoon Yolanda have been towards Tacloban City, the hardest hit area, which ignored other areas that were needing relief aid. A UN assessment of nine municipalities in Leyte two weeks after the typhoon (UNOCHA OCHA, 2013) reported that "food appears to be effectively distributed in some [areas], but not effectively or evenly distributed in others...[T]he more remote communities are not notified adequately or are required to walk in for what remains available." As noted in an Oxfam briefing after Yolanda (Oxfam, 2013), "a wider problem is that the levels of assistance vary depending on location...Relief operations largely began in urban areas and then spread slowly into adjoining districts and beyond, but the limited number of heavy vehicles and warehouse facilities in hubs such as Tacloban has delayed distribution."

In what follows, we develop an optimization model which determines the optimal post-disaster distribution from supply hubs to affected municipalities and determines the optimal positioning of transportation vehicles. The model optimizes fairness of distribution (by using an objective that considers backlog of municipalities weighted by the composite indices from a prioritization matrix), as well as timeliness (by coordinating facilities and appropriately stationing vehicles). Pre-positioning family food packs (from Section 4.1) achieved the goal of reducing response time. However, after a post-disaster distribution has been planned, the timeliness is also affected by how the limited vehicles are stationed. Clearly, there will be shorter response times in areas where the hubs have many stationed vehicles.

We first introduce the notation that will be used in our model. Let $T$ be the number of time periods in the disaster response phase. Let $V$ be the set of municipalities. We denote by $q_j$ the quantity of pre-positioned supply at municipality $j \in V$, where $q_j = 0$ if there is no pre-positioned supply. Let $M$ be the set of transportation modes (e.g. truck, plane, ship). We denote by $U_m$ the total number of vehicles of mode $m \in M$ that have to be stationed in hubs, and $V_m \subseteq V$ is the set of municipalities that are candidate hubs for vehicles of mode $m$. If a vehicle of mode $m$ is stationed at hub $j$, then we denote by $\mu_{mj}$ the average service time (in days per unit), which is the average time the vehicle is in use in one roundtrip divided by the average load size. The number of vehicles of mode $m$ that are stationed in hub $j$ is $u_{mj}$.

Let us focus on a given municipality $j \in V$. At the start of each period, municipality $j$ receives deliveries coming from other municipalities and sends deliveries to other municipalities. We denote by $f_{ijtm}$ the number of units to be sent from municipality $i$ to $j$ at the start of period $t$ with transportation mode $m$. After the deliveries are completed, the net inventory at municipality $j$, which we denote by $I_{jt}$, is used to meet new demand, which we denote by $d_{jt}$. If the demand is less than the available supply, then there is a surplus at the end of period $t$, and we denote the total surplus as $Y_{jt}$. If the demand exceeds the available supply, then there is a backlog at the end of period $t$, and we denote the total backlog as $B_{jt}$. Backlog or surplus at the end of period $t$ is carried over to the next period $t + 1$.

The following table summarizes the notation that we discussed above:

**Parameters:**

| | |
|---|---|
| $V$ | the set of municipalities |
| $\lambda_j$ | the weighted preferential composite index of municipality $j$ |
| $q_j$ | the quantity of pre-positioned supply at municipality $j \in V$ |
| $d_{jt}$ | the new demand at municipality $j$ at period $t$ |
| $M$ | the set of transportation modes |
| $V_m$ | the set of candidate hubs for vehicles of transportation mode $m$ |
| $U_m$ | the number of transportation vehicles of mode $m$ |
| $\mu_{mj}$ | the average service time (days per unit) of a transportation vehicle of mode $m$ stationed at hub $j$ |

**Decision variables:**

| | |
|---|---|
| $f_{etm}$ | the number of units sent on edge $e$ at the start of period $t$ using transportation mode $m$ |
| $u_{mj}$ | the number of vehicles of transportation mode $m$ stationed at hub $j$ |
| $I_{jt}$ | the net inventory at municipality $j$ at period $t$ before account for new demand |
| $B_{jt}$ | the backlog at municipality $j$ at the end of period $t$ |
| $Y_{jt}$ | the surplus at municipality $j$ at the end of period $t$ |

Let us now develop the objective function that we will use for the post-disaster distribution problem. An important quantity for a municipality is the current percentage backlog, which is defined as the current backlog divided by the cumulative demand. Using our notation, the percentage cumulative demand at municipality $j$ at period $t$ is:

$$\frac{B_{jt}}{\sum_{s \leq t} d_{js}}.$$

The percentage backlog is an indicator for whether a municipality's needs are being met by the distribution of relief goods. The percentage backlog can take any value between 0 and 1. If the percentage backlog is 1, then this implies that there has been no inflow of supply into the municipality since the start of the post-disaster period. If the percentage backlog is 0, then all of the municipality's needs post-disaster have been met. However, as has been discussed earlier, a disaster manager might have different prioritizations in post-disaster response for different municipalities. We take this into account by minimizing, for each time period $t$, the weighted sum of percentage backlogs

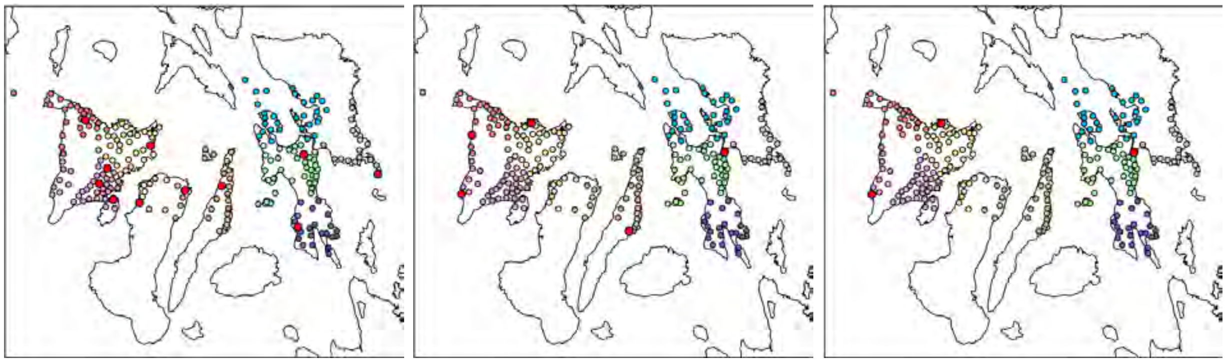
$$\sum_{j\in V}\left(\lambda_j \times \frac{B_{jt}}{\sum_{s\le t} d_{js}}\right),$$

where $\lambda_j$ is prioritization composite index of municipality $j$ (higher values of $\lambda_j$ denote municipalities with high prioritization). By weighing the backlog by the index, the optimization model will try to reduce backlogs in municipalities with a higher value index value.

Hence, the post-disaster distribution optimization model solves:

$$\begin{aligned}
\underset{\mathbf{u},\mathbf{B},\mathbf{Y},\mathbf{I},\mathbf{f}}{\text{minimize}} \quad & \sum_{t=1}^{T}\sum_{j\in V}\left(\lambda_j \times \frac{B_{jt}}{\sum_{s\le t} d_{js}}\right), && \\
\text{subject to} \quad & I_{jt} - d_{jt} = Y_{jt} - B_{jt}, && \forall j \in V, t \in [1,T], \\
& I_{jt} = Y_{j,t-1} - B_{j,t-1} + \sum_{m\in M}\sum_{e\in\delta^+(j)} f_{etm} - \sum_{m\in M}\sum_{e\in\delta^-(j)} f_{etm}, && \forall j \in V, t \in [1,T], \\
& Y_{j0} = q_j, B_{j0} = 0, && \forall j \in V, \\
& \sum_{m\in M}\sum_{e\in\delta^-(j)} f_{etm} \le Y_{j,t-1}, && \forall j \in V, t \in [1,T], \\
& \sum_{e\in\delta^-(j)} f_{etm} \le u_{mj}/\mu_{mj}, && \forall m \in M, j \in V_m, \\
& \sum_{j\in V_m} u_{mj} = U_m, && \forall m \in M, \\
& u_{mj} \in \mathbb{Z}^+, \mathbf{B} \ge \mathbf{0}, \mathbf{Y} \ge \mathbf{0}, \mathbf{f} \ge \mathbf{0}. &&
\end{aligned} \tag{4.14}$$

The first constraint is that in a given period and municipality, there either is a surplus or a backlog. The second constraints are the inventory dynamics, where the net inventory available in a period consists of backlog or surplus carried over from the previous period plus inflows minus outflows. The third constraints are the initial conditions for surplus and backlog in a municipality. The fourth constraints specify that the total outflows in a municipality cannot exceed the surplus inventory carried over from the previous period. The fifth constraints specify that the total outflow from a municipality using a particular transportation mode cannot exceed the installed capacity weighted by the average service time. The sixth constraint specifies that the sum of installed capacity over all municipalities must equal the available capacity.



(a) Trucks (b) Ships (c) Planes

Figure 10: The solutions of post-disaster vehicle positioning. Nodes with the same color belong in the same cluster. Red nodes are hubs for transportation vehicles.

Optimization problem (4.14) is a tractable mixed integer linear program which can be solved using commercial off-the-shelf solvers such as ILOG CPLEX. We ran the optimization problem on data from Typhoon Haiyan and Figure 10 shows the transportation hubs based on the solution of the model.

# 5 Computational experiments from Typhoon Yolanda data

On November 8, 2013, Typhoon Yolanda made landfall in the Visayas islands in the Philippines, with strongest winds in recorded history of 195 mph. In the typhoon's aftermath, there have been an estimate of more than 6,000 casualties and more than 14 million people affected. In this section, we will further discuss details of the computational experiments of the optimization models on data gathered from Typhoon Yolanda in 2013.

## 5.1 Data Gathering

Data gathering was a long process that took a few weeks due to the lack of available data, and that we had to assemble the data from several different sources. In what follows, we describe to the best extent possible the steps we took to gather data that we use for the experiments.

### 5.1.1 Municipality properties

We gathered information on municipalities that were affected by Typhoon Haiyan from several public sources (NSCB, 2014; PhilGIS, 2013). The following table is representative of the type of information that we gathered:

| Code | Municipality | Province | Region | Longitude | Latitude | Income Class | Population |
|---|---|---|---|---|---|---|---|
| 83701000 | Abuyog | Leyte | VIII | 125.03 | 10.68 | - | 57,146 |
| 63001000 | Ajuy | Iloilo | VI | 123.02 | 11.15 | 2nd | 47,248 |
| 83702000 | Alangalang | Leyte | VIII | 124.86 | 11.21 | 2nd | 46,411 |
| 83703000 | Albuera | Leyte | VIII | 124.73 | 10.91 | - | 40,553 |
| 71201000 | Albuquerque | Bohol | VII | 123.96 | 9.63 | 5th | 9,921 |

We used the NSCB municipality code as a unique identifier for a municipality for the computational experiments.

The next data we collected was to recreate the Visayas transportation network (road, sea routes, and air routes). Given the lack of data on the road network in Visayas, we used Google Maps to query information on national highway road distances and connections between municipalities, and enter them manually on to a csv file. It only took a few days to complete this procedure since the major road network in Visayas is very sparse. For future implementations, it is possible to automize this step by creating a script that automatically scrapes data from Google Maps. The following table shows examples of the information that we gathered:

| Municipality 1 | Province 1 | Code 1 | Municipality 2 | Province 2 | Code 2 | Road distance (km) |
|---|---|---|---|---|---|---|
| Buruanga | Aklan | 60405000 | Malay | Aklan | 60412000 | 6.5 |
| Malay | Aklan | 60412000 | Nabas | Aklan | 60414000 | 26.2 |
| Nabas | Aklan | 60414000 | Ibajay | Aklan | 60406000 | 11.1 |
| Ibajay | Aklan | 60406000 | Tangalan | Aklan | 60417000 | 15.2 |
| Nabas | Aklan | 60414000 | Pandan | Antique | 60611000 | 11.5 |

We used Ports.com to find information on seaports and existing sea routes and their distances in the Visayas region. There are a total of 46 municipalities with seaports. We used the distance information to create a matrix of sea route distances. The following is part of the sea route distance (in miles) matrix:

| | Seaport | Allen | Bacolod | Bais | Barcelona | Baybay | Borongan |
|---|---|---|---|---|---|---|---|
| Seaport | | 84801000 | 64501000 | 74604000 | 64509000 | 83708000 | 82604000 |
| Allen | 84801000 | - | - | - | - | - | - |
| Bacolod | 64501000 | - | - | - | 44.82 | - | - |
| Bais | 74604000 | - | - | - | 95.63 | - | - |
| Barcelona | 64509000 | - | 44.82 | 95.63 | - | - | 139.24 |
| Baybay | 83708000 | - | - | - | - | - | - |
| Borongan | 82604000 | - | - | - | 139.24 | - | - |

To gather data on air routes, we used the Visayas Logistics Map (see Figure 3b) to list the municipalities that the map shows have airports or airstrips. There are a total of 23 municipalities with airports or airstrips. For simplicity, we assume that there is an air route between any two municipalities in this list, and the distance of the air route is simply the straight line distance.

Figure 11 shows a visual representation of the data we gathered on the Visayas transportation network. The grey nodes are the municipalities plotted based on their geographical coordinates on

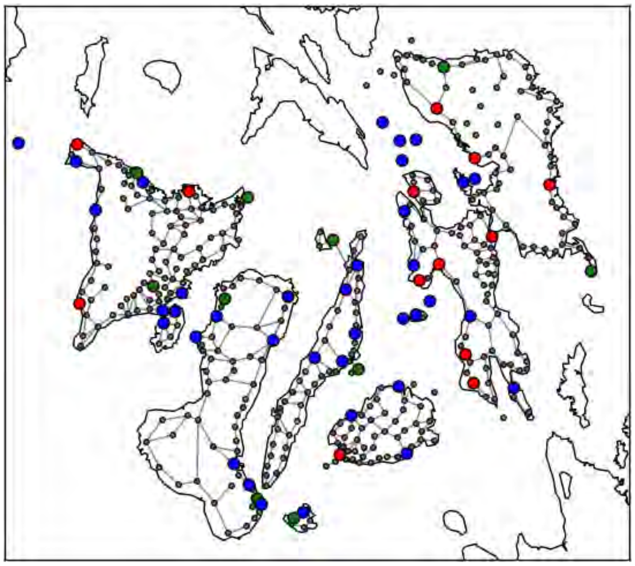


Figure 11: Grey nodes represent municipalities. Blue nodes represent municipalities with a seaport. Green nodes represent municipalities with an airport. Red nodes represent municipalities with a seaport and an airport. Grey edges connecting municipalities represent major roads.

the map. The blue nodes represent municipalities containing seaports. The green nodes represent municipalities containing an airport or airstrip. The red nodes are municipalities with both a seaport and an airport/airstrip. Grey lines connecting municipalities are segments of major roads or highways.

### 5.1.2 Typhoon Haiyan supply and demand

We compiled data on the total affected population by municipality from Typhoon Haiyan based on Situational Reports released by NDRRMC (NDRRMC, 2013). All NDRRMC Situation Reports can be accessed through ReliefWeb.int. A total of 44 provinces were affected by the typhoon, 574 municipalities in Regions IV-A, IV-B, V, VI, VII, VIII, X, XI and CARAGA. The data we gathered is in the following format:

| Municipality | Province | Code | Affected Families | Affected Persons |
|---|---|---|---:|---:|
| Altavas | Aklan | 60401000 | 5,450 | 26,905 |
| Balete | Aklan | 60402000 | 5,409 | 27,045 |
| Banga | Aklan | 60403000 | 8,281 | 33,955 |
| Batan | Aklan | 60404000 | 8,171 | 34,084 |
| Buruanga | Aklan | 60405000 | 3,000 | 17,213 |

We assume that there is one regional warehouse per affected region by Typhoon Yolanda.

## 5.2 Methodology

We now discuss the methodology in the computational experiments. For simplicity, we isolate the computational experiments to the municipalities that are within 100 kilometers from the path of the typhoon.

### 5.2.1 Pre-positioning FFPs in temporary storage

- We implemented the three-phase approximation to the pre-positioning problem in Section 4.1 with the data. First, we define the clusters for each municipalities using k-means with 8 clusters. Figure 8 shows the result of the clustering algorithm. The details of the clusters in the figure are given in the following table:

| Cluster Color | Cluster Center | No. of Municipalities |
|---|---|---:|
| Salmon | Alimodian, Iloilo | 26 |
| Deep sky blue | Jaro, Leyte | 30 |
| Pale green | Tuburan, Cebu | 34 |
| Khaki | Daram, Western Samar | 38 |
| Slate blue | Malinao, Aklan | 22 |
| Plum | Lemery, Iloilo | 39 |
| Tan | Sogod, Southern Leyte | 29 |
| Silver | Gen. MacArthur, Eastern Samar | 17 |

- We created a master transportation graph with arcs corresponding to road connections, sea connections, and air connections. The distances in each arc is in travel time (assuming trucks travel in roads, ships travel in sea, and planes travel by air).

- We created a graph for the inter-cluster pre-positioning problem with one warehouse node for each regional warehouse, one temporary storage node in each cluster center, and one demand site in each cluster center.

- First stage arcs between a regional warehouse to a temporary storage nodes are created if there exists a transportation path between the two (through a combination of road, sea route, or air route). The arc distance between the two is equal to the length of the shortest path in the transportation graph. A second stage arc is created for each combination of temporary storage location and demand site for which there is a path. The distance of the arc is equal to the length of the shortest path in the transportation graph.

- The nominal demand in each demand site is equal to the cluster's aggregate nominal demand. We assume a demand uncertainty set that allows demand with no more than a 20% average deviation from the nominal demand.

- We assume that each regional warehouse stores 5 million units each.

- We solve the inter-cluster pre-positioning problem (4.12). The solution is visualized in Figure 9a. The details of the solution is shown in the following table:

| Cluster Color | Cluster Center | Units from Tacloban | Units from Cebu | Units from Iloilo |
|---|---|---|---|---|
| Salmon | Alimodian, Iloilo | 0 | 0 | 2,804,427 |
| Deep sky blue | Jaro, Leyte | 0 | 1,110,163 | 0 |
| Pale green | Tuburan, Cebu | 0 | 0 | 635,824 |
| Khaki | Daram, Western Samar | 0 | 322,547 | 0 |
| Slate blue | Malinao, Aklan | 0 | 324,425 | 0 |
| Plum | Lemery, Iloilo | 4,767,081 | 0 | 0 |
| Tan | Sogod, Southern Leyte | 0 | 0 | 1,451,743 |
| Silver | Gen. MacArthur, Eastern Samar | 293,918 | 62,258 | 0 |

- We solve the intra-cluster pre-positioning problem (4.13) given the cluster supplies in the table above. Assuming that each cluster can only have a maximum of two storage areas. The candidate storage locations that we chose are municipalities that have a National Food Authority (NFA) warehouse. The total number of NFA warehouses in the regions affected by the typhoon are 44. Figure 9b visualizes the solution of the intra-cluster pre-positioning problem.

### 5.2.2 Distribution of FFPs post-disaster

- We assume that there are five days in the post-disaster distribution time horizon.
- We assume that new demand occurs every other day, since family food packs are assumed to address the needs of a family of five for two days.
- We assume that the pre-positioned supply of the previous computational experiments will be available for the system post-disaster. We will call locations with pre-positioned supply a "supply hub".
- We assume three types of transportation vehicles: trucks, ships, planes. We will call locations that are airports, air strips, or seaports as "transportation hubs". The following table shows the values for the load size, time to load, and the total number of vehicles:

| Vehicle | Mode | Speed | Load size | Loading time | Number of vehicles |
|---|---|---|---|---|---|
| Truck | Land | 80 kph | 3,000 | 0.5 hr | 50 |
| Ship | Sea | 20 kph | 160,000 | 10.0 hr | 5 |
| Plane | Air | 480 kph | 2,000 | 0.5 hr | 5 |

- We created an directed graph where there is a node for every municipality. Edges originate from a supply hub or a transportation hub to any municipality that has a path to it. The length of the edge is equal to the shortest path distance in the transportation graph.
- Any supply hub or transportation hub is a candidate location for a vehicle. We calculate the average service times from a supply hub or a transportation hub $j$ using transportation mode

$m$ by:

$$\mu_{mj} = \frac{2 \times \text{Ave. distance of } j \text{ to neighbors} + \text{Loading time of } m}{\text{Load size of } m}$$

- Using these model parameters, we solve (4.14). The model's recommended location of transportation hubs is visualized in Figure 10. The distribution plan is too complicated to visualize.

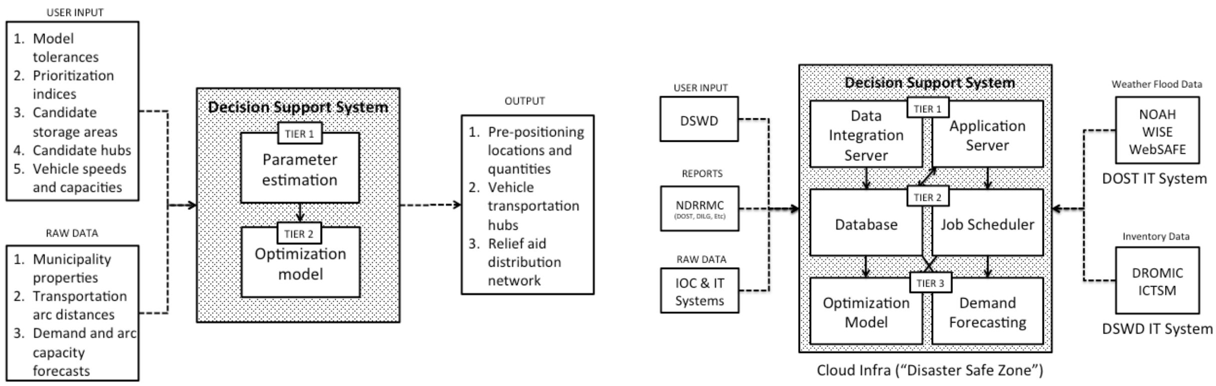
# 6 Decision Support Tool Implementation

The optimization models developed in Section 4 can be used as a building block for a decision support tool for disaster managers in pre-disaster and post-disaster operations. Figure 12a illustrates one simple embodiment of a decision support tool, which we implemented with a user interface in Excel. The user can input model parameters, including model tolerances, the prioritization indices for municipalities, the list of candidate storage ares, the list of candidate transportation hubs, and vehicle speeds and capacities. The model also reads csv files containing details of municipality properties, transportation arc distances, and demand and arc capacity forecasts. The inputs are read by a computer program implemented in Python that uses the input to estimate the model parameters. Then the program creates a CPLEX optimization model with these parameters through the Python CPLEX API. The model takes only a few seconds to solve and the output is plotted and logged into a csv file.

In a project funded by the Department of Science and Technology entitled "Pre-positioning and allocation of relief supplies GIS-based support system for disaster preparedness and response" (a project in collaboration with Ateneo de Manila University and IBM Philippines), we plan for the optimization model to be one of the fundamental components in a cloud-based decision support tool for disaster planning, which couples numerical weather models, machine learning models for prediction, and the optimization models. Figure 12b illustrates the envisioned system context diagram. In this system, the tool will automatically fetch data from DOST and DSWD IT systems. However, in case live data is unavailable, the tool can still function independently by allowing users to encode data manually, import from files, or even use previous data stored in the cloud. Reports and results of simulation can be exported and viewed locally without internet connection using document viewers and map viewers like Google Earth. All sensitive data will be encrypted in the database and user access is restricted through authentication.

# 7 Conclusions

Efficient humanitarian operations is a pressing need in the disaster-prone Philippines. In this report, we introduced optimization models for efficient pre-positioning, supply allocation and vehicle positioning. There are many other challenges in analytics for humanitarian operations which have been touched upon, but not directly addressed in this report. Firstly, demand forecasting is difficult, but crucial for planning. There are sophisticated weather forecasting models available to predict




(a) Simple embodiment

(b) Cloud-based embodiment

Figure 12: System context diagrams

typhoon tracks, however these forecasts are subject to high uncertainty, and the weather forecasts have to be converted to demand forecasts to be used in supply chain models. In this report, we addressed demand uncertainties by using ideas from robust optimization by creating demand uncertainty sets. Another challenge is that supply is uncertain, due to supply being not only from prepositioned supply, but also from irregular donations. A last challenge is that in the humanitarian logistics landscape, there are multiple humanitarian organizations (NGOs) operating in parallel in the same landscape. Hence, there is a risk of duplicating efforts.

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