Leveraging System Dynamics Modeling to Help Understand Humanitarian Food Supply During Disaster Response

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We model problematic elements of the food supply chain within a humanitarian crisis context with system dynamics. After simulating various policies for dealing with these issues, we offer a number of actionable recommendations. Having the ability to manage both priority and non-priority donations led to the best overall performance.

INTRODUCTION

The two main areas of humanitarian logistics are continuous aid work and disaster relief (Kovacs and Spens, 2007). The general phases of disaster relief operations include preparation, immediate response, and reconstruction (Kovacs and Spens, 2007). During the preparation phase, responding agencies can take critical measures to limit the effects of disasters; however, many donors want their contributions to go directly to help victims, which shortchanges *preparation* operations and overemphasizes *response* operations. Kovacs and Spens's (2007) review of the humanitarian logistics literature concludes that the main problem in the immediate response phase of disaster relief operations is rooted in coordination of supply with the unpredictability of demand and the resultant difficulties of transporting relief items (because of degraded infrastructure) to disaster victims. This is particularly true of non-priority donations, which can create storage and distribution problems in the disaster-ravaged areas (Fessler, 2013). All of these types of issues form the focal point of the present paper.

In particular, we examine the problem of distributing food to a disaster-stricken area shortly after the onset of the catastrophe. We focus on food due to the better attainment of data to help calibrate our system dynamics simulations. Our resulting recommendations, however, may apply equally to water and/or medical aid distribution in similar humanitarian responses. The point is simply that we seek "big picture" policy recommendations to help the decision makers prioritize their time and efforts during the chaotic aftermath of a disaster. The extant literature is sparse with short-term operational response during relief programs. Filling this gap is the primary motivation for this paper.

The rest of this paper is organized as follows. A literature review is provided in the next section. Following that, we formally provide the objective and approach to this problem. Our system dynamics model and assumptions are then described, followed by the results of our various simulations. We conclude with recommendations and possible future directions.

LITERATURE REVIEW

Humanitarian logistics, defined as "a special branch of logistics managing response supply chain of critical supplies and services with challenges such as demand surges, uncertain supplies, critical time windows and vast scope of its operations" (Apte 2009), has received increased attention from researchers. There are several well-written literature reviews on the subject, each very informative with its own emphasis (Altay and Green, 2006; Kovacs and Spens, 2007; Natarajarthinam et al., 2009; Pettit and Beresford, 2009; Overstreet et al., 2011). Two salient reviews include Cozzolino (2012) and Kunz and Reiner (2012).

Cozzolino (2012) provides a detailed review of the current state of knowledge on humanitarian logistics. One chapter focuses on humanitarian logistics and supply chain management. The author notes that, despite some disagreement in the literature, disaster management includes the stages of mitigation, preparation, response, and reconstruction. Additionally, Cozzolino mentions that coordination and collaboration among all actors involved in the humanitarian response deserve attention and study. Achieving efficient operations during the first days and weeks after a disaster is critical and understanding the humanitarian supply chain is the key to the needed efficiency. Cozzolino explains that effectiveness in the short term ensures saving time and lives within the disaster affected populations, while efficiency in the long term ensures saving costs and helps in rebuilding more livelihoods. Her call to understand effective supply chain operations in the short term is one focus of the present paper.

Kunz and Reiner (2012) provide a meta-analysis of research conducted in the area of humanitarian logistics. They reviewed 174 papers published between 1993 and 2011 using content analysis. One of their primary contributions was the development of a theoretical framework presenting exogenous situational factors impacting humanitarian logistics. Four primary situational factors are identified: government, socio-economic, infrastructure, and environment. One of our key investigations revolves around port and road degradation and its subsequent impact on supplying a disaster-stricken area with necessary food. In this sense we examine the infrastructure situational factor.

The many complexities involved with humanitarian operations during disaster relief lead to a number of logistical challenges that scholars have identified and defined well in the literature (Altay 2008, Çelik et al. (2012), Goncalves 2008). A full review of the many logistical challenges faced by managers of humanitarian operations is beyond the scope of this study; however, the most relevant are as follows:

- Disasters yield poor and unpredictable operating conditions. Disabled infrastructure, such as supply ports and roads, slows relief operations.
- Structured logistics processes are often not available because of damaged or inadequate information and communication systems.
- Limited resources and inappropriately assessed needs often drive the relief effort and supply chain.
- Unsolicited donations can overwhelm and bottleneck the supply chain and disrupt the appropriate allocation of resources. This problem is worse for non-priority donations.

We include all of these challenges in our model.

The magnitude of a disaster relief response, and the number of humanitarian actors involved, suggests that the logistics of humanitarian response has a systemic nature and must work with systematic tools to understand appropriate solutions better. The timing and delays that exist in a humanitarian supply chain create a complex social system that lends itself well to system dynamics modeling. System dynamics is a well-established simulation method for analyzing complex social systems and has been used successfully in modeling humanitarian operations (Goncalves 2008; Besiou and Van Wassenhove, 2011; Besiou et al., 2014). Besiou, et al. (2014), study both long-term development and short-term disaster response programs in terms of vehicle to aid in the response. However, there is no current system dynamics model that captures the short-term humanitarian response for food supply from an operational point of view. In this study, by examining the distribution of food relief, we provide this model and aim to construct recommendations from the resulting insights.

OVERVIEW OF THE SYSTEM DYNAMICS METHOD

System dynamics (SD) is a modeling approach typically used for policy analysis and design (Forrester, 1961). The SD approach is best suited for application to dynamic problems arising in complex systems characterized by interdependence, mutual interaction, information feedback, and circular causality. The system dynamics approach involves the following:

- Defining problems dynamically, in terms of graphs over time; in system dynamics, these are called "reference modes."
- Striving for an endogenous, behavioral view of the significant dynamics of a system, a focus inward on the characteristics of a system that themselves generate or exacerbate the perceived problem; this is called a "dynamic hypothesis."
- Thinking of all concepts in the real system as continuous quantities interconnected in loops of information feedback and circular causality
- Identifying independent stocks or accumulations (levels) in the system and their inflows and outflows (rates).
- Formulating a behavioral model capable of reproducing, by itself, the dynamic problem of concern. The model is usually a computer simulation model expressed in nonlinear equations, with the stocks being integrations of the flows mentioned in the last point.
- Deriving understandings and applicable policy insights from simulations done using the resulting model.
- Implementing changes resulting from model-based understandings and insights (System Dynamics Society, 2014).

The loops mentioned in the third bullet point come in two varieties:

- Reinforcing feedback, which amplifies disturbances in the loop. Some feedback theorists refer to these as positive feedback loops.
- Balancing feedback, which dampens disturbances in the loop. Some feedback theorists refer to these as negative feedback loops.

The unique contribution of SD to policy analysis is not the notion that feedback is important (an idea that has been around in various forms for centuries) but is the practical application of this fundamental concept in the form of models that can be tested, calibrated, and refined in a rigorous and scientific way (Forrester and Senge, 1980; Homer, 1996; Morecroft, 1985; Randers, 1980; Richardson, 1991; Sterman, 2000; Sterman, 2001).

Previous studies have applied the system dynamics approach to a number of public policy problems with great success; two examples include municipal planning (Forrester, 1969) and public health resource coordination (Homer and Hirsch, 2006). Many disaster preparedness issues are well suited to system dynamics analysis.

SYSTEM DYNAMICS IN HUMANITARIAN LOGISTICS

A handful of studies to date have incorporated system dynamics modeling to understand humanitarian operations (Goncalves 2008; Besiou and Van Wassenhove 2011; Heaslip, et al., 2012; Besiou et al., 2014; Berariu, et al., 2015; Berariu, et al. 2016a; Berariu, et al., 2016b). Goncalves (2008) notes the many challenges faced by humanitarian organizations and suggests that we need tools to help understand the complex systems, in terms of the structures and policies that regulate performance, within which the organizations operate. He goes on to note that system dynamics can be such a tool, and can help managers learn in the complex setting of humanitarian operations. His study uses a system dynamics model to show that overemphasis on short-term relief efforts can hamper capacity building of the organization, which then hampers its longer-term ability to respond to disasters. His view of the longer-term makes his model somewhat less operational (Richmond, 1993), i.e. too abstract, than a model focused on short-term disaster relief. Nevertheless, Goncalves's (2008) study is a good example of how to use system dynamics to create stylized simulations and can ultimately better help decision makers to understand the long-term effects of policy decisions and to explore new strategy.

A study by Besiou and Van Wassenhove (2011) analyzes a well-defined subsystem of humanitarian operations using system dynamics to simulate field-vehicle fleet management. Their study is more operational (it focuses on truck fleets), but still examines long-term decision making, that is, continuous aid work, as opposed to disaster response. However, Besiou and Van Wassenhove (2011) state that beyond their example of vehicle management, additional areas of humanitarian operations would be well suited to research using system dynamics. Besiou and Van Wassenhove (2011) conclude by noting that system dynamics has the ability to represent accurately the complexities of humanitarian operations, and they give their support to the system dynamics approach as an appropriate tool studying humanitarian systems.

Heaslip et al. (2012) employ a systems-based perspective to capture the coordination of humanitarian operations by military and civilian organizations. Their systems analysis and design technique is used to develop a system dynamics model to help describe the interactions between various stakeholders and involved components. Their model is primarily designed to provide a visualization of the interrelationships between the actors and stakeholders involved in a humanitarian logistics in the hopes that they can be better understood among the various agencies.

Besiou, Pedraza-Martinez, and Van Wassenhove (2014) used a system dynamics model to examine field-vehicle fleet management. Their focus was the effect of donor behavior on the humanitarian organization's ability to direct donations to the most efficient and effective allocation of vehicle fleets. Their model showed that as "earmarked" donations increased, the organization's ability to direct resources effectively and efficiently diminished, resulting in a reduction in disaster response service level of up to fifteen percent.

Berariu, et al. (2015) create causal loop diagrams to help provide decision makers with information regarding the cascading effects of natural disasters and their impact on critical infrastructure: transportation, electricity, and human health. They used two case studies, the European flood of 2002 and the European heat wave of 2003, to investigate if the identified behavior occurred in real-world cases. Both cases demonstrated that cascade effects negatively affect critical infrastructure, but some of the assumed interdependencies did not appear in the analysis of the European heat wave of 2003. Their causal loop diagrams provide a visualization to help understand cascade effects impact on disaster relief operations.

Berariu, et al. (2016a) create a model to train decision makers on flood response. They develop a system dynamics model that captures the complex settings of floods. This model is used to as a training tool where decision makers conduct what-if analysis with various scenarios to help them understand the key aspects of responding to a flood. Their work appears to be the only documented study that develops a system dynamics model for educational purposes in flood response.

Berari, et al. (2016b) present a system dynamics model, allowing simulation of resource deployment during a flood. They focus on managing the "hoarding behavior" of needed commodities of an affected population with the aim of supporting decision makers by raising awareness of the complex interdependencies during disaster relief. They extend the understanding of the impact of various factors and interdependencies when there is sudden demand and limited resources must be deployed. In particular, they show that a possible stock-out can occur and that adjusting the number of vehicles during the response may take longer to reach a desired equilibrium. They suggest preventive measures such as raising the awareness with the affected population that it is important to avoid hoarding behavior and studying ways to help the population be more sufficiently prepared for disasters such as floods.

In contrast to these previous works, the present research applies system dynamics to short-term, operational, disaster-response phenomena in humanitarian operations. Thus, we add to the existing literature, which includes no system dynamics models that capture the short-term humanitarian response from an operational point of view. In this study, we provide such a model and aim to construct recommendations from the insights gained. In particular, we focus on food supply to an afflicted area.

OBJECTIVE AND APPROACH

Problem Definition

An earlier section listed the many issues that arise during disaster response:

- Disasters yield poor and unpredictable operating conditions. Disabled infrastructure, such as supply ports and roads, slows relief operations.
- Structured logistics processes are often not available because of damaged or inadequate information and communication systems.
- Limited resources and inappropriately assessed needs often drive the relief effort and supply chain.
- Excessive donations can overwhelm and bottleneck the supply chain and disrupt the appropriate allocation of resources. This problem is worse with non-priority donations.

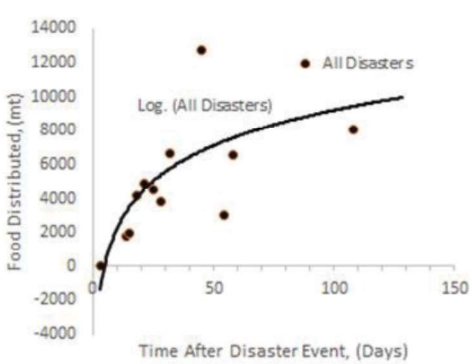
The aim of the present paper is to include these elements in a system dynamics model focusing on supplying needed food to a disaster-stricken area, to simulate various policies for dealing with them, and to make recommendations based on the results.

Reference Mode

To help understand the problem, system dynamics typically uses graphs of the behavior over time of relevant variables. Modelers call these “reference modes” because they refer to them as checks on model outputs. The reference modes demonstrate behavior of a model input over time.

We have chosen to focus on food, one of the vital important supplies needed after a disaster. While other necessities are also vitally important, such as water and medical supplies, data collected and easily accessible is difficult to obtain. We were, however, able to find and aggregate data from the World Food Programme for food distributed during three disasters (the Haiti earthquake of 2010, the Philippines typhoon of 2013, and the Afghanistan floods of 2014). Figure 1 shows that the delivery of food rises rapidly in the immediate aftermath of a disaster, but levels off after 150 days or so.

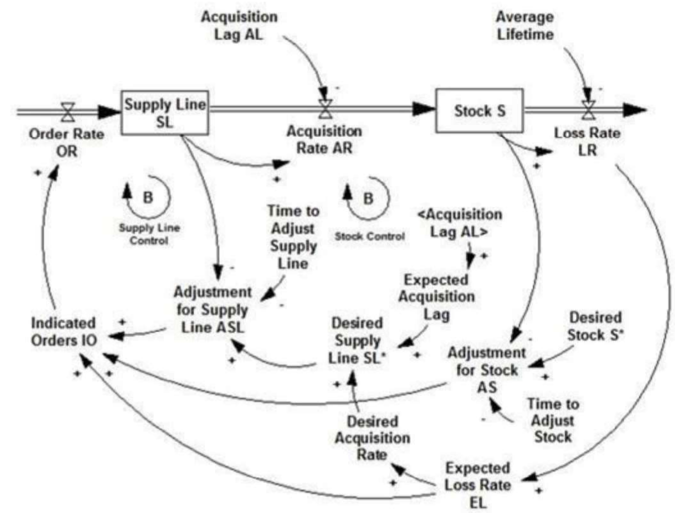
FIGURE 1
REFERENCE MODE FOR FOOD DELIVERY AFTER THE ONSET OF A DISASTER



Dynamic Hypothesis

We assert that the delivery of humanitarian food supplies is a special case of the familiar Stock Management Structure from system dynamics (Sterman, 2000, chapter 17). We show its generic structure in Figure 2.

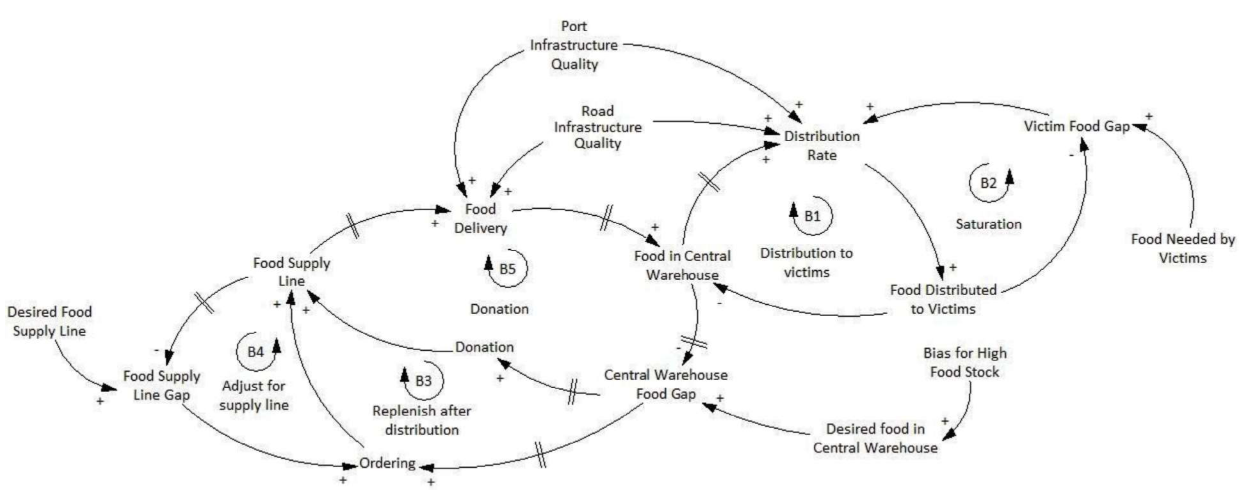
FIGURE 2
GENERIC STOCK MANAGEMENT STRUCTURE



In the Stock Management Structure, a decision maker needs to maintain the level of a stock *S* (in our case, food in a central humanitarian warehouse) by replenishing the stock's units as the decision maker delivers them, but at the same time keeping in mind previously ordered units in the pipeline. One key to the Stock Management Structure is its many delays of physical flows and of perceptions.

We show our dynamic hypothesis in a causal loop diagram in Figure 3. It shows five loops, all balancing, along with some specific features of humanitarian response that differ from the generic Stock Management Structure.

FIGURE 3
DYNAMIC HYPOTHESIS



- Loop B1, “Distribution to victims,” shows the central activity in humanitarian response—distribution of food aid to disaster victims. Increases in Food in the Central Warehouse increase the Distribution Rate, which increases Food Distributed to Victims, which in turn reduces the amount of Food in the Central Warehouse.
- Loop B2, “Saturation,” shows how food distribution slows down as the agency meets the needs of the disaster-stricken population. Increases in Food Distributed to Victims reduce the size of the Victim Food Gap, which reduces the Distribution Rate and, in turn, reduces the Food Distributed to Victims. This loop creates the reference mode: the amount of food the agency distributes levels off and ends as the disaster-stricken population gets all the food it needs.
- Loop B3, “Replenish after distribution,” is the first part of the Stock Management System. As food moves out of the Central Warehouse, the agency orders replacement food.
- Loop B4, “Adjust for supply line,” modifies the amount of food ordered based on what the agency knows is in the pipeline.
- Loop B5, “Donation,” is where donors add food to the pipeline as they react to the need for food. As the Gap in the Central Warehouse Food increases, Donations increase (after a delay). This increases Food in the Supply Line, which increases Food Delivery and Food in the Central Warehouse, closing the Gap.

We do not show it in Figure 3, but a well-known feature of the Stock Management Structure is knowledge of what is in the warehouse and knowledge of what is in the supply line. These relate to Loops B3 and B4; the chaos of the aftermath of disasters often reduces knowledge of existing or ordered food stocks, and makes these two variables relevant to this research. We include them in the full model.

Figure 3 shows three exogenous features peculiar to the humanitarian response version of the Stock Management Structure:

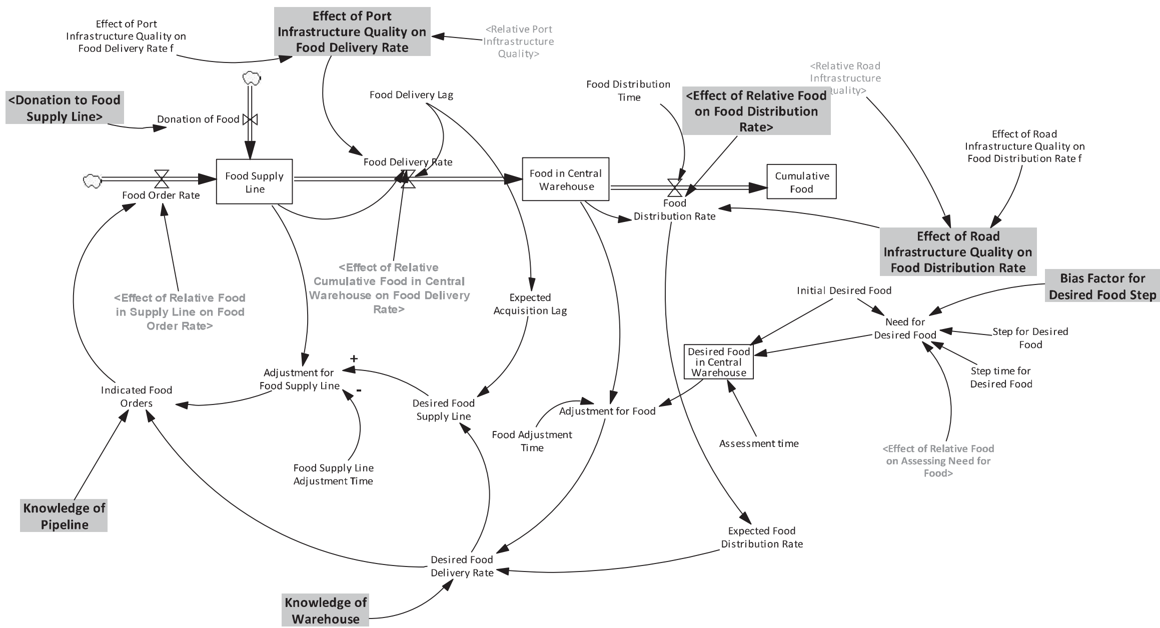
- **Road Infrastructure Quality**. Prior to a disaster, the road infrastructure in an affected country is adequate to ensure both delivery and distribution of food. After a disaster, poor road conditions slow down both of these flows.
- **Port Infrastructure Quality**. Prior to a disaster, the port infrastructure in an affected country is adequate to ensure both delivery and distribution of food. After a disaster, poor port conditions slow down both of these flows.
- **Bias for High Food Stock**. The shock of a disaster may cause responders to overestimate the need for higher levels of food in the system.

Stock and Flow Model

Figure 4 shows the stock management structure of the full system dynamics model. Its foundation is the generic stock management structure. Boldface items highlighted in gray are the features peculiar to the humanitarian disaster response context:

- Effect of Road Infrastructure Quality (see Figure 5)
- Effect of Port Infrastructure Quality (except for different variable names, the structure is the same as what we show in Figure 5)
- Effect of Relative Food (Figure 6)
- Effect of Food Donation (Figure 7)
- Effect of Bias for High Food Stock
- Knowledge of Food in Central Warehouse
- Knowledge of Food in Supply Line
- Effect of priority donations
- Effect of non-priority donations

FIGURE 4
THE FULL MODEL OF THE HUMANITARIAN FOOD DELIVERY. (VARIABLES IN <> BRACKETS ARE IN OTHER "VIEWS" IN THE VENSIM SOFTWARE)



We address the first four items using table functions. After a disaster, the ratio of actual infrastructure (either ports or roads) to desired infrastructure drops, so we use an upward-sloping function to reduce the flow of food in the early days, as infrastructure damage is high, while raising the flow as the region repairs its infrastructure. To control the distribution of food as the population gets what it needs, we use a downward-sloping table function that gradually shuts off the flow of food as the ratio of actual to needed approaches one. We formulate the food donation sectors by using a mildly upward-sloping table function (Figure 8) that reacts to the "Pressure to Donate" created by the ratio of what donors would normally like to see in the Central Warehouse and what is suddenly needed after a disaster. We address bias and logistical knowledge with parameters.

FIGURE 5
INFRASTRUCTURE VIEW

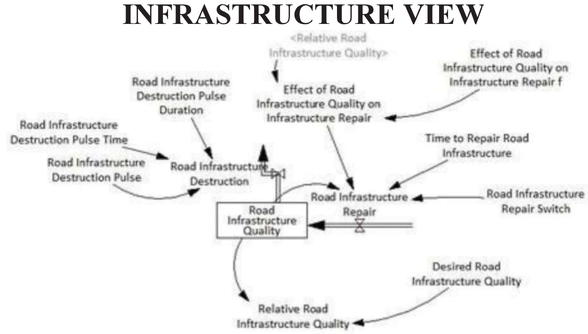


FIGURE 6
FOOD VIEW

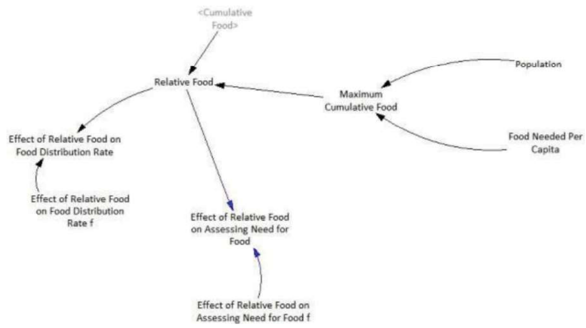


FIGURE 7
DONATION VIEW

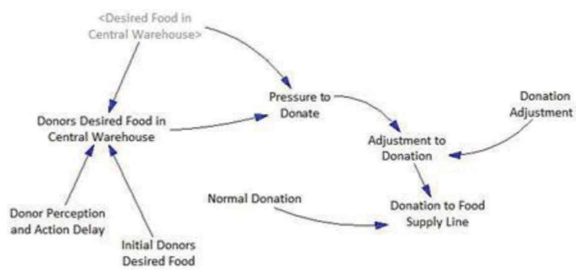
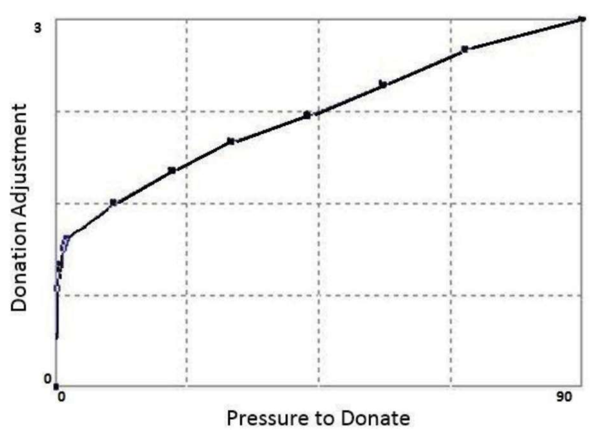


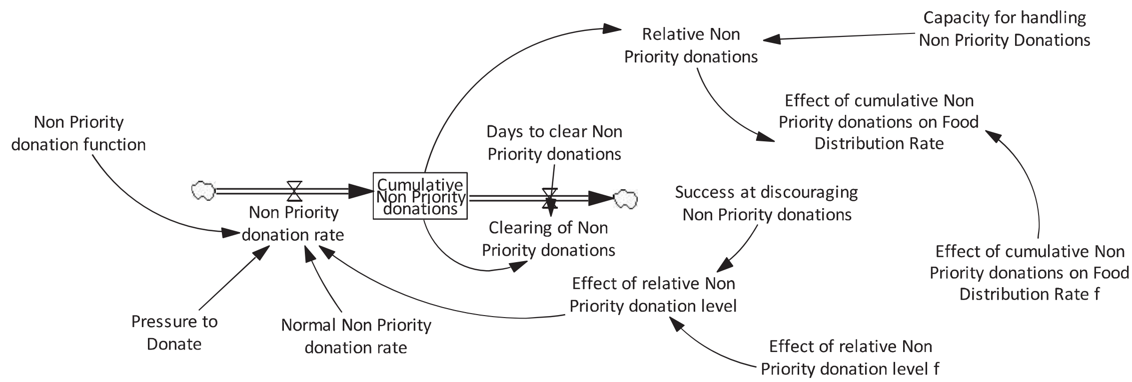
FIGURE 8
DONATION ADJUSTMENT TABLE FUNCTION



Holguín-Veras et al. (2013) group in-kind donations into three categories: high priority donations, low priority donations, and non-priority donations. Non-priority donations, if not properly handled, can significantly slow down disaster response efforts. So far in this paper we have not examined the effects of non-priority donations. To address this, we added a bit of structure to the donor behavior section of the model (see Figure 9). Much research (Holguín-Veras et al., 2014) has shown that there are only two ways to control non-priority donations: (1) Discourage them from arriving at all and (2) Clear them out as quickly as possible. Figure 9 shows that were the disaster response agency "Successful at discouraging

Non-priority donations," the first method for controlling such donations, it would stem the inflow "Non-priority donation rate." The figure furthermore shows that, were any non-priority donations to end up in the stock of "Cumulative Non-priority donations," it could use the outflow "Clearing of Non-priority donations," which is governed by the number of days it would take to do the clearing. Lastly, the non-priority donations feed into a function that, as the literature shows, impedes the delivery of food.

FIGURE 9
MODEL STRUCTURE FOR NON-PRIORITY DONATION



MODEL ASSUMPTIONS AND INPUTS

Model Parameters

Figure 10 shows the parameters (and their units) that we used in the simulation scenarios we discuss in a later section. Each scenario has a 150-day time horizon. Since supply line and central warehouse managers would want to control their inventories, we used table functions, using maximums of 25,000 and 50,000 metric tons, respectively, to cap those stocks.

FIGURE 10
PARAMETERS USED IN SIMULATION SCENARIOS

Scenarios	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	Equil	Base	No repair	No knowl	Dbl bias	Damp donation	Enc Donation	No Donation	Scenarios 5+7	In-kind poor	In-kind sm cap	In-kind lge cap	In-kind 20 day dest	In-kind 5 day dest	In-kind sm cap 5 day dest
Initial Desired Food (metric tons)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Step for Desired Food (metric tons)	0	40000	40000	40000	40000	40000	40000	40000	40000	40000	40000	40000	40000	40000	40000
Step time for Desired Food (day)	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
Bias factor (dmls)	1	1	1	1	2	1	1	1	2	1	1	1	1	1	1
Population (people)	2M	2M	2M	2M	2M	2M	2M	2M	2M	2M	2M	2M	2M	2M	2M
Food Needed Per Capita (metric tons)	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Food Adjustment Time (days)	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
Food Supply Line Adjustment Time (days)	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
Food Delivery Lag (days)	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5
Food Distribution Time (days)	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8
Knowledge of Pipeline (dmls)	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
Knowledge of Warehouse (dmls)	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
Maximum Food in Supply Line	25K	25K	25K	25K	25K	25K	25K	25K	25K	25K	25K	25K	25K	25K	25K
Maximum Food in Central Warehouse	50K	50K	50K	50K	50K	50K	50K	50K	50K	50K	50K	50K	50K	50K	50K
Time to Repair Road Infrastructure (days)	60	60	60	60	60	60	60	60	60	60	60	60	60	60	60
Road Infrastructure Repair Switch (dmls)	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1
Desired Road Infrastructure Quality (dmls)	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Road Infrastructure Destruction Pulse (dmls/day)	0	75	75	75	75	75	75	75	75	75	75	75	75	75	75
Road Infrastructure Destruction Pulse Time (days)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Road Infrastructure Destruction Pulse Duration (days)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Time to Repair Port Infrastructure (days)	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30
Port Infrastructure Repair Switch (dmls)	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1
Desired Port Infrastructure Quality (dmls)	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Port Infrastructure Destruction Pulse (dmls/day)	0	75	75	75	75	75	75	75	75	75	75	75	75	75	75
Port Infrastructure Destruction Pulse Time (days)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Port Infrastructure Destruction Pulse Duration (days)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Initial Donors Desired Food (metric tons)	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Normal Donation (metric tons/day)	315	315	315	315	315	315	315	315	315	315	315	315	315	315	315
Donation Adjustment table (dmls)	Mod up sloping	Mod up sloping	Mod up sloping	Mod up sloping	Mod up sloping	Flat	Steep up sloping	Mod up sloping	Steep up sloping	Mod up sloping	Mod up sloping	Mod up sloping	Mod up sloping	Mod up sloping	Mod up sloping
Capacity in MT	1M	1M	1M	1M	1M	1M	1M	1M	1M	1M	10	50	1M	1M	10
Days to clear IK donations	150	150	150	150	150	150	150	150	150	150	150	150	20	5	5

Model Assumptions

Here are the highlights of the assumptions we made:

- We assume a population of 2 million people in the affected area.
- Each person requires an average of 0.02 metric tons of food, cumulatively, over the 150-day period (approximately 0.25 pounds of food per person per day). This number was arrived at by using the three disasters we discussed earlier in reference to the reference mode. You may wish to think of this as high-calorie bars with a very long shelf life.
- Each of the adjustments and delivery times in the food stock management system has an associated delay, as we show in Figure 10.
- Damage from the disaster happens in a one-day pulse.
- It takes 3 days for the disaster response agencies to assess the level of need for food.
- Port and road infrastructures sustain 75% damage from the disaster.
- It takes 30 days to repair the port infrastructure, and 60 days to repair road infrastructure.
- Once the disaster strikes, donors give 315 metric tons of priority donation food per day to disaster response agencies. We calculated this average donation amount from various World Food Programme sources (World Food Programme, 2010, 2014).

MODEL RESULTS

Results of Simulation Scenarios

The equilibrium scenario shows all outputs flat. We do not show it here because we expect this result, given that in the base scenario there has been no disaster and no donation. By contrast, the "base" scenario has a disaster and its concomitant need for more food in the central warehouse, road and port infrastructure damage and repair, and donation spurred by the disaster. Figure 11 shows the results for the three major stocks: Food in the Supply Line, Food in the Central Warehouse, and the Cumulative Food Distributed. As one might expect, there is an early spike in the Food Supply Line (curve 1), followed by a reduction as the responders meet the population's food needs. The Cumulative Food delivered to the population (curve 3) levels off as responders meet the required need; this mirrors the reference mode we show in Figure 1. However, Figure 11 shows that food donors continue to donate, and the resulting food in the supply line goes to the Central Warehouse, where it piles up (curve 2). This, according to observers like Altay (2008), is a very common scenario following a disaster.

FIGURE 11
RESULTS OF THE BASE SCENARIO

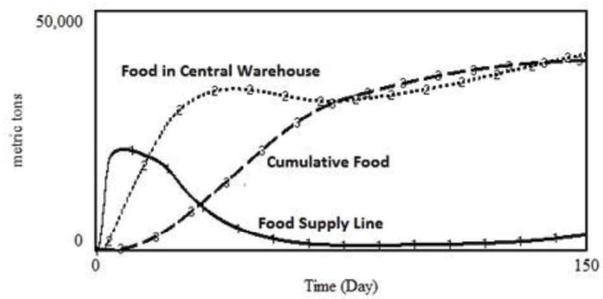


Figure 12 shows the results of a scenario similar to the base scenario, but where no repair of any infrastructure occurs, i.e. the roads are only 25% effective for the entire period. As expected, the Supply Line (curve 1) never quite empties out, and the Cumulative Food distributed gets to the population more slowly—and the response agency never quite meets the population's needs (curve 3).

FIGURE 12
NO INFRASTRUCTURE REPAIR

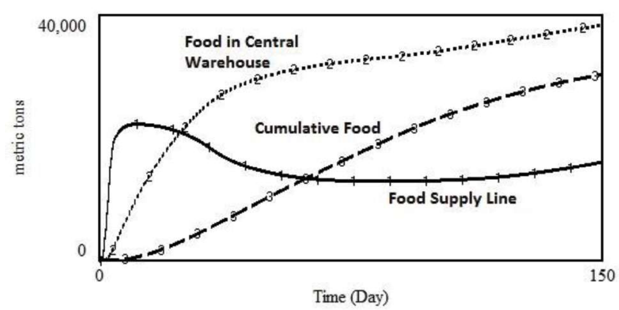
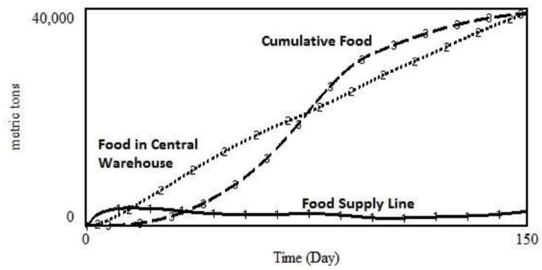


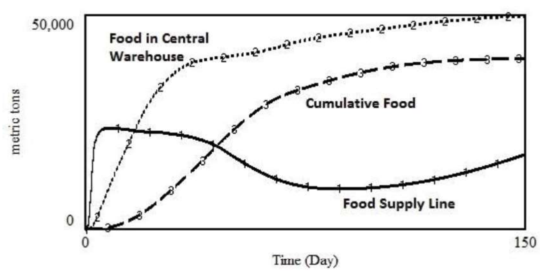
Figure 13 shows the results of a scenario where the response agency has zero knowledge of what is in its Supply Line or its Central Warehouse. The result is very interesting: the population gets all the food it needs (curve 3), and the Food Supply Line (curve 1) does not spike. However, the Food in the Central Warehouse (curve 2) continues to build, which is the reason that the first two mentioned stocks behave so well. *Because* of its ignorance of the situation, the agency never restocks of its *own* accord; it is the *donors* who fill the Supply Line (actually, *overfill* it). We confirmed this with a scenario (not shown) where all the parameters were the same as this scenario, except donations were zero. It was indistinguishable from the equilibrium scenario, meaning that, in the absence of knowledge of its supply line, a disaster response agency meets the needs of the population by relying on whatever donations show up. (Another scenario not shown indicated that, with 50 percent knowledge of its pipeline, the agency had a more robust Supply Line and met the needs of the population a bit more quickly, as one would expect.)

FIGURE 13
NO PIPELINE KNOWLEDGE



In the immediate aftermath of a disaster, damage assessors for the response agency might overestimate the need for food. Figure 14 shows the results of a scenario with double the bias for the step increase in desired food. As one might expect, the result is that Supply Line (curve 1) spikes a bit early on, and the agency meets the food needs of the population (curve 3) a bit earlier. However, the Food in the Central Warehouse (curve 2) piles up to much higher levels than needed.

FIGURE 14
DOUBLE BIAS



We wanted to assess the effects of a dampening of the donors' ardor. Therefore, we altered, in two ways, the table function that controls priority Donation to the Food Supply Line:

1. When the ratio of Donors Desired Food in the Central Warehouse to the Agency's Desired Food in the Central Warehouse was below one, we eliminated all donations.
2. When that ratio exceeded one, we reduced the Donation Adjustment from 1.2 to 0.75, which is a significant dampening of donation.

Figure 15 shows the results, which are modest but interesting. Compared to the base scenario, there is little change to Food in the Supply Line and Cumulative Food (curves 1 and 3, respectively), but the Food in the Central Warehouse (curve 2) is lower. In terms of lower costs and less waste, there are clear benefits to the agency to managing the ardor of its donors.

FIGURE 15
DAMPENED DONATION

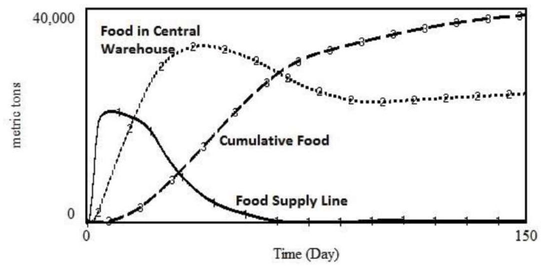
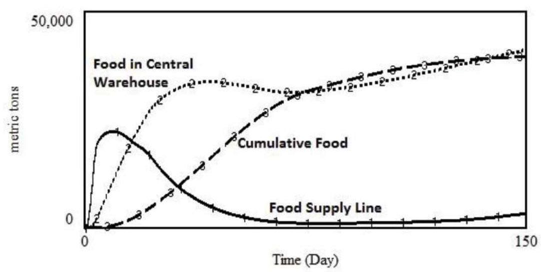


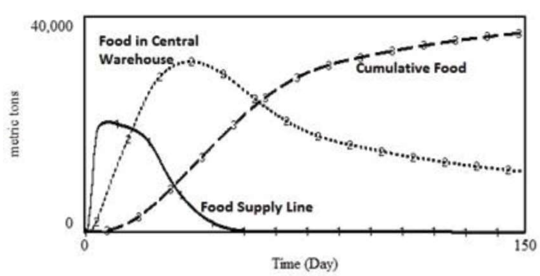
Figure 16 shows the results of a scenario that did the opposite of the last one—it simulated what would happen if the agency *encouraged* priority donation. We did this by steepening the table function that controls Donation to the Food Supply Line. The results, compared to the base scenario, were modest. This is because the Pressure to Donate that feeds into the table function is at its highest in the early days after the disaster. As food comes rolling in, the Pressure to Donate drops, regardless of how steep the table function is.

FIGURE 16
ENCOURAGED DONATION



To see what would happen were the agency to cut off priority donations altogether, we did a scenario, which we show in Figure 17, where the Normal Donation was zero. The results also were dramatic, with Food in the Central Warehouse (Curve 2) at much more manageable levels. However, one subtle effect was that the population received its needed food much less quickly, and it did not have its entire need met by the end of the simulated period. We conclude that a modest level of priority donation is desirable.

FIGURE 17
NO DONATION



Lastly, we did a scenario that combined two previous policies: we doubled the bias and encouraged donation. The results, which we show in Figure 18, were almost identical to those we showed in Figure

14. This came about because the greater gap at the beginning, caused by the bias, raised donations early, but the delivery of food shut donations off later, resulting in mostly no difference from the double bias policy alone.

FIGURE 18
DOUBLE BIAS AND ENCOURAGED DONATION

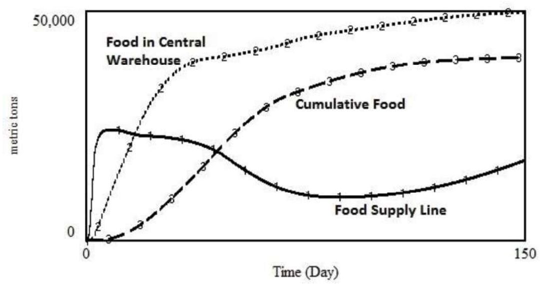
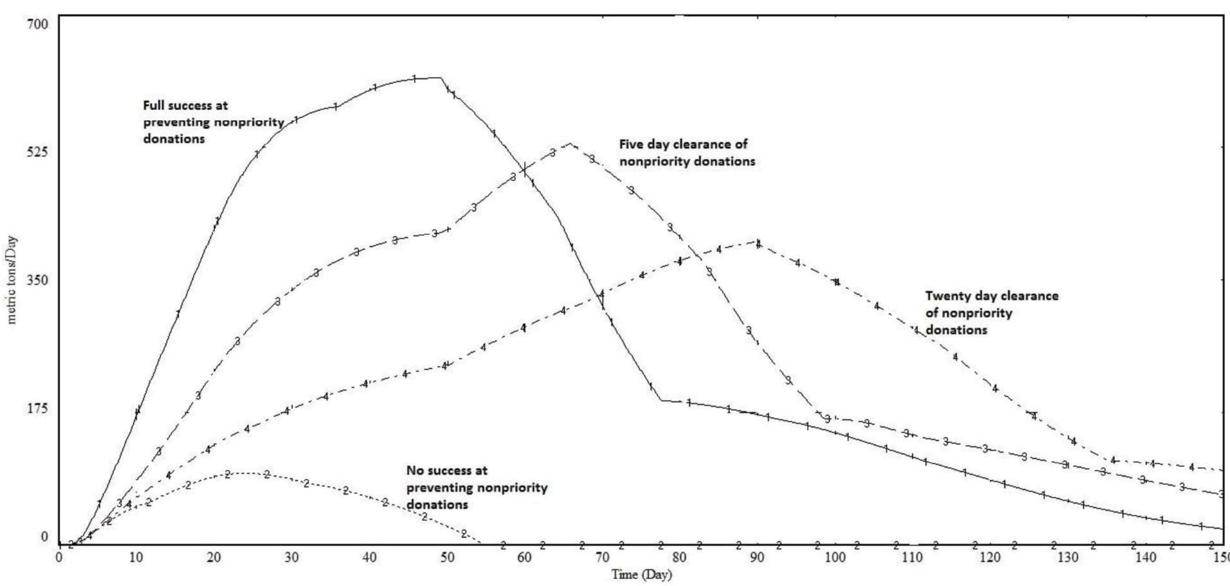


Figure 19 shows the effects on the food distribution rate of various policies for handling non-priority donations. If the organization is fully successful at preventing non-priority donations, there is no difference compared to the earlier version of the model (curve 1). However, if the organization has no success at preventing non-priority donations, the effect on the food distribution rate is profound (curve 2): the slowing effect is so great that overall food trickles in and then stops on day 55. However, if the organization cannot prevent non-priority donations, but *can* clear them, the food distribution rate improves, although it is not as good as preventing those donations. The figure shows that clearing the donations out in five days (curve 3) is far better than doing so in 20 days (curve 4).

FIGURE 19
EFFECTS ON FOOD DISTRIBUTION RATE OF VARIOUS POLICIES FOR HANDLING NON-PRIORITY DONATIONS



Since failure to prevent or to clear non-priority donations cuts off the Food Distribution Rate entirely, we will omit it from the discussion and recommendations below. Our model shows that preventing or quickly clearing non-priority donations is of absolute importance.

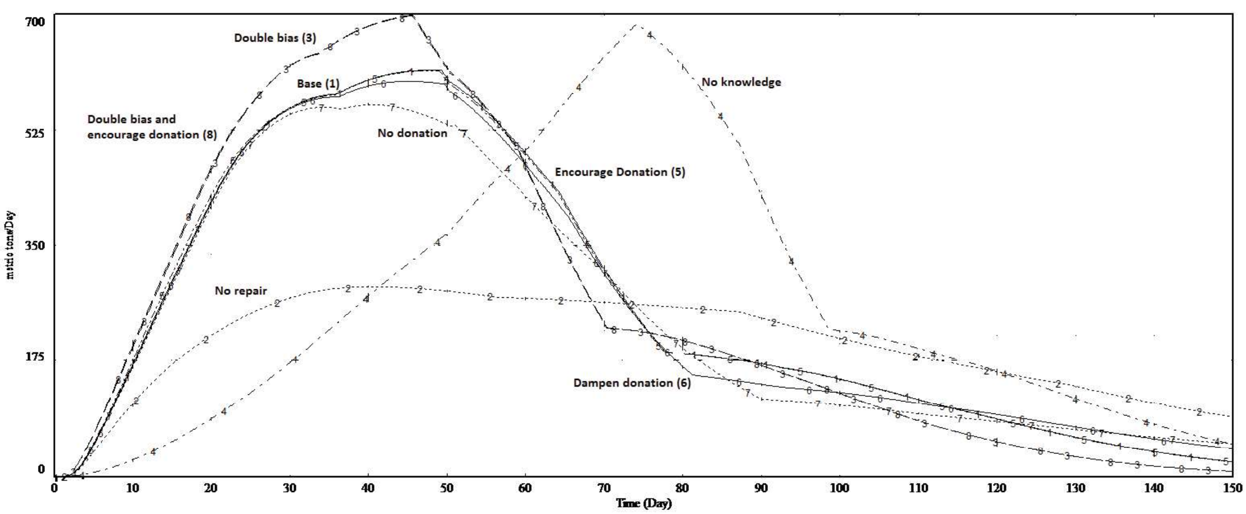
DISCUSSION AND RECOMMENDATIONS

Discussion

Of all the variables in our model of the Humanitarian Stock Management System, the most important, since it involves getting food to people in need, was the Food Distribution Rate to disaster victims. Figure 20 shows the Food Distribution Rate under the various policy scenarios, which reveals some interesting implications of the various policies:

- Having no knowledge of the pipeline (curve 4) means that needy recipients get their food much more slowly than all the other policies, except the clearly bad "no repair" one.
- Delay in repair of infrastructure (curve 2) is, as might be expected, very damaging to the disaster response effort. This policy takes the longest, by far, to get food to recipients, and even then, it does not fully meet their needs.
- The double bias and double bias along with encouraged (priority) donation policies get the food to victims faster than most of the other reasonable policies, but at the cost of piling up inventory in the Central Warehouse (see curve 3 in Figure 18).

FIGURE 20
FOOD DISTRIBUTION RATE FOR VARIOUS POLICIES



Recommendations

From these figures, we may infer the differential desirability of various policies:

1. It is straightforward that disaster response agencies do all they can to avoid bias in the early days. Assessments of the Desired Level of Food in the Central Warehouse should be fact-based and free of panic. The "Double Bias" and "Double Bias and Encouraged Donation" scenarios clearly showed the problems with not taking this recommendation: large amounts of wasted food with little improvement in relief to victims.
2. It is equally straightforward that disaster response agencies and local authorities do all they can to repair port and road infrastructure as quickly as possible. The "No Repair" scenario showed less waste but the worst relief performance.
3. Disaster response agencies should develop good methods for keeping track of what is in their Central Warehouses and what is in the Supply Line. Failure to do so results in much slower distribution of food to victims. It is interesting that the "No Knowledge" simulation scenario showed less waste (lack of system knowledge encouraged hyper-conservative ordering), but at the cost of very slow initial response (kept going mostly from uncontrolled donations).

4. Disaster response agencies should strike a balance between encouraging and dampening donations. This is similar to recent research that found that “non-earmarked” donations gave response organizations greater flexibility, and therefore greater efficiency and effectiveness, at deploying the proceeds of their donations (Besiou et al., 2014; Aflaki and Pedraza-Martinez, 2016). Having no donations at all would work to some extent, *but only* if all other policies worked well. Our results showed that, in most cases, having too many donations mostly clogged up the Central Warehouse. However, *managing* donations in a way that started them only after the initial period, and at a dampened level, led to less waste with roughly equivalent relief to victims. Of the three simulation scenarios dealing with donation, “Encourage Donation,” “Dampen Donation,” and “No Donation”, only “Dampen Donation” (in the sense of managing, not eliminating, it) had good performance on waste reduction (actually the best on this measure) and relief (second only to the “Double Bias” scenario).
5. Disaster response agencies should do everything they can to prevent non-priority donations from arriving at relief sites. Our simulation showed that failing to do this would be catastrophic, as it would slow down the Food Distribution Rate to a trickle.
6. If disaster response agencies are not able to stem the flow of non-priority donations to relief sites, they should develop the ability to clear them as quickly as possible. Our simulation scenarios showed that five-day clearance was significantly better than twenty-day clearance, indeed almost as good as prevention.

Figures 21 and 22 add the results from an “optimal policies” scenario (curve 9 in both figures) that follows all the recommendations: there is no early bias, authorities repair port and road infrastructures in half their normal time, responders have perfect knowledge of their supply line and central warehouse inventory, and they dampen (but do not eliminate) priority donations. Food in the Central Warehouse is at its lowest level other than when response agencies cut off donations entirely, and Cumulative Food distributed to victims is highest (and fastest) other than when there are bias and uncontrolled donations.

FIGURE 21
FOOD IN CENTRAL WAREHOUSE, OPTIMAL POLICY MIX

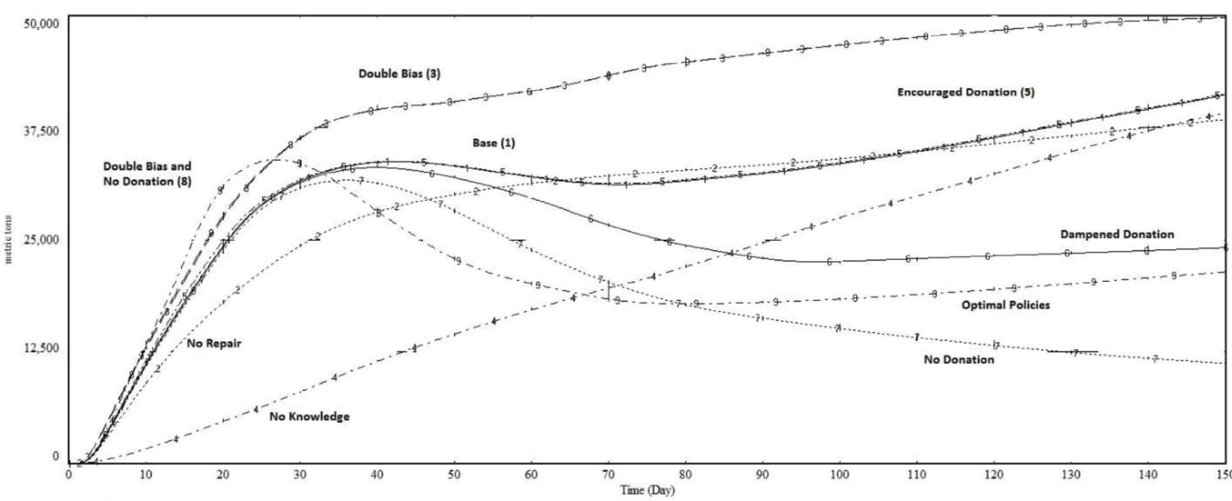
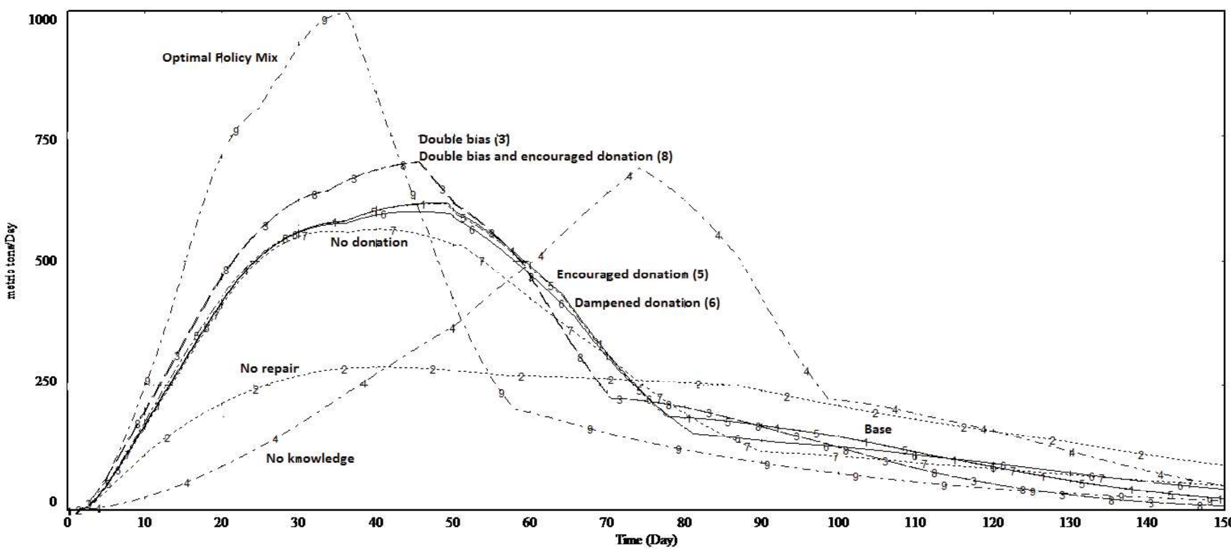


FIGURE 22
FOOD DISTRIBUTION RATE, OPTIMAL POLICY MIX



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