Investing in Disaster Management Capabilities versus Pre-positioning Inventory: A New Approach to Disaster Preparedness

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Abstract

Disaster preparedness has been recognized as a central element in reducing the impact of disasters worldwide. The usual methods of preparedness, such as pre-positioning relief inventory in countries prone to disasters, are problematic because they require high investment in various locations, due to the uncertainty about the timing and location of the next disaster. Investing in disaster management capabilities, such as training staff, pre-negotiating customs agreements with countries prone to disasters, or harmonizing import procedures with local customs clearance procedures, has been recognized as a way to overcome this constraint. By means of system dynamics modeling, we model the delivery process of ready-to-use therapeutic food items during the immediate response phase of a disaster, and we analyze the performance of different preparedness scenarios. We find that pre-positioning inventory produces positive results for the beneficiaries, but at extremely high costs. Investing in disaster management capabilities is an interesting alternative, as it allows lead time reductions of up to 67% (18 days) compared to a scenario without preparedness, at significantly lower costs than pre-positioning inventory. We find that the best performance can be achieved when combining both preparedness strategies, allocating part of the available funding to disaster management capabilities and part to pre-positioning inventory. We analyze 2,828 such combined scenarios to identify the best mix of preparedness strategies for different levels of available funding. On the basis of our findings, we provide recommendations for relief organizations on how to allocate their preparedness budget.

1. INTRODUCTION

Natural and man-made disasters strike unpredictably every year, claiming thousands of victims worldwide. Millions of people are affected by the direct consequences of these disasters, and their survival depends on disaster relief assistance provided by governments and international relief organizations. This assistance must be provided within the first hours following the disaster in order to increase the survival rate of the affected populations. The first priorities are locating the victims (e.g., in the case of an earthquake), delivering health care to the injured victims, and providing water, food, and shelter to the survivors. These tasks require complex logistical activities, as the needed supplies are rarely available directly at the location where the disaster struck. These logistical activities, generally referred to as humanitarian logistics, are hampered by several barriers, such as destroyed transport and communication infrastructures, custom clearance procedures, and operational bottlenecks at key access points, such as airports, harbors, or border crossings. Further, when disasters strike in developing countries, relief organizations may face additional challenges. The local government does not always cooperate with the international relief organizations, security problems impede access to the victims, and a population's extreme poverty increases its vulnerability. The uncertainty of the demand also poses a challenge to relief organizations, as precise data related to the number and location of victims are unavailable in the first hours following a disaster.

In order to speed up disaster relief assistance and increase its effectiveness, and thus reduce the impact of disasters worldwide, academics and practitioners are increasingly calling for the implementation of disaster preparedness (Duran et al., 2011; Gatignon et al., 2010; Jahre et al., 2009; Kovács et al., 2010; Perry, 2007; Van Wassenhove, 2006). This preventive phase of disaster management can be defined as all of the activities that can be performed by the population, the government, and relief organizations before a disaster strikes, with the aim of decreasing its potential devastating effects (Van Wassenhove, 2006). Such preparation efforts and the related uncertainty about the occurrence of unfavorable events are well established in traditional risk management fields (e.g., financial services). However, in the field of humanitarian aid, such proactive risk-hedging actions are considerably hampered, since donors traditionally only finance response efforts once a disaster has occurred (Jahre and Heigh, 2008).

The most well-known form of disaster preparation suggested in the literature is the pre-positioning of relief supplies in countries prone to disasters (see Table 1). However, this is problematic, because pre-positioning requires high investment and holding costs at various locations, due to the high levels of uncertainty regarding the timing and location of the next disaster. In addition, product expiry is a major problem, as there is no inventory turnover between crises (Whybark, 2007). For these reasons, rather than pre-positioning supplies, Van

Wassenhove (2006) proposed that relief organizations invest in disaster management capabilities (DMC). Investing in DMC can be done, for example, by training staff to be prepared to operate in a new country, developing and disseminating best practices on the basis of past disasters, educating the local population, pre-negotiating agreements with suppliers and governments, harmonizing procedures with local government requirements, or securing cooperation with local governments and NGOs (Table 2 provides a complete list with references). Investing in such capabilities, rather than in physical pre-positioned assets, has several benefits. First, the DMC developed by an organization can be deployed worldwide, in contrast to pre-positioning supplies that have to be duplicated in various locations. Second, DMC (especially those related to import processes) allow organizations to deliver supplies quickly from a centralized warehouse when a disaster occurs. Third, it costs less to invest in DMC than to pre-position supplies in large quantities in various locations.

Our paper intends to evaluate the effects of investing in DMC through system dynamics modeling. We model the delivery process of ready-to-use therapeutic food (RUTF) items during the immediate response phase of a disaster. We chose these items because of their growing strategic importance in relief aid. Indeed, in 2007, the UN World Health Organization (WHO) announced a "shift from hospital-based to community-based treatment for severe acute malnutrition with RUTF" (UNICEF, 2009, p.4). Due to these recommendations, as well as the high effectiveness of RUTF treatments (Tectonidis, 2006), the demand for such items sharply increased, posing numerous challenges for relief supply chains.

By comparing a scenario without preparedness with one in which supplies have been pre-positioned in the country and one in which investments in DMC have been made, we demonstrate the strong improvement potential of disaster preparedness activities. We address the following research questions in detail: (i) How does pre-positioning inventory and investing in DMC improve the delivery of relief supplies during the immediate disaster response, in comparison to an import scenario without preparedness? (ii) What is the potential of pre-disaster investment in DMC, as compared to pre-positioning, for reducing the costs of the preparedness phase? (iii) What is the optimal mix of pre-positioning inventory and investing in DMC?

Our paper is structured as follows. First, we provide an outline of the recent literature on disaster preparedness in humanitarian logistics. After providing an overview of the applied system dynamics methodology, we introduce our specific model and the various disaster relief scenarios. Next, we present the results of our modeling, analyze different combinations of scenarios, and conduct a sensitivity analysis of our main parameters. We then discuss our findings against the background of cost considerations as well as the previous literature in the field of humanitarian logistics. Finally, we conclude the paper by highlighting the main findings of our study and their managerial implications.

2. THEORY

The International Federation of Red Cross and Red Crescent Societies (IFRC) defines a disaster as “a sudden, calamitous event that seriously disrupts the functioning of a community or society and causes human, material, and economic or environmental losses that exceed the community’s or society’s ability to cope using its own resources” (Natarajarathinam et al., 2009, p. 537). Given this definition, the response to a humanitarian disaster generally requires external (international) assistance. This assistance may come from the local military or civil defense, but it comes most often from relief organizations, which have the knowledge, capabilities, and resources to help the populations in crisis. Due to ongoing demographic growth, migration movements, and climatic shifts, there is strong evidence that the frequency and effects of humanitarian disasters (such as flooding, droughts, and famines) will increase (Whybark, 2007); therefore, there is a growing need for research in this field.

Van Wassenhove (2006) distinguished four phases of humanitarian disaster management: mitigation, preparedness, response, and rehabilitation. The first two phases occur before a disaster strikes, and they aim at reducing the disaster’s impact. They are hard to implement at reasonable costs, because the place, time, type, and magnitude of the disaster cannot be known in advance (Duran et al., 2011; Rawls and Turnquist, 2010). However, these phases play a crucial role in increasing the effectiveness of the response phase (Charles and Lauras, 2011; Gatignon et al., 2010; Görmez et al., 2011; Jahre and Heigh, 2008; Van Wassenhove, 2006).

Despite the strong potential of preparedness activities, several authors have found that relief organizations often neglect this phase, because donors insist that their money be spent directly on helping victims (Duran et al., 2011; Kovács and Spens, 2007; Maon et al., 2009; Sandwell, 2011; Schulz and Blecken, 2010; Whiting and Ayala-Öström, 2009). Similarly, Jahre and Heigh (2008) found that donations are often earmarked for specific disaster response activities, while more funds would be needed to cover the necessary investments for warehousing the relief items and maintaining permanent supply chain structures. Funding pre-disaster activities can therefore be seen as a form of insurance policy against an uncertain future disaster, which most donors are not willing to pay for (Tatham and Pettit, 2010). However, there are donors who realize that a lack of investment in preparedness activities leads to the chronic vulnerability of communities and excessively high costs during the response phase (Majewski et al., 2010).

By specifically searching for mentions of all disaster preparedness activities in an extensive collection of 174 academic papers compiled by Kunz and Reiner (2012b), we identified two groups of preparedness activities: physical and intangible.

Physical preparedness activities embrace all proactive investments in tangible resources in disaster-prone countries, such as stocking various kinds of inventories or building infrastructure. In this respect, authors most often suggest pre-positioning relief supplies in warehouses (Table 1). Since such investments are specific to one location and can hardly be reallocated to disasters occurring in other countries, such a strategy generally leads to high investment costs that donors are often reluctant to finance. As an additional obstacle, Kovács and Spens (2009) found that the lack of pre-disaster exemptions from customs duties limits the ability of organizations to stock in-country inventories during the preparedness phase.

Investment in…	**Preparedness activities**
Inventory	- Pre-positioning relief supplies in disaster-prone countries (Adivar and Mert, 2010; Altay and Green, 2006; Altay et al., 2009; Balcik and Beamon, 2008; Duran et al., 2011; Görmez et al., 2011; Hale and Moberg, 2005; Jahre and Heigh, 2008; Jahre et al., 2009; Kovács and Spens, 2009, 2011; Mete and Zabinsky, 2010; Oloruntoba and Gray, 2006; Pettit and Beresford, 2005; Rawls and Turnquist, 2010; Taskin and Lodree, 2011; Tomasini and Van Wassenhove, 2009; Van Wassenhove, 2006)
Infrastructure	- Communication equipment and information technology needed for disaster response (Pettit and Beresford, 2005) - Building tsunami-proof housing in protected locations (Perry, 2007) - Building earthquake-resistant infrastructure (Natarajarathinam et al., 2009) - Building pre-disaster infrastructure, such as distribution centers, road networks, hospitals, emergency power plants (Kovács and Spens, 2009)

Table 1. Types of physical preparedness activities.

In what we define as intangible preparedness activities, Van Wassenhove (2006) recommended investing in five key elements of preparedness: human resources, knowledge management, process management, resources, and community. In this paper, we refer to these elements as disaster management capabilities (DMC). Investing in such DMC enables relief organizations to be well prepared and to possess the necessary abilities to respond swiftly to a disaster. These capabilities are often generic and multi-deployable, and can be shared among countries. Thus, high levels of responsiveness to a disaster can be ensured with significantly less initial investment. In Table 2, we present the intangible preparedness activities that are discussed in the academic literature, and categorize them into Van Wassenhove's (2006) framework of five key elements of intangible preparedness activities.

Investment in…	**Preparedness activities**
Human resources	- Training staff (Altay and Green, 2006; Perry, 2007; Pettit and Beresford, 2005; Van Wassenhove, 2006) - Hiring disaster mitigation and preparedness specialists (Benson *et al.*, 2001) - Hiring and training local staff to respond to disasters (Van Wassenhove, 2006)
Knowledge management	- Learning from previous disaster response experiences and developing best practices (Charles and Lauras, 2011; Van Wassenhove, 2006) and "preparedness templates" for different types of disasters (Day et al., 2012) - Early warning systems (Oloruntoba, 2010; Van Wassenhove, 2006) - Decision-making models and tools (Adivar and Mert, 2010; Balcik and Beamon, 2008; Banomyong and Sopadang, 2010; Day et al., 2009; Görmez et al., 2011; Mete and Zabinsky, 2010; Nolz et al., 2010; Özdamar, 2011; Rawls and Turnquist, 2010; Taskin and Lodree, 2010; Tovia, 2007; Ukkusuri and Yushimito, 2008) - Disaster damage (e.g., earthquake) scenarios (Barbarosoglu and Arda, 2004)
Process management	- Pre-negotiating agreements with suppliers and logistics providers (Altay et al., 2009; Duran et al., 2011; Kovács and Spens, 2007; Van Wassenhove, 2006) - Preparing organizational structures, response plans within relief organizations, and arrangements with other organizations (Altay and Green, 2006; Görmez et al., 2011; Jahre et al., 2009; Oloruntoba, 2010; Pettit and Beresford, 2005)
Resources	- Preparing financial resources for quick disaster response (Van Wassenhove, 2006) - Postponing and pooling resources (Jahre and Heigh, 2008; Kovács and Tatham, 2009; Tomasini and Van Wassenhove, 2009)
Community	- Educating vulnerable communities to recognize specific pre-disaster events and to respond appropriately (Banomyong et al., 2009; Benson et al., 2001; Kovács and Spens, 2009; Oloruntoba, 2010; Perry, 2007; Van Wassenhove, 2006) - Assessing economic and physical vulnerabilities of populations in disaster planning (Perry, 2007) - Cooperating with local governments, military, humanitarian organizations, and businesses in order to establish framework agreements or permanent networks of actors (Jahre et al., 2009; Van Wassenhove, 2006)

	- Negotiating customs agreements with local governments (Kovács and Tatham, 2009) - Disaster planning by local governments and NGOs, in collaboration with local communities (Adivar and Mert, 2010; Perry, 2007)

Table 2. Types of intangible preparedness activities (based on Van Wassenhove, 2006).

3. METHODOLOGY

In order to quantify the delivery performance improvement and preparedness cost reduction potential of the pre-disaster investments in humanitarian logistics, we employed system dynamics modeling using empirical data. Specifically, we modeled the delivery process of RUTF items during the immediate response phase of a disaster. In particular, we analyzed how the performance of this delivery process can be improved by pre-positioning inventory and investing in DMC capabilities. Our model was fed by primary data collected from a case study of four relief organizations (Kunz and Reiner, 2012a), which allowed us to first develop a "mental database" of the problem (Forrester, 1994), and then to build a model based on practitioners' experiences. We also used publicly available secondary data from producers' and relief organizations' websites, as well as media reports about past disasters. Combining these data sources allowed us to develop as realistic a model as possible.

We chose to use this methodology for several reasons. First, system dynamics models allow for the consideration of interacting feedback loops (Reiner and Natter, 2007), of which there are several examples in our model. Dynamic problems containing feedback loops cannot be solved through standard optimization methods, which are suitable for static systems that are free of feedback loops (Sterman, 1991). Other methods, such as queuing networks, also fail to grasp the full complexity of our dynamic system. Second, our model includes time delays, as the demand of beneficiaries is satisfied only for a given period, before returning in the pool of demand. The effects of such delays must be studied through dynamic models, allowing the consideration of dependencies over multiple periods (Reiner and Natter, 2007). The functions in our model are nonlinear (e.g., S-shaped curve representing the customs clearance processing capacity), and can therefore be modeled particularly well through system dynamics (Sterman, 2000). Finally, multi-period inventory systems are dynamic by nature, enabling them to be thoroughly studied through system dynamics (Forrester, 1961). An additional benefit of using quantitative system dynamics models is that they allow for the exploration and evaluation of alternative scenarios in a risk-free manner, making their impact on the performance of the system testable (Santos et al., 2002). Another reason for using system dynamics is that this modeling tool is highly appreciated and well understood by managers, because it enriches brainstorming and has a lower reliance on hard data than other methods (Jahangirian et al., 2010). For these reasons, and because alternative methodologies such as optimization or queuing networks are not well adapted, we decided to use system dynamics for this study.

Moreover, several researchers have confirmed the good fit of this method for the field of disaster management. Altay and Green (2006) found that the social and political nature of disaster operations management makes this field suitable for research approaches such as system dynamics, which can integrate soft factors into operations analysis. According to Besiou et al. (2011), system dynamics modeling is well adapted to gain insight into systems that have multiple actors, high levels of uncertainty, and complexity, as found in disaster operations. This appropriateness is reflected by three recent studies that applied system dynamics to humanitarian operations. Gonçalves (2008) used this methodology to model the development of organizational capabilities and the efficiency of the relief efforts of humanitarian organizations. In a follow-up study, the author analyzed the trade-off between providing relief assistance and building capacity in relief organizations (Gonçalves, 2011). Besiou et al. (2011) used this methodology to assess different scenarios of vehicle fleet management in humanitarian operations. The authors used this tool to determine the long-term costs of different scenarios and to identify the scenario that best satisfied the needs of a particular organization over several years. They recognized the lack of real-world data for their models as a limitation of their research. This is where our study ties in, by explicitly integrating empirical data gathered through previous case study research into the system dynamics modeling approach.

4. MODEL

Given the difficulties that relief organizations face in obtaining funding for pre-disaster activities, this research study aimed to quantify and compare the effects of three basic scenarios: no preparedness activity (Scenario A), investment in physical preparedness activities (Scenario B, pre-positioning of inventory), and investment in intangible preparedness activities (Scenario C, investing in DMC). In particular, we modeled the delivery process of RUTF food items, Plumpy'nut sachets (Nutriset, 2012), during the immediate response phase of a disaster. We ran the system dynamics model over 180 periods (days), with a time interval (Δt) of 1 day. We chose this duration to ensure that we covered the entire disaster response phase. The length of this phase is highly variable depending on the type and magnitude of the disaster; some organizations consider it to last up to 90 days (Kovács and Spens, 2007), while others consider it to last until the next harvest (IFRC, 2011).

In order to reduce the complexity and isolate the phenomenon under study, we developed a simplified model of the importation process of Plumpy'nut sachets (Fig. 1). The standard input parameters of the basic model are listed in Table 3.

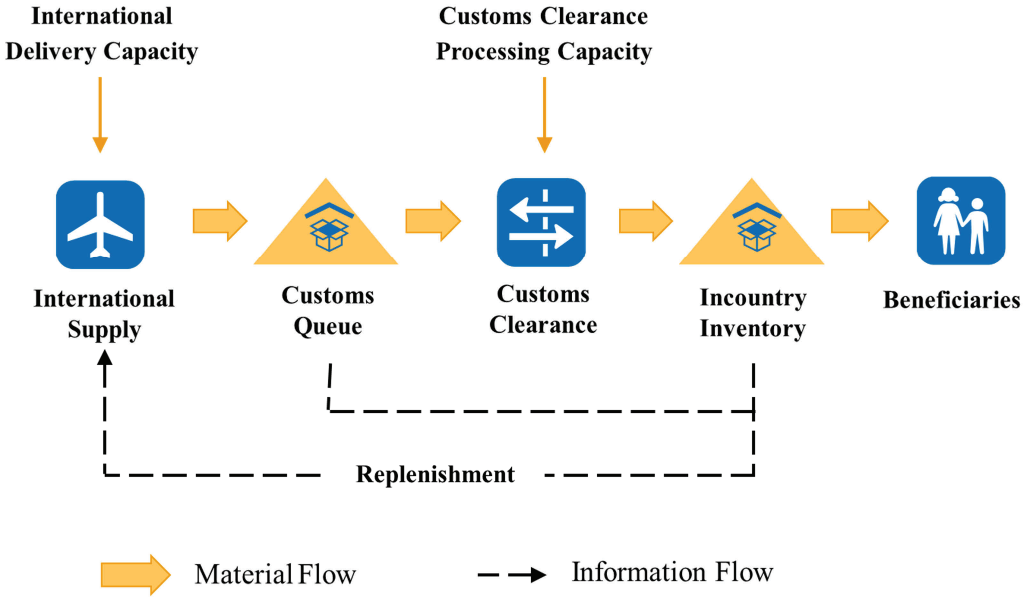

Fig. 1. Simplified model of the importation process for relief supplies.

Parameters		**Value**
Initial Demand		500,000 beneficiaries
Time Interval (Δt)		1 day
Customs Clearance Processing Capacity	Maximal Fractional Capacity Increase	0.30
	Initial Capacity	200 kits/day
	Maximal Capacity	100,000 kits/day
Lifetime of Demand Satisfaction		10 days
Maximal Daily Supply Capacity		38,820 kits/day (100 tons)
Average Duration of Treatment		8 weeks (56 days, 5.6 deliveries)
Fraction Returning Demand		0.82
Buffer Inventory (I_b)		100,000 kits
Purchase Price		€6.96/kit
Transport Cost $_{Slow}$ (sea + road)		€0.734/kit
Transport Cost $_{Fast}$ (air)		€4.76/kit
Yearly Inventory Holding Cost (financial + physical costs)		25% of purchase cost
Yearly Inventory Amortization Rate		50% of purchase + transportation cost

Table 3. Standard input parameters.

We defined *Initial Demand* as 500,000 beneficiaries, corresponding to the number of children suffering from severe acute malnutrition in the 2011 Horn of Africa crisis (IRIN, 2011). In our deterministic model, *Buffer Inventory (I_b)* has the function of smoothing the replenishment order quantities, and its level was defined at 100,000 kits in order to avoid inventory oscillations. Using the information provided on Nutriset's website, the producer of Plumpy'nut (Nutriset, 2012), we were able to quantify the number of sachets needed to serve the needs of these children. The unit in our model is a kit of 28 sachets, which covers the needs of one child for 10 days (parameter *Lifetime of Demand Satisfaction*). After this period, the beneficiary flows again into the pool of demand. At the end of the average length of eight weeks of treatment, the beneficiary leaves the demand pool because his or her needs are definitively satisfied. This is modeled through the constant *Fraction Returning Demand* in equation 1, which represents the proportion of the demand (0.82) flowing again into the pool of demand after each period. Due to this proportion, the total demand decreases exponentially over time. We consider that a residual demand will always exist, and therefore we did not limit the returning demand to the eight weeks of treatment. Due to the ten days of *Lifetime of Demand Satisfaction*, there is no returning demand during the first ten days following the disaster (see equation 1).

$$Returning\ Demand_{\ t} = \begin{cases} 0, & for\ t \leq 10 \\ Fraction\ Returning\ Demand \cdot \frac{Temporarily\ Satisfied\ Demand_{\ t-1}}{Lifetime\ of\ Demand\ Satisfaction}, & for\ t > 10 \end{cases} \quad (1)$$

Temporarily Satisfied Demand (see equation 2) represents the pool of beneficiaries that are currently satisfied (i.e., have received a kit within the last ten days), but who may need aid again once they have consumed their kit. *Temporarily Satisfied Demand* decreases over time because the pool of demand decreases, leading to fewer and fewer deliveries to beneficiaries. In addition, as shown in the last part of equation 2, after each period, a fraction of the *Temporarily Satisfied Demand* leaves this pool.

$$Temporarily\ Satisfied\ Demand_{\ t} = Temporarily\ Satisfied\ Demand_{\ t-1} + Deliveries\ to\ Beneficiaries_{\ t-1} - \frac{Temporarily\ Satisfied\ Demand_{\ t-1}}{Lifetime\ of\ Demand\ Satisfaction} \quad (2)$$

The pool of demand is modeled as shown in equation 3.

$$Demand_t = Demand_{t-1} + Returning\ Demand_{t-1} - Deliveries\ to\ Beneficiaries_{t-1} \quad (3)$$

In our simplified model, relief items arrive as *International Supply* by airplane, as shown in Fig. 1. Orders are placed on a daily basis, following a periodic review, order-up-to-level replenishment policy, described in Appendix A. The maximal daily supply capacity is 100 tons per day (i.e., 38,820 kits). This figure was chosen because it corresponds to the maximal payload of the Antonov AN-124, a large cargo plane that was used in the aftermath of the floods in Haiti in 2004 to deliver RUTF (WFP, 2004). This fast transportation mode by airplane costs 2.40 USD/kg (UNICEF, 2009), corresponding to €4.76/kit. After arriving at the airport, the supplies enter the *Customs Queue*, where they sit until they go through the *Customs Clearance* procedure. In our Scenarios A (no preparedness) and B (pre-positioning of inventory), the processing capacity of the clearance procedure is extremely low immediately after the disaster (200 kits/day), due to unprepared staff and a lack of clearly established procedures on the part of both the government and the relief organization. This capacity then progressively increases until it reaches the maximal processing capacity of 100,000 kits per day, following an S-shaped curve. We modeled this growth with a logistic growth function (Sterman, 2000), which is characterized by a decreasing *Fractional Capacity Increase* leveling out at zero, while the processing capacity increases until it reaches *Maximal Capacity*, as shown in equation 4.

$$Fractional\ Capacity\ Increase_{\,t} = Maximal\ Fractional\ Capacity\ Increase \cdot \left(1 - \frac{Processing\ Capacity_{\,t-1}}{Maximal\ Capacity}\right) \quad (4)$$

The *Processing Capacity* is calculated as shown in equation 5, resulting in the S-shaped curve represented in Fig. 2.

$$Processing\ Capacity_{\,t} = Processing\ Capacity_{\,t-1} \cdot (1 + Fractional\ Capacity\ Increase_{\,t}) \quad (5)$$

From customs clearance, the items are sent to the *In-country Inventory* as described below in equation 6. This equation shows that in each period, all items in the *Customs Queue* are cleared through customs and flow to the *In-country Inventory*, but they never exceed the customs *Processing Capacity* in this period.

$$Outflow\ Customs\ to\ Incountry\ Inventory_{\,t} = MIN(Customs\ Queue_t, Processing\ Capacity_t) \quad (6)$$

From the *In-country Inventory*, the items are dispatched directly to the beneficiaries, following the decision rule in equation 7. According to this rule, all of the items in the inventory are delivered directly to the beneficiaries, as long as the demand is higher than the inventory level. In our purely theoretical model, neither last mile distribution nor repackaging time is included. We made this simplification in order to isolate the phenomenon under study, that is, the effect of preparedness.

$$Deliveries\ to\ Beneficiaries_t = MIN(Incountry\ Inventory_t, Demand_t) \quad (7)$$

The international supply flowing into our model is defined by a replenishment strategy depending on the *Demand* and the *Pipeline Inventory*, described in detail in Appendix A.

5. BASIC SCENARIOS

Modeling three different basic scenarios enables us to compare the effects of preparedness on delivery performance and costs. Table 3 presents the input parameters for the basic model, and Table 4 provides the variable scenario parameters.

<table>
<tr><th colspan="2"></th><th>Scenario A
No Preparedness</th><th>Scenario B
Pre-positioning of Inventory</th><th>Scenario C
Investment in DMC</th></tr>
<tr><td colspan="2">Pre-positioned Inventory</td><td>0</td><td>500,000 kits</td><td>0</td></tr>
<tr><td rowspan="3">Customs Clearance Processing Capacity</td><td>Maximal Fractional Capacity Increase</td><td>0.3</td><td>0.3</td><td>1</td></tr>
<tr><td>Initial Capacity</td><td>200 kits/day</td><td>200 kits/day</td><td>10,000 kits/day</td></tr>
<tr><td>Maximal Capacity</td><td colspan="3">100,000 kits/day</td></tr>
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Table 4. Scenario-specific parameters.

5.1. Scenario A: No preparedness

In Scenario A, no preparedness activity is carried out before the disaster. This scenario corresponds to the basic model presented in the previous section, and allows us to demonstrate the effects of the other two scenarios. The customs clearance daily processing capacity increases slowly, following the S-shaped curve shown in Fig. 2 (blue line).

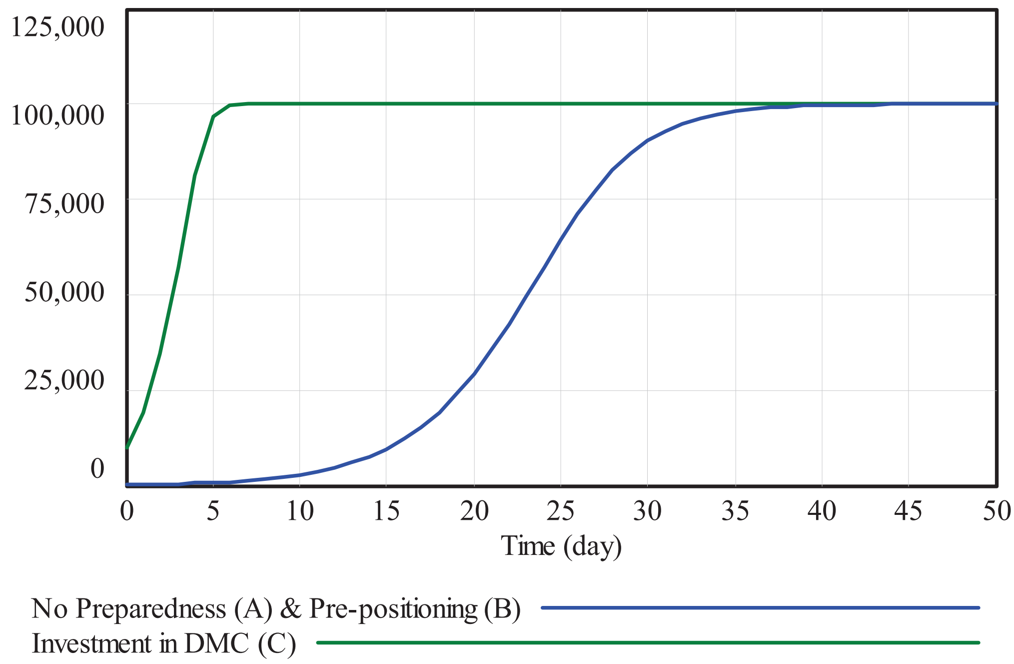

Fig. 2. Daily processing capacity of customs clearance.

5.2. *Scenario B: Pre-positioning of inventory*

In Scenario B, we model the effect of pre-positioning physical inventory in a warehouse in the country prior to the disaster. This is achieved by setting an initial value of 500,000 Plumpy'nut kits to the *In-country Inventory* variable. We chose this quantity because it corresponds to the number of beneficiaries in our model. Further, we confirmed the relevance of this inventory level by comparing it with values recommended in a previous analysis of the Plumpy'nut supply chain (UNICEF, 2009). Indeed, the authors of that previous study recommended a pre-positioned inventory level of approximately 1 time the average monthly demand (calculated based on data presented in UNICEF, 2009). Our pre-positioned inventory of 500,000 kits corresponds to 1.1 times the average monthly demand, and is thus consistent with this recommendation. Indeed, in our model the total order quantity over six months is 2.7 million kits, representing a monthly average of 450'000 kits.

In Scenario B, the demand of all beneficiaries is satisfied immediately after the disaster through the pre-positioned inventory. However, we do not model the returning demand as a peak occurring exactly after the ten days of the *Lifetime of Demand Satisfaction*; rather, we model it as a continuous returning demand starting from Day 10. This allows us to better reflect the reality. Indeed, the entire population of beneficiaries will not arrive at the point of distribution after ten days exactly. Returning demand is therefore also modeled as presented in equation 1.

The yearly preparedness costs (YPC) resulting from this scenario comprise holding costs (25%, financial + physical storage) and amortization costs (50% on purchase price and transport cost), as the inventory must be renewed every two years due to product expiry. The official purchasing price of Plumpy'nut is €2.7/kg (Pillon, 2012), or €6.96/kit. The pre-positioned inventory can be transported by a slow transport mode consisting of sea freight at a rate of $0.17 /kg (UNICEF, 2009), or €0.13/kg, plus road transport between the port and final destination, costing €0.15/kg between Mombasa and Kigali, for example (Choi et al., 2010). Adding up these rates provides a total cost for the slow transport mode of €0.28/kg, or €0.734/kit. The resulting total *Yearly Preparedness Cost (YPC)* for Scenario B can be formalized as a function of pre-positioned inventory *Ip*, as shown in equation 8.

$$YPC_{prepositioning}(I_p) = I_p \cdot [Price \cdot Holding\ Cost + (Price + Transport\ cost_{Slow}) \cdot Amortization] \quad (8)$$

Introducing the parameters from Table 3 into this equation, we find a YPC of €5.583 per pre-positioned kit. Our pre-positioned inventory of 500,000 kits thus costs €2.79 million per year.

5.3. Scenario C: Investment in Disaster Management Capabilities

In Scenario C, the relief organization applies intangible preparedness activities in the focal country, such as those presented in Table 2. In particular, the organization invests in DMC at the level of the importation and customs clearance procedure. For example, the relief organization's staff members are trained to handle the importation and clearance procedure correctly. They analyze the existing customs regulations and procedures of the focal country in order to make sure that the organization is able to deliver all of the needed documents quickly in the event of a disaster. In terms of knowledge management, the organization collects information about past disasters in this country, creates a risk profile of the country, and develops possible disaster scenarios. Regarding process management, the organization develops a set of operations procedures for customs clearance in this country. If possible, the organization pre-negotiates agreements with clearing agents in the country that may assist in handling the importation process in a disaster. International and local organizations can be contacted in order to prepare possible cooperation agreements. Resources are also prepared that allow the organization to respond immediately in a disaster. The organization can, for example, identify well-qualified local staff, such as logistics assistants, who can be hired immediately if a disaster occurs, and thus help to speed up the clearance process. The local community is also involved in the preparation effort. A meeting with relevant officials in the country allows the relief organization to forge a relationship with key people at the customs office who can help in case of a disaster. A memorandum of understanding and customs agreements are negotiated with the local government, and procedures are harmonized with the country's requirements. Common disaster response plans are developed with the relevant institutions in the country. In our Scenario C, we consider that making these investments in DMC results in a customs clearance processing capacity that increases much faster than in the other scenarios. We model this faster increase by changing the parameters of the S-shaped processing capacity curve, as presented in Table 4. The resulting processing capacity curve can be seen above in Fig. 2 (green line).

The costs for this preparedness scenario can also be estimated. Instead of considering investing in DMC as a one-time investment, we take it as a recurring expense occurring every year. As the investment in DMC almost exclusively requires manpower, we estimate it through the cost of staff dedicated to preparing and updating the DMC for a particular country. The full-time *Yearly Cost of Staff* is estimated to be €100,000, including the cost of traveling to the country. This amount is based on the yearly cost of one international staff member reported by one of our case study organizations (salary + travel), and its relevance was confirmed by another relief organization. We consider that the *DMC Preparedness Level* can be varied linearly by the relief organization, from 0% (no staff) to 100% (one full-time staff member) by changing the workload percentage of the staff dedicated to develop capabilities in this country. As the DMC preparedness level increases, the S-shaped curve depicted in Fig. 2 progressively moves from the blue curve (no investment in DMC, as in Scenarios A and B) to the green curve (full investment in DMC, as in Scenario C). The *YPC* of investing in DMC can thus be formalized as a function of *DMC Preparedness Level*, as shown in equation 9.

$$YPC_{DMC}(DMC\ Preparedness\ Level) = DMC\ Preparedness\ Level \cdot Yearly\ Cost\ of\ Staff \qquad (9)$$

In the current extreme case Scenario C, we assume the DMC preparedness level to be 100%, which results in a YPC of €100,000. Later in the paper, equation 9 will be used to calculate the YPC for any desired level of DMC preparedness level.

5.4. Validation of our model

Validating a systems dynamics model is an important step that ensures the validity of the findings (Barlas, 1996; Reiner et al., 2009). Barlas (1996) noted the difference between the philosophical and formal aspects of model validation (as cited in Reiner et al., 2009). Before formally validating the behavior and the results of the model, the validity of the internal structure of the model must be tested (Barlas, 1996; Sterman, 2000). In our case, we ensure this philosophical validation with the integration of established knowledge in our model (Miser and Quade, 1988). Indeed, our model is based on the findings from our previous case study research (e.g., easier clearance processes when previous relationships are established with the customs in a country, benefits of hiring staff dedicated to handling the customs clearance process, etc.). Empirical data from real-life disaster settings are also integrated in our model (e.g., maximal daily supply capacity of an aircraft, number of beneficiaries, level of pre-positioned inventory, number of items needed per beneficiary, etc.). On a more theoretical level, we integrate structural components that were successfully used in previous studies (Miser and Quade, 1988; Reiner et al., 2009), such as Sterman's (2000) logistic function that we use to model our S-shaped curve of the customs clearance processing capacity.

The second step of the validation is the test of the behavioral accuracy of the model, which we do by comparing the fit of the outcomes of the model with empirical historical data (Reiner et al., 2009). Given the methodology that we chose in our previous study (case study research), we do not have access to such historical data, and therefore cannot perform the statistical tests that are generally recommended, such as the mean absolute percent error (MAPE) or Theil's inequality (Lin et al., 2008; Oliva and Sterman, 2001; Reiner et al., 2009). However, we compare the general outcomes of the simulation (shape of graphs) with the "mental database" (Forrester, 1994) we developed through our case study research. We also compare specific output figures (e.g., lead-time, customs processing capacity) with the empirical results of our case study research. For example, several practitioners whom we interviewed during the case study mentioned customs clearance lead times of up to four weeks when no previous relationships were established with customs, which corresponds to the lead time found in Scenario A of our model (around 30 days after the disaster; see Fig. 4). The respondents also mentioned that once DMC have been developed, customs clearance lead times are usually between one and five days, which is consistent with the results of our model. Finally, we perform some extreme conditions tests similar to those of Besiou et al. (2011), for example, by extending the simulation period (up to 400 days) and checking if the model behaved correctly. We also analyze the robustness of our results through a sensitivity analysis, as described in section 7, by checking the variation of the outputs when varying some input parameters.

5.5. Limitations of our model and scenarios

The aim of our model is to compare preparedness scenarios by varying only those parameters relevant to the preparedness activities. In order to isolate the problem under study, we neglect various parameters that are relevant to the overall process of providing humanitarian relief in reality. For example, we do not include any variability in our model, nor do we include parameters such as transport time.

Another limitation of our model is its narrow focus on a single disaster, single country, and single organization. The interactions, interdependencies, and repercussions between the organizations and the multiple countries affected by the same disaster are common features of real disaster situations that increase the complexity of humanitarian relief management; however, we neglect such aspects in our model, as we deliberately focus on the effects of preparedness on delivery performance.

6. RESULTS

6.1. Performance

We run our simulation model for the three basic scenarios described above, which allows us to compare the efficiency of the different preparedness strategies.

Fig. 3 shows that without any preparedness activity (Scenario A), there is a strong build-up of inventory in the customs clearance queue, which can be reduced by pre-positioning supplies in the country (Scenario B). The build-up can even be entirely avoided by investing in DMC, as shown in our example at the level of the customs clearance process (Scenario C), which leads to a sharper increase in the customs clearance processing capacity. Indeed, full customs processing capacity is achieved on the 7th day following the disaster, compared to the 40th day without investments in DMC (see Fig. 2).

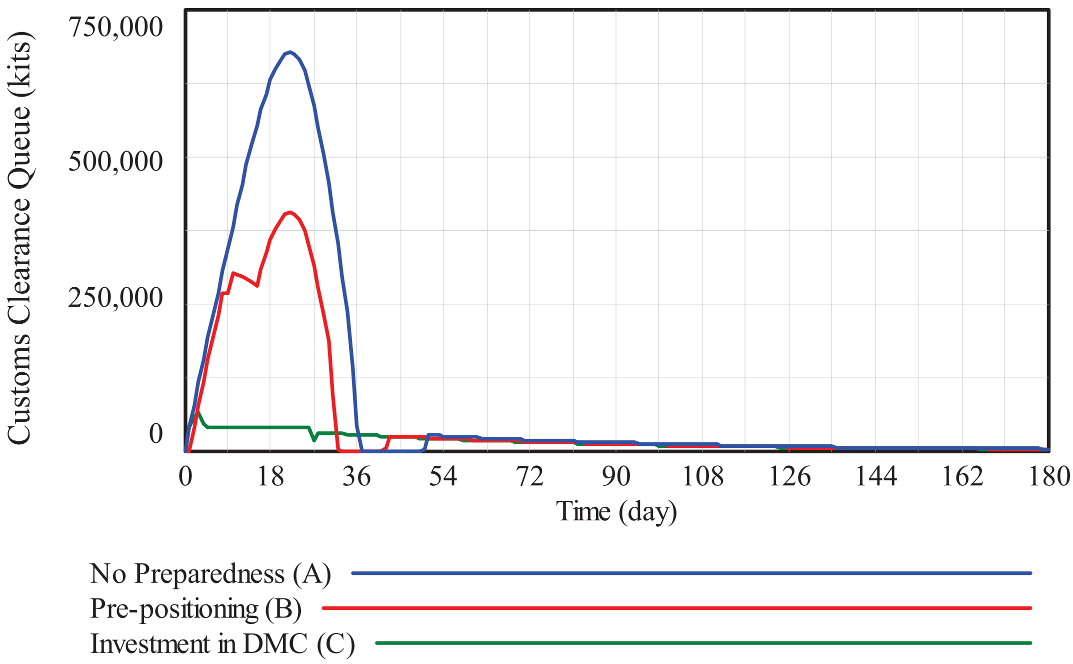

Fig. 3. Customs clearance queue.

Fig. 4 presents the service level of the deliveries of Plumpy'nut kits. Without preparedness (Scenario A), the service level increases slowly and reaches 100% on the 30th day after the disaster. With the pre-positioning of inventory (Scenario B), the service level is 100% during the first 10 days and then drops to 5% because the returning demand cannot be satisfied by the international supply, as items are still waiting in the customs queue. As the customs processing capacity increases, more supplies are cleared and delivered to beneficiaries, and the service level increases again up to 100%. If investing in DMC (Scenario C), the service level increases faster than without preparedness, and reaches 100% on the 25th day after the disaster. While this five-day difference between Scenarios A and C may seem insignificant, a closer look at Fig. 4 shows that the two scenarios lead to highly different results during the first days of the simulation. Indeed, on the 4th day after the disaster, Scenario C reaches 13% service level, while Scenario A remains at 0.08% service level.

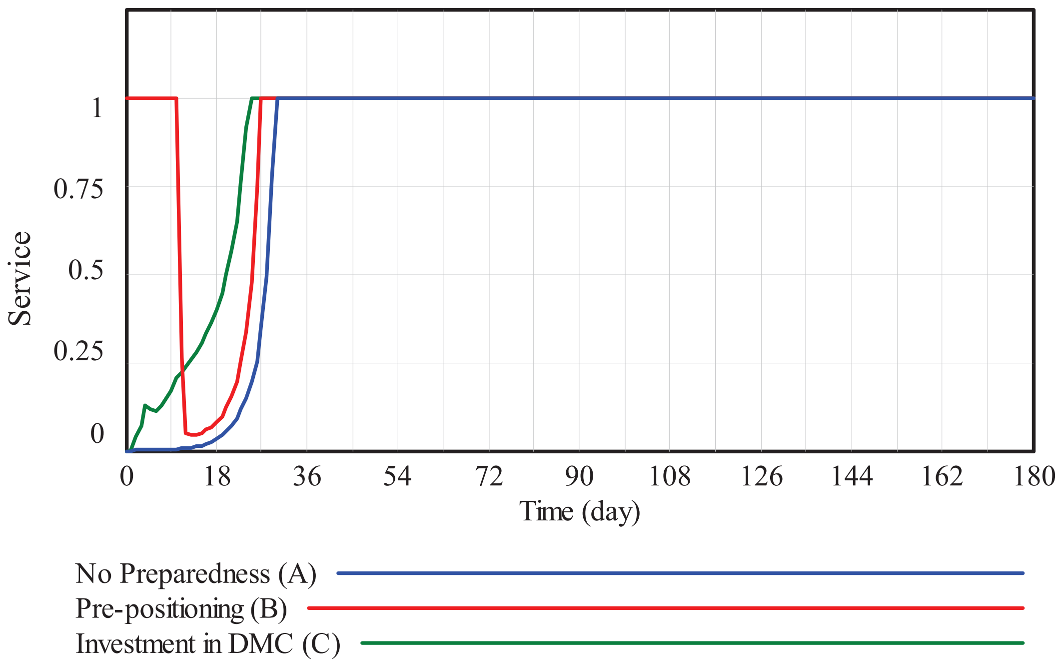

Fig. 4. Service level.

Since the daily service levels represented in Fig. 4 do not take into account absolute numbers of unsatisfied beneficiaries, we compute the *Average Service Level* as described in equation 10. This indicator also allows us to better compare the performance of scenarios over the whole disaster response period.

$$Average\ Service\ Level = \frac{\sum_{t=1}^{180} Deliveries\ to\ Beneficiaries_t}{\sum_{t=1}^{180}\ Demand_t} \quad (10)$$

Applying this formula, we found an *Average Service Level* of 18% for Scenario A, 58% for Scenario B, and 36% for Scenario C.

Fig. 5 presents another performance indicator, the daily non-satisfied demand, which gives indications about the delivery lead time. Without preparedness (Scenario A), the demand is satisfied slowly and only reduces significantly from the 20th day following the disaster. With the pre-positioning of supplies (Scenario B), the entire demand is satisfied immediately, and returning demand arises after 10 days. With the investment in DMC (Scenario C), the demand is satisfied relatively quickly, once the customs clearance process reaches its full capacity.

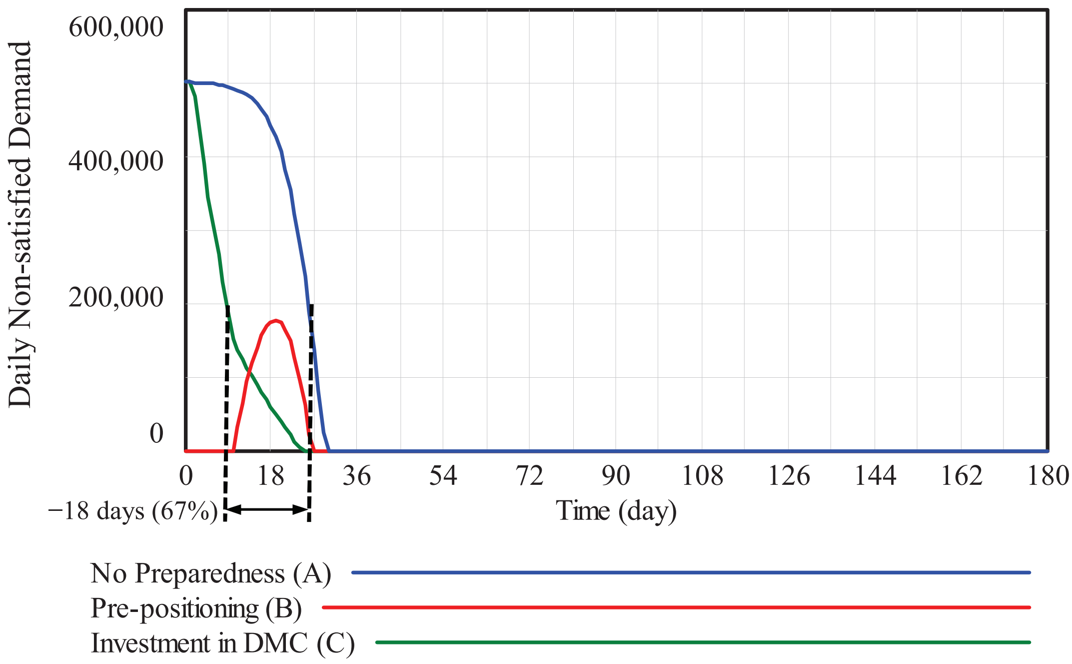

Fig. 5. Non-satisfied demand.

From Fig. 5, it can be seen that in Scenario C, the needs of the first 300,000 beneficiaries are met after 9 days, while it takes 27 days to reach the same level without preparedness (Scenario A). A potential lead time reduction of 18 days for serving the first 300,000 beneficiaries (−67%) can therefore be realized when investing in DMC. Due to its irregular shape, Scenario B cannot be compared in this way with the two other scenarios. Thus, we introduce another indicator that allows us to compare scenarios over the whole disaster response period, namely, the *Cumulative Non-satisfied Demand*, computed as presented in equation 11.

$$Cumulative\ Nonsatisfied\ Demand = \sum_{t=1}^{180} Nonsatisfied\ Demand_t \quad (11)$$

We find a *Cumulative Non-satisfied Demand* of 12.07 million for Scenario A, 1.91 million for Scenario B, and 4.73 million for Scenario C.

6.2. Costs

Investing in a pre-positioned inventory of 500,000 kits (Scenario B) leads to a YPC of €2.79 million, while investing in DMC (Scenario C) costs €100,000 per year. So far, we have only compared preparedness costs, which occur every year in every country where the relief organization wants to be prepared for a disaster.

The *Response Cost* in the case of a disaster is another important cost, and it also varies depending of the scenario chosen. Indeed, the pre-positioned inventory can be transported by a slow transport mode (sea + road), which costs less than air delivery for supplies that are not pre-positioned. Therefore, the total response cost can be calculated as presented in equation 12, as a function of pre-positioned inventory I_p.

$$Response\ Cost(I_p) = Total\ Order\ Quantity \cdot Price + I_p \cdot Transport\ Cost_{Slow} + (Total\ Order\ Quantity - I_p) \cdot Transport\ Cost_{Fast} \tag{12}$$

For a *Total Order Quantity* of 2.7 million kits (as in Scenario B or C), taking into consideration the costs of the different transport modes (see Table 3), we arrive at the response cost function presented in equation 13. We can see that each kit pre-positioned in the country lowers the response cost by €4.027.

$$Response\ Cost(I_p) = 31{,}983{,}719 - 4.027 \cdot I_p \tag{13}$$

Applying equation 13 to our scenarios, we find a response cost of €30 million for Scenario B and €32 million for Scenario C (and A). The lower cost for Scenario B can be explained by the cheaper transport mode of pre-positioned kits.

In summary, comparing our two preparedness scenarios shows that investing in DMC (Scenario C) leads to lower yearly preparedness costs (−€2.69 million), but higher response costs in the case of a disaster (+€2 million). On the basis of these values, we see that the additional response cost resulting from Scenario C is compensated by a lower preparedness cost, even in less than one year.

7. MIXED SCENARIOS AND SENSITIVITY ANALYSIS

Up to this point, we considered only extreme case scenarios of no preparedness (Scenario A), pre-positioning of inventory (Scenario B), and investing in DMC (Scenario C), which led to different results in terms of performance and cost. While these extreme case scenarios offer interesting insights, they do not provide sufficient details for decision support. Therefore, we extend our analysis to a set of 2,828 mixed scenarios, consisting of both pre-positioning inventory and investing in DMC, under the constraint of different levels of YPC. These mixed scenarios allow us to respond to "what if" questions, by analyzing the effect of changing various parameters in the model.

The *YPC* resulting from the mix of scenarios (equation 14) is a combination of equations 8 and 9, and is a function of the chosen pre-positioned inventory level and DMC preparedness level.

$$\begin{aligned} YPC(I_p, DMC\ Preparedness\ Level) &= YPC_{prepositioning} + YPC_{DMC} \\ &= I_p \cdot [Price\ \cdot Holding\ Cost + (Price + Transport\ cost_{Slow}) \cdot\ Amortization)] \\ &+ DMC\ Preparedness\ Level \cdot\ Yearly\ Cost\ of\ Staff \end{aligned} \tag{14}$$

In order to provide decision-makers with realistic decision support information, we decide to set the YPC as fixed (i.e., the available yearly preparedness budget), and vary the DMC preparedness level (i.e., the portion of funding allocated to investing in DMC). The residual available funding is allocated to pre-positioning inventory, as described in equation 15. For 28 levels of YPC, we then run 101 scenarios (i.e., 0.01 steps), ranging from DMC preparedness levels of 0% to 100%.

$$I_p(DMC\ Preparedness\ Level)\ = \frac{YPC - (DMC\ Preparedness\ Level \cdot\ Yearly\ Cost\ of\ Staff)}{YPC_{prepositioning}\ per\ kit} \tag{15}$$

When running the 101 scenarios for a YPC of €500,000, for example, we obtain the graph presented in Fig. 6. We can see that for a given YPC, the cumulative non-satisfied demand decreases significantly until a DMC preparedness level of approximately 50%. We also see that the average service level increases until a DMC preparedness level of 85% is reached; however, the service level only slightly changes above a DMC preparedness level of 50%.

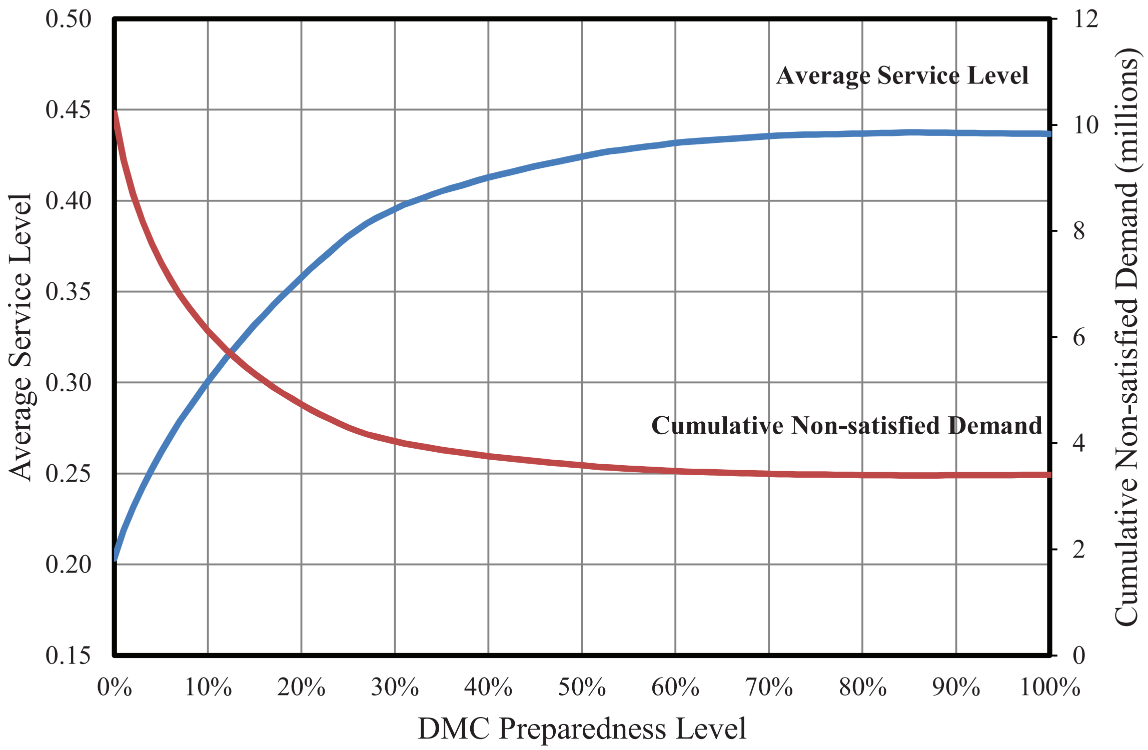

Fig.6. Average Service Level and Cumulative Non-satisfied Demand as a function of DMC Preparedness Level, with a given YPC of €500,000.

In order to further validate these findings, we perform a sensitivity analysis by computing the average service level and cumulative non-satisfied demand with 28 different fixed YPC levels, from €100,000 to €2.8 million (i.e., €100,000 steps, but €200,000 steps are shown). Fig. 7 depicts the average service level as a function of the DMC preparedness level for different YPCs. Again, we see a strong increase in the average service level below a certain DMC preparedness level. The scenario in which we invest a YPC of €2.8 million reaches almost a 100% average service level, because this scenario allows for the pre-positioning of 500,000 kits, corresponding exactly to the beneficiaries' initial demand. The average service levels achieved in the extreme case Scenarios A, B, and C are represented in dashed lines in Fig. 7, and it is interesting to see that they generally achieve much worse results than the mixed scenarios.

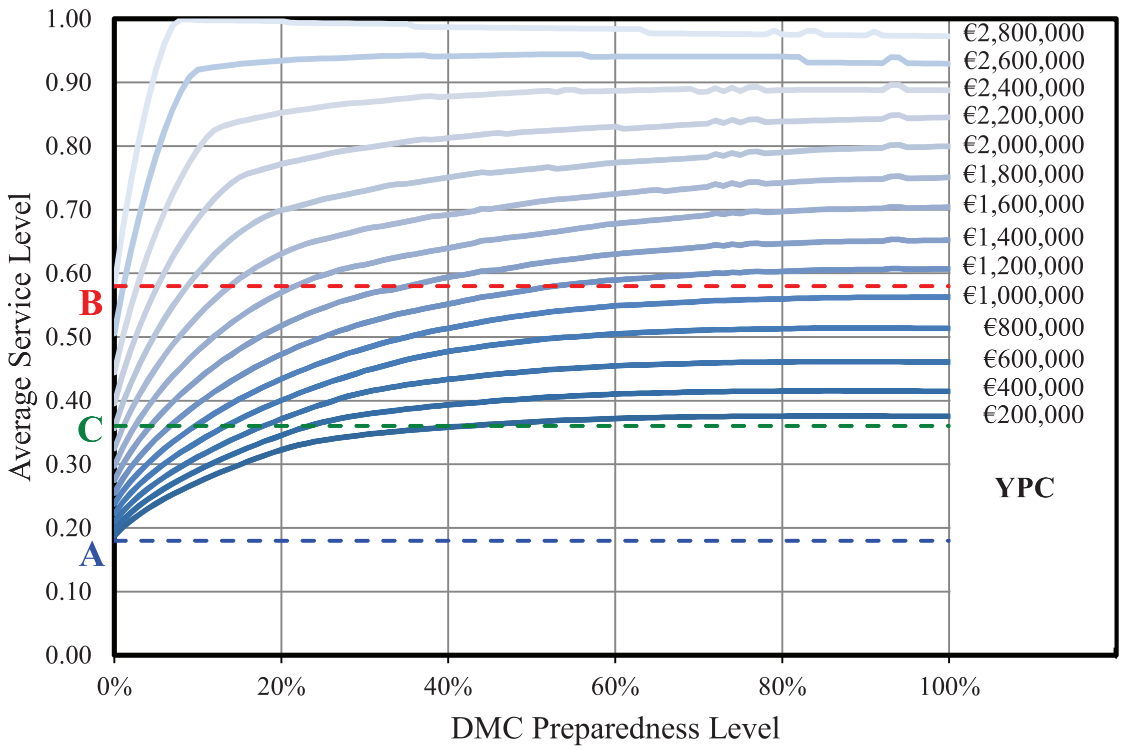

Fig. 7. Average Service Level as a function of DMC Preparedness Level, for different YPCs.

Fig. 8 presents the cumulative non-satisfied demand as a function of the DMC preparedness level, for different YPCs. We see that there is a steep decrease in cumulative non-satisfied demand below a certain DMC preparedness level. Furthermore, the distance between the different YPC curves is not the same; therefore, a constant increase in YPC does not have a constant effect. Indeed, the reduction of cumulative non-satisfied demand per additional money spent on preparedness is larger from €200,000 to €1 million YPC than it is above €1 million YPC. The cumulative non-satisfied demand achieved in extreme case Scenarios A, B, and C is also represented in this figure (dashed lines).

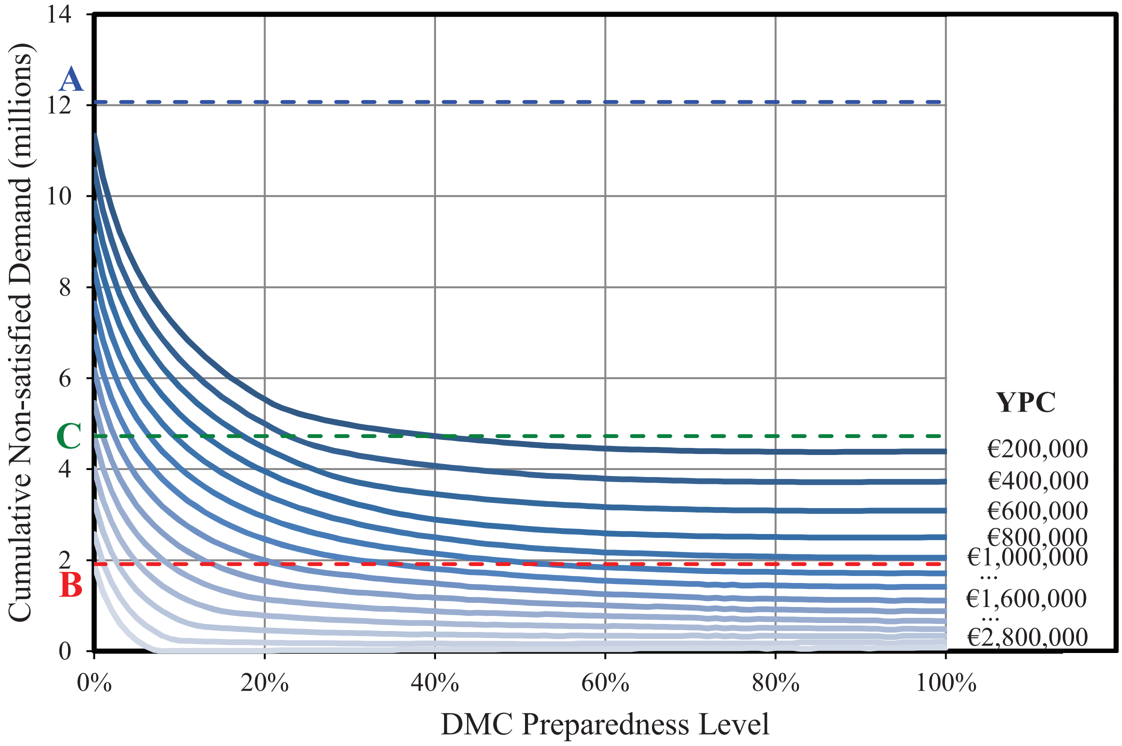

Fig. 8. Cumulative Non-satisfied Demand as a function of DMC Preparedness Level, for different YPCs.

In Fig. 9, we present the results of the sensitivity analysis as a function of YPC. The different curves represent the different DMC preparedness levels in steps of 10%. As the figure illustrates, a DMC preparedness level of less than 10% is never adequate, irrespective of the total YPC available for preparedness. Further, we see that the higher the DMC preparedness level is, the more linear the curve becomes. Based on Fig. 9, we estimate that our results are robust for scenarios in which the DMC preparedness level is equal to or higher than 10%. Fig. 9 also confirms the finding from Fig. 6 that the DMC preparedness level should ideally be 50% or higher.

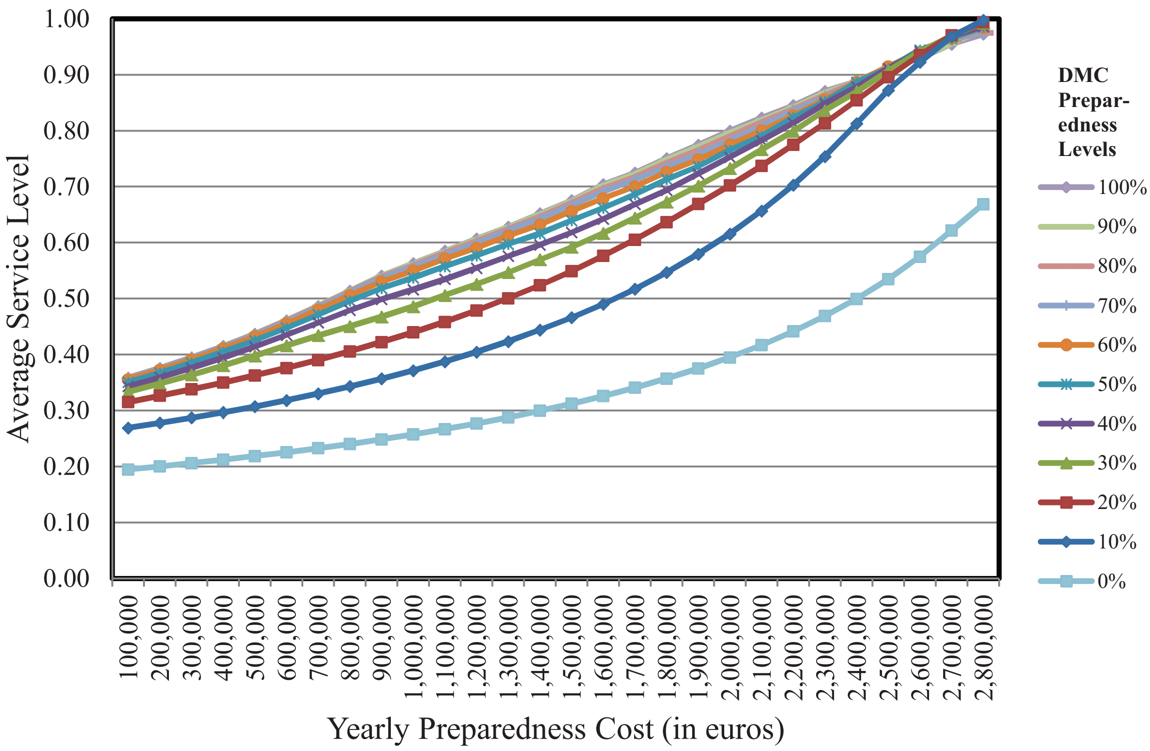

Fig. 9. Average Service Level as a function of YPC, for different DMC Preparedness Levels.

8. DISCUSSION

The results of modeling the three extreme case scenarios and the mixed scenarios warrant closer consideration and discussion. Scenario A, with no pre-disaster preparedness activities, led to weak results, because the highest proportion of the relief items was delivered only weeks after the disaster struck. This was confirmed by the head of the logistics services of a major relief organization, who explained that in countries where no pre-clearance process exists, it takes three-to-four weeks between the first import authorization request and the actual arrival of goods in the country (Kunz and Reiner, 2012a). Our results also clearly confirmed the opinion of several authors who insisted on the importance of preparation before a disaster (e.g. Kovács et al., 2010; Perry, 2007; Van Wassenhove, 2006).

The results of this simulation model also confirmed the positive effect of the physical pre-positioning of inventory in disaster-prone countries (Scenario B), which has been supported by many researchers (see Table 1). By pre-positioning the right number of relief supplies in a country prior to a disaster, the entire demand can be satisfied immediately after the disaster hits. Therefore, the pre-positioning of supplies produces good results for the beneficiaries, particularly right after the disaster occurs. Afterwards, non-satisfied demand grows again, as depicted in Fig. 5. The average service level achieved in this scenario was the highest (58%, compared to 36% in Scenario C and 18% in Scenario A), and the cumulative non-satisfied demand was the lowest (1.91 million, compared to 4.73 million in Scenario C and 12.07 million in Scenario A). This scenario also yielded favorable results in the event of a disaster, in terms of response costs, as pre-positioned items can be delivered by a slow transport mode (sea + road), leading to a significant response cost reduction. Hence, this scenario is especially suitable for countries with a high probability of disasters. However, this scenario involves high holding costs for the relief organizations. The product expiry of pre-positioned inventory is also an issue (Whybark, 2007), which leads to high amortization costs. The Plumpy'nut sachets, for example, can be stored for a period of 24 months (Nutriset, 2012), and then they must be used or disposed of. The pre-positioned inventory therefore led to a YPC of €2.79 million (see cost function in equation 8). These high costs, as well as the risks of not using the pre-positioned inventory in case of non-disaster, explain why international donors are unwilling to pay for such investments. This reluctance was confirmed by Tatham and Pettit (2010), who found that most donors are not ready to pay for an expense that can be considered an "insurance policy" against future disasters.

Scenario C, in which the relief organization invests in DMC instead of pre-positioned inventory, provides an interesting alternative to Scenarios A and B. Indeed, in Scenario C, the demand was satisfied much quicker than in Scenario A (lead time reduction of 67%), and the average service level (36%) and cumulative non-satisfied demand (4.73 million) were far better than the case without preparedness. Moreover, the preparedness costs were much lower than in Scenario B (−€2.69 million). Indeed, using empirical data, we estimated the cost of building up and maintaining DMC in one country to be €100,000 per year, corresponding to one full-time staff member working on the DMC preparedness activity. Such a high level of work power assigned to preparedness in one single country is high, but we decided to take a maximal estimate for this extreme case scenario to be on the safe side. Indeed, allocating more than one staff member to one country would not make economic sense, as in our opinion the activities described in Table 2 cannot be performed better by adding additional staff. This assumption was confirmed by the logistics director of a major relief organization. While investing in DMC leads to much lower preparedness costs, this scenario involves higher transportation costs in a disaster response. Indeed, in this scenario, all items have to be sent by air to the country hit by the disaster, whereas in Scenario B, the pre-positioned inventory can be transported by a cheaper transport mode (sea + road). Using the real transport costs reported for Plumpy'nut items, we found a difference of €4.027 per kit of pre-positioned inventory, meaning that more pre-positioned inventory means lower response costs. However, this difference represents only a slight increase (+6.7%) in response costs, and it is more than compensated by the reduction of YPC already after one year of preparedness. While the expected occurrence frequency of a disaster cannot be predicted due to unknown probabilities (Day et al., 2012), it can nevertheless be mentioned that Scenario C is becoming increasingly beneficial the lower the expected occurrence of a disaster is.

The mixed scenarios as well as the sensitivity analysis provide interesting insights. First, we developed different mixed scenarios by varying the DMC preparedness level, under the constraint of a fixed YPC. For a given YPC of €500,000, we found that the best results in terms of average service level and cumulative non-satisfied demand are achieved with a DMC preparedness level of approximately 50% or higher (i.e., spending €50,000 on DMC), and spending the rest of the available YPC (i.e., €450,000) on pre-positioning inventory. We also found that spending the entire YPC on pre-positioning always leads to lower performance compared to investing, even partially, in DMC. This was seen, for example, in Fig. 8, as a mixed scenario with a €2.8 million YPC is able to satisfy nearly 2 million additional cumulative demand compared to Scenario B (red dashed line), which costs almost the same. Similarly, Fig. 7 showed that spending €2 million YPC only on pre-positioning inventory leads to the same average service level as spending €200,000 in YPC in a mixed scenario. Further, Fig. 7 showed that the range of ideal DMC preparedness levels is rather large (e.g., between 50% and 100% with €500,000 YPC), which demonstrates the robustness of our results. The robustness of the different amounts of YPC was also confirmed in Fig. 9, in which we observed an almost linear relationship between average service level and YPC, especially for DMC preparedness levels above 20%. Finally, we found that the higher the YPC, the less each marginal increase of spending on preparedness reduces the cumulative non-satisfied demand. In particular, Fig. 8 demonstrated that the marginal decrease of cumulative non-satisfied demand for each additional €200,000 YPC was highest below €1 million.

As a concluding remark to this section, we will address the practical application of our paper. Indeed, we considered a single organization approach in our model, but the reality is more complex, as several relief organizations work in the same country and pursue similar objectives. If left uncoordinated, pre-disaster investments in DMC made by several organizations in the same country may lead to confusion among the country's officials, as well as to a considerable duplication of activities. Therefore, we believe that a core condition for successful investment in DMC is that a coordination body oversees the preparedness activities undertaken in the country. This coordination could be handled by a United Nations (UN) organization, such as the Logistics Cluster. This inter-agency coordinating body, led by the UN World Food Programme (WFP), brings together relief organizations and UN agencies, and pursues the aim of coordinating activities and sharing information among implementing partners in disaster-affected countries (Logistics Cluster, 2012).

9. CONCLUSION

Our study compared three disaster response scenarios by means of a dynamic modeling approach. We found that the pre-positioning of inventory leads to good results in terms of demand satisfaction, but at high costs that can barely be financed by the existing funding mechanisms. As a valuable alternative to such pre-positioning of inventory, we found that investments in DMC can achieve remarkable results at much lower costs. Compared to the scenario without preparedness, we found that a lead time reduction of 18 days (−67%) can be achieved, for example, by preparing and harmonizing importation processes, training staff, and negotiating customs agreements with the government prior to the disaster. Based on our setting, we found that investing in DMC leads to a reduction of YPC of €2.69 million compared to the pre-positioning of inventory.

However, the results of our mixed scenarios revealed that better results can always be achieved with a combination of pre-positioning inventory and investing in DMC. The recommended proportion to be spent on pre-positioned inventory and DMC depends on the level of available funding (YPC); however, in general, it is advisable to spend about 50% of the maximal DMC preparedness cost and allocate the rest of the available funding to pre-positioning inventory. Through our sensitivity analysis, we found that the marginal improvement of performance obtained for each additional euro spent on preparedness decreased above €1 million of YPC. In other words, it will cost much less (i.e., €1 million) to reduce the non-satisfied demand from 12 to 2 million than to reduce it further from 2 million to 0 (i.e., €1.8 million). Nevertheless, it is important to mention that all these figures apply to our specific model and are presented here only to illustrate our findings; they should not be considered as generalizable rules. Indeed, a real case setting should be modeled and simulated specifically to find the optimal mix of scenarios and level of preparedness funding.

On the basis of our findings, we recommend that donors finance more preparedness activities in countries prone to disasters. We recommend that relief organizations mix pre-positioning and DMC preparedness strategies in a proportion such that the best performance is achieved with the given budget. They should, in any case, allocate a part of their preparedness budget to build up the most promising DMC, such as training staff, negotiating customs agreements with local governments, or harmonizing importation procedures with the specific country. Such intangible preparedness activities have a strong potential to reduce lead time and non-satisfied demand when compared to settings without preparedness, while involving limited costs. From the perspective of the findings derived from our model, this would mean allocating one staff member to developing DMC in two countries (corresponding to the optimal 50% DMC preparedness level, and neglecting synergies between countries). The remaining funding could then be allocated to pre-positioning inventory in a country. We encourage one of the major UN organizations (e.g., the Logistics Cluster of the WFP) to coordinate the intangible preparedness activities undertaken by relief organizations in countries prone to disasters. Finally, we encourage local governments to support and cooperate with relief organizations in such preparedness activities.

ACKNOWLEDGMENTS

This work was supported by the Swiss National Science Foundation (FNS grant 143578) and the University of Neuchâtel. It was carried out while the first author was employed by University of Neuchâtel.

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APPENDIX A – Replenishment strategy

The international supply flowing into our model is defined by a replenishment strategy depending on the *Demand* and the *Pipeline Inventory.* The *Order Quantity* is defined as shown in equation A1, and cannot exceed the maximal daily supply capacity of 38,820 kits mentioned earlier (i.e., payload of one cargo plane).

$$Order\ Qtity_t = \begin{cases} Demand_t - Pipeline\ Inventory_t + DDLT_t & , Demand_t > Pipeline\ Inventory_t \\ Base\ Stock\ Replenishment_t & , Demand_t \leq Pipeline\ Inventory_t \end{cases} \quad \text{(A1)}$$

$$Pipeline\ Inventory_t = Customs\ Queue_t + Incountry\ Inventory_t \quad \text{(A2)}$$

If the *Demand* is lower than the *Pipeline Inventory*, a base stock replenishment is performed as presented in equation A3.

$$Base\ Stock\ Replenishment_t = \begin{cases} DDLT_t - Pipeline\ Inventory_t + I_b & , DDLT_t \geq Pipeline\ Inventory_t \\ I_b - Pipeline\ Inventory_t & , DDLT_t < Pipeline\ Inventory_t < I_b \\ 0 & , Pipeline\ Inventory_t \geq DDLT_t \geq I_b \end{cases} \quad \text{(A3)}$$

If the *Demand During Lead Time* (*DDLT,* equation A4) is higher than the *Pipeline Inventory* (equation A2), a base stock replenishment order equal to the difference between the *DDLT* and the *Pipeline Inventory,* plus a *Buffer Inventory (I_b)* quantity is placed. *Buffer Inventory (I_b)* aims at smoothing the replenishment order quantities. Indeed, its level was defined at 100,000 kits in order to avoid inventory oscillations. If the *Pipeline Inventory* is higher than *DDLT* but lower than the *Buffer Inventory (I_b),* the difference between *Buffer Inventory (I_b)* and *Pipeline Inventory* is ordered. If the *Pipeline Inventory* is higher than the *DDLT* and the *Buffer Inventory (I_b)*, no order is placed.

DDLT is calculated with a ten day moving average of past demand and the customs clearance flow time. Because of the ten days chosen for the moving average, the calculation of *DDLT* has been adapted to the first ten days. During this time, it is calculated based on the average demand since Day 0 (see first line in equation A4). The *Flow Time Customs Clearance* is calculated by using the function "QUEUE AGE AVERAGE" of our simulation software (Vensim). At each period, this function returns the average age of the items which are in the *Customs Queue*. We used this function because it provided realistic results during the first days of the simulation, when throughput is extremely low and the customs queue very long.

$$DDLT_t = \begin{cases} \dfrac{Cumulative\ \ Demand_{\ t}}{t}, & t \leq 10 \\ Flow\ Time\ Customs\ Clearance_{\ t} \cdot Moving\ Average\ of\ Demand_{\ t}, & t > 10 \end{cases} \tag{A4}$$

$$Cumulative\ Demand_{\ t} = \sum_{i=1}^{t} Demand_i \tag{A5}$$

$$Moving\ Average\ of\ Demand_{\ t} = \frac{\sum_{i=t-10}^{t} Demand_i}{10}, \qquad for\ \ t > 10 \tag{A6}$$

APPENDIX B – Acronyms

DMC	Disaster Management Capabilities
YPC	Yearly Preparedness Cost
RUTF	Ready-to-Use Therapeutic Food