Cost-Effectively Responding to Forecastable and Unforecastable Food Aid Needs: A Supply Chain Demonstration Model

A Report from the Food Aid Quality Review

Prepared by:

Ozlem Ergun
Stephen Vosti
Keziban Rukiye Tasci
Weijia Jing
Beatrice Rogers
Patrick Webb

January 2021

This report was made possible by the generous support of the American people through the support of the United States Agency for International Development's Bureau for Humanitarian Assistance (USAID/BHA) and the legacy Office of Food for Peace (FFP) under the terms of Contract No. AID-OAA-C-16-00020, managed by Tufts University.

The authors have no conflict of interest to declare.

January 2021

Recommended Citation

Ergun, Ozlem; Vosti, Stephen; Tasci, Keziban Rukiye; Jing, Weijia; Rogers, Beatrice; Webb, Patrick. 2021. *Cost-Effectively Responding to Forecastable and Unforecastable Food Aid Needs: A Supply Chain Demonstration Model*. A Report from the Food Aid Quality Review. Boston, MA: Tufts University.

For correspondence, contact:

Patrick Webb
Friedman School of Nutrition Science and Policy
Tufts University
150 Harrison Avenue
Boston, MA 02111
patrick.webb@tufts.edu

ACRONYMS

BHA	Bureau for Humanitarian Assistance
CSB+	Corn-Soy Blend Plus
DM	Demonstration Model
DP	Distribution Point
EDP	Extended Delivery Point
FAQR	Food Aid Quality Review
FDP	Final Delivery Point
FFP	The Office of Food for Peace
HSC	Humanitarian Supply Chain
MS	Management Science
MT	Metric Ton
OR	Operations Research
PTH	Planning Time Horizon
SGM	Sorghum Bulk
UN	United Nations
USAID	United States Agency for International Development
USD	United States Dollar
USDA	United States Department of Agriculture
WFP	World Food Programme
WH	Warehouse
YSP	Yellow Split Peas

TABLE OF CONTENTS

EXECUTIVE SUMMARY

Millions of tons of food aid are distributed each year by the U.S. Agency for International Development's (USAID) Bureau for Humanitarian Assistance (BHA) and the legacy Office of Food for Peace (FFP). Yet, needs always exceed the food aid resources available to meet them. Efficiency gains in existing supply chains offer potential for closing this gap. On-time delivery of food aid matters greatly, and there are trade-offs between supply chain efficiency and on-time delivery that decision-makers must be aware of and consider when making procurement, prepositioning, and shipping decisions.

We co-developed, with USAID and other partners, a supply chain optimization demonstration model (DM) to assess the range of potential efficiency and effectiveness gains associated with alternative investments in and management of the food aid supply chain. The DM addresses, separately and jointly, forecastable (largely predictable) demand and unforecastable sudden-onset demand. The DM estimates the costs of alternative policy choices in responding to demand, as well as implications for on-time delivery of food aid products.

The DM is built upon data obtained from USAID and the U.S. Department of Agriculture (USDA) on food aid procurement, shipping, and warehousing over the 2011-2016 period. While some of the site-specific circumstances (e.g., warehouse costs) and commodity-specific characteristics (e.g., levels and seasonal variations of commodity prices) may have changed since 2016, the basic structure of the food aid supply chain has not changed substantially since then, nor have underlying factors and interactions among them that influence the efficiency and timeliness of supply chain operations. Therefore, we believe that the patterns of results and insights reported below are representative of what one would expect today, and useful for exploring future investments in the supply chain and changes in its management. Needless to say, a concerted effort should be made to connect the current data streams that underlie the model to future data series; doing so would make it useful for informing operations and ongoing discussions regarding strategic investments. The following core messages emerged from the DM model simulations based on the 2011-2016 data.

USAID Policies and Practices for Managing On-going Food Aid Demand – The DM was used to estimate cost reductions and improved on-time food aid deliveries based on changes to current supply chain operations and policies. Some potential gains are substantial, others less so:

- *Extending the Planning Time Horizon*: In the context of a high-volume commodity, yellow split peas, delivered to the Somali region of Ethiopia, shifting from a 3-month to a 4-month planning time horizon (PTH) for decision-making equates to an ~$3.3 million USD annual reduction in overall supply chain costs. Extending the PTH to 6 months nearly doubles cost savings (to ~$6.3 million USD), but extending the PTH to 12 months has minimal effects on total savings (increasing to ~$6.5 million USD). Savings are greatest for procurement and ocean shipping (~$2.3 million and ~$1.3 million, respectively). On-time delivery improves from ~85% to ~99% by shifting from a 3-month to a 4-month PTH.
- *Food Aid Product Prepositioning*: Prepositioning reduces costs, but only in the context of a 4-month PTH, and especially when the amounts prepositioned are moderate and products are warehoused near final distribution points.

- *US-Flag Rules*: Reducing the proportion of commodities carried by US-flagged vessels reduces overall supply chain costs of delivering food aid products by ~2%, and oceanic transport costs by up to ~7.5%.

Investments in the Global Food Aid Supply Chain – The DM was used to explore potential options for changing the structure of the food aid supply chain. Serious infrastructure constraints faced in many contexts (such as lack of capacity at Eritrean ports) are acknowledged, although the extent of investments and effort needed to enhance these were not possible to include here. However, we highlight four examples of the kinds of options that could be explored in future years:

1. *Using Additional Ports in the Horn of Africa*: Despite past infrastructure deficiencies and related delays and fees, the use of additional ports like Assab and Massawa (if upgraded to be fit for purpose) could reduce food aid product flows from Djibouti and Mombasa, thereby reducing costs at those ports, and potentially bring food aid supplies geographically closer to target populations in northern Ethiopia. However, lead-times associated with inland transportation infrastructure are high, and the overall size of these target populations within Ethiopia is small relative to others in Ethiopia. The DM suggests that total cost savings associated with opening these new ports would be modest (never exceeding ~3% cost savings) and on-time delivery would not be affected. These modest savings would be eroded by higher overland transportation costs attributable to limited supply of trucks and poor-quality roads.
2. *Use and Locations of Global Warehouses*: Choices need to be made regarding the number and location of global warehouses to be opened and the intensity with which they are used. The key decision criteria, once again, are economic efficiency and on-time delivery. The DM was used to identify a collection of warehouse opening and intensity-of-use options, depending on warehouse inventory/handling costs and on the urgency of meeting food aid needs. In only one case (low penalty for not meeting sudden-onset demand and high inventory costs) does the DM suggest that no warehouse be opened. As penalties for failing to meet on-time delivery rise and as inventory costs fall, more and different combinations of warehouses emerge as economically optimal choices. Generally, Mombasa is the first warehouse to open, followed by Djibouti as concerns over urgency continue to rise. Finally, under high penalties for not meeting on-time delivery requirements, the Houston warehouse is opened, replacing the Djibouti warehouse. Equally important, the intensity of use of warehouses changes as late-delivery penalties and warehouse costs rise.
3. *Large Increases in Sudden-Onset Demand*: Third, the DM was used to examine the effects on costs and on-time delivery of a very large increased sudden-onset demand in Ethiopia. Not surprisingly, meeting this surge in sudden-onset demand requires opening and making much more intensive use of the Port of Djibouti. Meeting *all* on-time demand, once again, requires opening of the Houston port.
4. *Large Disruptions in the Global Supply Chain*: We simulated one large disruption in the global supply chain for food aid products – the unavailability of the Port of Mombasa. As expected, the DM suggests that the Djibouti port would replace the Mombasa port when inventory costs are relatively low and penalties for late delivery are also relatively low. When inventory costs rise, the relatively inexpensive but poorly connected opening an in-land warehouse at Addis Ababa becomes a cost-effective option. If late-delivery penalties and inventory costs are very high, international ports are not used; all food aid products are

shipped via Houston. Overall, the unavailability of the Mombasa port increases total costs by approximately $4 million USD per year.

What Can the DM Do for USAID? – Needless to say, many other DM simulations can be run, but the fundamental question at this juncture is what can the supply chain optimization demonstration model do for USAID? Our response to that question is three-fold.

- *A Richer and More Transparent Conceptual Framework*: The DM can help put additional structure to the conceptual framework that already underlies USAID/BHA objectives and activities – i.e., how best to think about the competing objectives of efficiency and meeting the needs of food aid recipients in timely ways.
- *Guidance on Operations*: The DM can help inform discussions and decisions related to operations and strategic investments by simulating situations that might arise, especially in the context of sudden-onset demand. The DM remembers and applies all of the global supply chain details (commodity prices, global shipping and storage constraints, etc.) and their interactions that supply chain managers cannot possibly recall or use.
- *Assessing the Effects of Bilateral Discussions*: USAID/BHA is not alone in determining which food aid products are shipped to which countries, and when. Bilateral discussions with countries play important roles in fine-tuning on-going and sudden-onset demand, and how and when that demand will be met. Moreover, these bilateral discussions change over time, as do the individuals participating in them. No model can include all of the details associated with these discussions or their effects on food aid decisions. However, the DM can identify efficient and effective supply chain management options that are *not* influenced by these bilateral discussions, and thereby provide an estimate of the efficiency and effectiveness losses associated with them. This information can be useful in managing bilateral discussions.
- *Preparing for a Challenging New Food Aid World*: Perhaps most importantly, the DM can help USAID/BHA prepare for an increasingly needy, uncertain, and more volatile world. Climate change and civil unrest will likely increase the demand for, and the uncertainty associated with, food aid, with consequences for program costs and the ability to meet food needs in timely ways. How can the DM help USAID/BHA *prepare* for this new world? By using the DM to simulate the impacts of strategically selected future scenarios identified by BHA on costs and on-time deliveries, and then to help develop plans for exigencies. More specifically, the DM can be used to explore (independently and jointly) the impacts of larger food aid needs, increasing uncertainty of the timing of these needs, and increased volatility of the prices of food aid products on the costs and on-time deliveries of the current food aid supply chain. The model can also be used to assess the implications of major disruptions in the supply chain and identify cost-effective work-arounds. Examined jointly, the results of these strategically chosen DM simulations can help identify patterns of efficient and effective BHA responses to future food aid needs, as well as help identify the circumstances under which key investments and/or policy changes will be needed, and the implications of failing to make them on costs and on-time deliveries. In the end, no model can predict the future, but this DM can examine the effects of alternative possible futures, and thereby help USAID prepare for those that do emerge.

1. INTRODUCTION

1.1. IMPORTANT ISSUES FACED BY USAID

Almost eight hundred million people in the developing world were facing food insecurity in 2018 (USAID- Agriculture and Food Security, 2018) and the role of food aid in helping to meet these needs becomes clearer each year. The United States Agency for International Development (USAID) Bureau for Humanitarian Assistance (BHA), the world's largest contributor of food assistance, responded to assessed needs by providing over 4 million Metric Tons (MT) of bulk commodities and over 2 million MT of packaged commodities between April 2011 and September 2016 (Tasci, et al., 2019). The total value of these food aid products was over $3 billion USD and the cost of shipping these items from the United States (U.S.) to recipient countries was more than $1 billion USD. In 2018, the U.S. contributed nearly $1 billion in commodities to the World Food Programme (WFP) alone. This represents a huge commitment on the part of USAID to meeting food needs of the very poorest people on the planet. However, this commitment carries significant budgetary and (hence) political costs. In any political climate, identifying more cost-effective strategies for meeting the U.S.'s global commitment to reducing food insecurity is a priority.

While there have been some changes in the types of the food aid products delivered and in product purchasing arrangements, some in response to system-wide reviews and recommendations (Ruttan, 1993) (Barret & Maxwell, 2005) (Melito, 2009) (Webb, et al., 2011) (Grossman-Cohen, 2012) (Barrett, 2017) and others in response to searches for alternative procurement methods (Grossman-Cohen, 2012) (Lentz, Passarelli, & Barrett, 2013) (Ferrière & Suwa-Eisenmannb, 2015) (Nikulkov, Barrett, Mude, & Wein, 2016) (Gautam, 2019), the core mechanisms for procuring, transporting, and distributing have remained essentially unchanged (apart from technological innovations and investments in transportation infrastructure, etc.). These mechanisms are governed by a series of policies, practices, and rules that may influence the efficiency of the overall BHA system.

Against this institutional backdrop, USAID faces the following realities. First, food aid needs always exceed the resources available to meet them; efficiency gains must be found to close this gap. Second, on-time delivery of food aid matters greatly, and there are trade-offs between supply chain efficiency and on-time delivery that decision-makers must be aware of and consider when making procurement, prepositioning, and shipping decisions. Third, the world viewed from the lens of BHA is becoming increasingly needy, uncertain, and more volatile.

How can BHA better equip itself to deal with inherent inefficiencies of current food aid mechanism *and* prepare itself for the broader set of new challenges that it will need to face?

1.2. KEY ISSUES ADDRESSED BY THE DEMONSTRATION MODEL

Over the last few decades, the importance of using mathematical modeling and analytics to support decision making in humanitarian operations have been gaining traction. The Special Issue of *Humanitarian Applications: Doing Good with Good OR*. (Ergun, Keskinocak, & Swann, 2011) highlights the importance of using operations research (OR) and management science (MS) techniques to analyze and optimize complex real-world humanitarian applications. Logistics management serves as a fundamental enabler for effective humanitarian aid operations and programming, and systematic

humanitarian supply chain (HSC) design and policymaking, based on OR techniques, can significantly improve the cost-effectiveness and the timeliness of responses to both on-going and sudden-onset food aid demand. For example, efforts to develop and use data and models to inform the operations of the UN World Food Programme (WFP), the largest humanitarian agency fighting hunger worldwide are documented in (Alvarenga, *et al*., 2010) and (Peters, *et al*., 2016). These and other documents describe the development of a supply chain optimization decision aid tool, its implementation at WFP, and the impacts of the improved decision-making to assist WFP's operations across departments and service areas.

Following this path, the FAQR team co-developed with USAID and other partners a supply chain optimization demonstration model (DM) to assess the potential efficiency and effectiveness gains associated with changes in selected BHA policies and practices, in selected decisions regarding the structure and use of the food aid supply chain that BHA might make, and in selected disruptions[1] to the global food aid supply chain. The DM is built upon data from USAID and the U.S. Department of Agriculture (USDA) on food aid procurement, shipping, and warehousing, and FAQR worked on assembling and analyzing these data (see Section 2.1). More specifically, preliminary data analyses highlighted several key sources of potential efficiency gains (Tasci et al. 2019), as follows:

1. Food production is seasonal, and there are seasonal patterns of demand for agricultural products as well. National and global storage capacity is insufficient to completely smooth out seasonal fluctuations in commodity prices, and these fluctuations potentially can be tapped for efficiency gains.
2. There is also marked seasonality in shipping costs, and it may be possible to exploit these seasonal variations to reduce costs. For example, based on the historical timing of purchases and seasonal price differences, if 50 percent of all food aid shipped between April 2011 and September 2016 could have been strategically delayed by one month to take advantage of lower shipping costs, approximately $32 million USD could have been saved. Inventory and handling cost might reduce or increase these savings, depending on seasonal patterns of food aid demand.
3. Taking advantage of seasonal swings in product prices and shipping costs requires decision-making and procurement timeframes that extend beyond the peaks and troughs of these products/services' market prices. Changes in purchasing rules, and perhaps in legislation, may be required to extend these timelines, and the benefits of doing so are likely to be substantial.
4. The class of shipping service is a key factor in determining the overall cost of moving food aid products. Across all ports, P1 (ships carrying U.S. flags) shipping costs were roughly 30 percent higher than P3 (ships carrying international flags) shipping costs. However, this

[1] Regarding food aid demand: on-going demand refers to the forecastable amounts of food aid that a given country will need; and sudden-onset demand refers to the *un*forecastable amounts of food aid that a given country will need, e.g., demand associated with extreme agroclimatic events. Regarding the timeframe for taking action, the planning time horizon (PTH) refers to timeframe during which decision-makers can take action on on-going demand for food aid; the longer the PTH the more visible on-going demand. Finally, we use the term 'disruptions' to refer to large, sudden events that do *not* affect food aid demand, but rather the food aid supply chain that delivers it, e.g., the unavailability of a warehouse due to (say) civil strife.

average does not reflect very substantial differences across ports. Advance planning and forward shipping contracts could allow for efficiency gains without compromising commitments to meet legal requirements[2]. To improve the timing of purchasing and shipping commodities, the introduction of analytics and mathematical optimization are recommended.

Against this backdrop, and the insights it provides regarding potential efficiency gains, the DM was designed to provide estimates of the costs of alternative BHA policy practices and choices, as well as their implications for the on-time delivery of foreseeable on-going demand and unforeseeable sudden-onset demand food aid products, separately and jointly.

1.3. THE CONTENT OF THIS REPORT

Section 2 sets out the structure and logic of the demonstration model, with attention paid to the two main sources of demand for food assistance, foreseeable/actionable (or on-going) demand and unforeseeable (or sudden onset) demand. Section 3 reports selected demonstration model results based on on-going demand. Section 4 reports selected results based on combining on-going and sudden-onset demand. Section 5 provides sets of conclusions and their implications for policy.

The body of this reports is written for a non-technical audience and therefore contains limited amounts of the details associated with the structure or functioning of the demonstration model, or of the data gathered and process that underlies the model. To fill this information gap, this document contains three technical annexes, each containing the details associated with the data underlying the demonstration model (Annex 1: Data Preparation), the mathematical models developed in the context of this project (Annex 2: Mathematical Models), and the solution methodologies developed and used to generate model solutions (Annex 3: Solution Methodologies).

Finally, two additional documents complement this Final Report. The first is a Report at the outset of this project that describes and analyzes recent historic BHA and legacy FFP operations (Tasci et al. 2019), and the second is a paper currently under review (Ergun et al. 2020). The reader is encouraged to read the annexes to this Final Report and the accompanying documents for a complete assessment of the activities and accomplishments associated with this project.

2. THE UNDERLYING DATA AND OVERALL STRUCTURE OF THE DEMONSTRATION MODEL

The demonstration model (hereafter referred to as DM) envisions two sources of demand for food aid. We refer to the first as forecastable demand (with different degrees of foresight, to be addressed below). Forecastable demand is commonly referred to as on-going demand – the amounts and types of food aid products that can reasonably be expected to be delivered to a given locale in any given time period, generally based on historical patterns. On-going demand may be relatively easy to predict, but for institutional and other reasons, it may not be immediately visible to those responsible for action. More on the issue of demand visibility, below. The second source of food aid

[2]According to cargo preference rule, 50% of food aid must be carried in U.S. flagged vessels.

demand is unforecastable demand, i.e., food aid needs that are random or stochastic, in terms of their timing, location, and volume. Unforecastable demand is commonly referred to as sudden-onset demand. The structure of the DM encompasses both sources of demand, as described below.

2.1 THE DATA UNDERLYING THE DEMONSTRATION MODEL

To move from the conceptual framing of a supply chain and the decision-making processes that govern it, as set out in **Figures 1** and **2**, below, data are required. Once the DM is anchored to data, the model's internal logic and responsiveness can be tested against the data on which it was constructed. At that point, users can generate quantitative estimates of baseline flows of food aid products, and the effects of changes in these flows brought about by changes in food aid demand and/or supply chain characteristics or management practices.

This DM is anchored on data provided by USAID, USDA, and national and international food aid supply chain partners. (See Annex 1 for details). The preparation of the underlying data began by gathering, organizing and exhaustively reviewing all available legacy FFP food assistance procurement and ocean transportation data from USAID and USDA over the period 2011-2016. The initial objective was to describe the past operations of the legacy FFP program and also to identify opportunities for improving cost-effectiveness. The next step was to fill data gaps to provide a more complete picture of the USAID food aid supply chain as an end-to-end system, from procurement to last-mile of in-country distribution.[3] Within BHA's operational structure, PVOs or IOs (generally referred to as partner organizations) are responsible for in-country deliveries after the aid commodities arrive at foreign discharge ports. Therefore, we worked with partner organizations to acquire in-country data and insights into last-mile operations and costs.

These data anchor the model not only in terms of physical flows of food aid products and their relative prices and delivery costs, but also in time. Hence, the 2011-2016 period is the historical backdrop for this analysis. For example, measures of seasonal fluctuations in shipping costs and in commodity prices are drawn from this period; the same is true for the levels of commodity prices and shipping costs, and for the on-going and sudden-onset demand for food aid. Some of these important parameters may have changed over time, absolutely and relative to one another. These updates and changes, once introduced into the DM, may lead to changes in model simulation results both in terms of supply chain efficiency and on-time demand satisfaction. However, the underlying structure of the USAID food aid supply chain and the policies and practices that govern it have not change substantially since the 2011-2016 period. Therefore, while some of the relative prices and specific model constraints may not precisely reflect today's prices or constraints, the DM, rooted in recent USAID historical data, can be used to examine the effects of selected changes in supply chain structure and management. Sensitivity analyses run alongside core DM simulation results presented below confirms these results are robust to changes in relative prices, etc., that may have occurred since the 2011-2016 period.

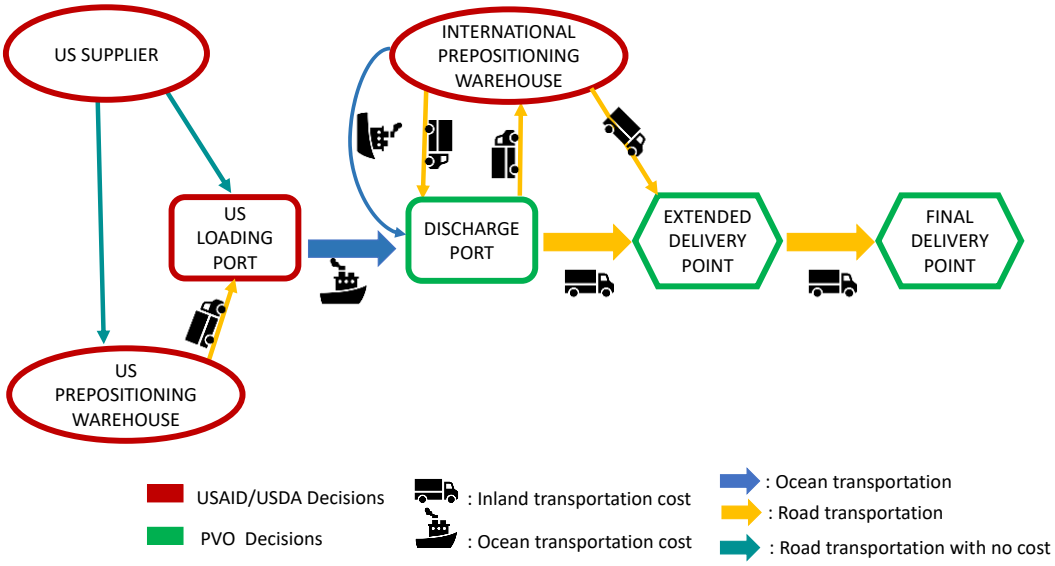
[3] Annex 1 contains complete descriptions of all of the data and data preparation methods that were used to parameterize the conceptual flow model contained in Figure 1.

At this point, the DM is just that, an internally consistent demonstration model anchored in recent historical USAID data and built upon a set of assumptions. The mathematical models that govern the DM are described in detail in Annex II. The main challenge and objective was to develop this DM and to test its internal consistency, and to use it to examine a set of core issues that continually arise in the context of the structure and management of the USAID food aid supply chain. This has been done and selected results and their interpretations are presented in what follows. The data underlying the DM can and should be updated, as well as the constraints and assumptions that govern it as the USAID food aid supply chain structure evolves over time; doing so would sharpen the estimates of effects and make the model results timelier.

2.2. FORECASTABLE DEMAND FOR FOOD AID

The objective of the DM is to minimize the total cost of procuring and delivering food aid products. **Figure 1** depicts the conceptual flows of products from suppliers, through warehouses, loading and discharge ports, extended delivery points (EDPs), to final delivery points (FDPs). Note that many of these steps, especially those generally associated with last-mile decisions are not taken by USAID. The DM is developed to focus on USAID decisions (boxes and ovals outlined in red in **Figure 1**), although data for the locations, capacities, etc. of elements of the supply chain managed by other organizations were included, as needed, to evaluate the end-to-end impact of USAID decisions. For example, the locations and capacities of EDPs, or the capacities of discharge ports, are not determined by USAID, but influence the impact of USAID decisions in terms of delivering food aid; hence, these details are included in the DM.

Figure 1: Conceptual USAID Supply Chain: Procurement, Transfer and Storage Sites, Commodity Routes, and Institutional Responsibilities (color codes)



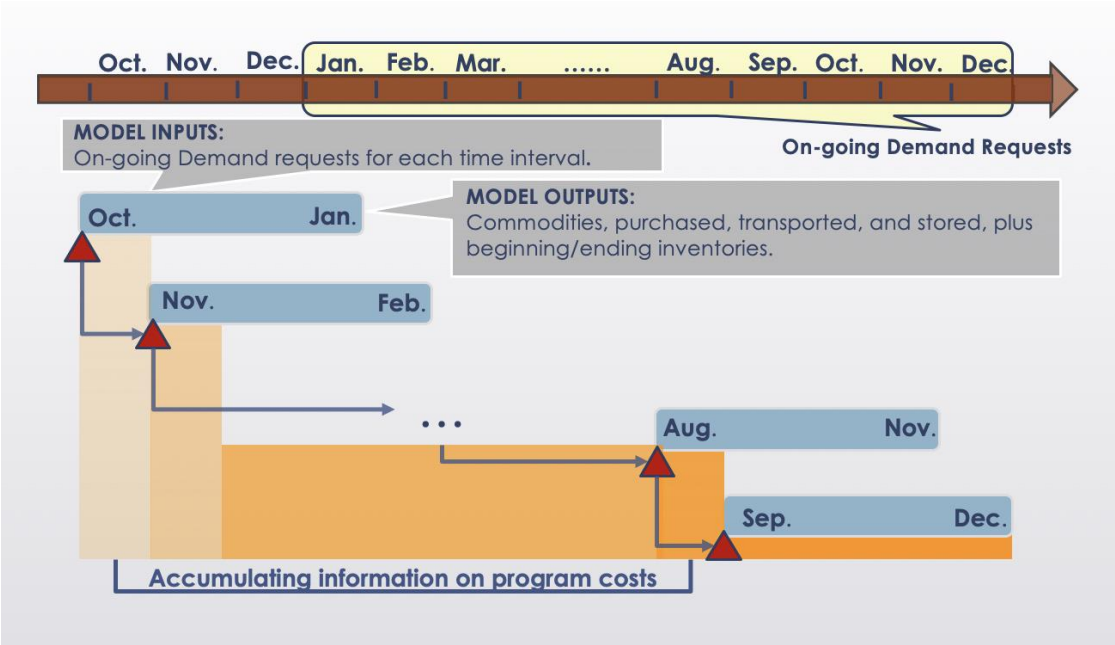
Since humanitarian aid is an urgent business with consequences for the late delivery of food, the DM specifically includes a penalty for shipments that arrive after the specified due date. The higher this conceptual penalty, the more intense the pressure within the DM to meet demand in a timely way, even if additional costs must be paid to do so.

The DM has an array of built-in constraints that are included and designed to capture the reality of the USAID supply chain along with a set of assumptions to be able to abstract out the most critical elements that govern the supply chain. Briefly, and for example, there are limits to the storage capacities of warehouses and the flow capacities of ports, oceanic shipping take time, and the in-flows, out-flows, and inventories of all warehouses must match. Also, there are regulatory constraints that must be met, e.g., satisfying the USAID flag rule based on the Cargo Preference Act of 1954. A complete set of model parameters and constraints is included in Annex 2.

Finally, in terms of the structure of the DM, a decision-making timeframe was adopted that captures the current operational modalities of BHA actors and also allows us to assess the effects on supply chain costs and effectiveness of adjustments to this reality. (See Annex 2 and Annex 3 for the mathematical expressions in the DM and the solution methodologies developed and used.) This decision-making timeframe is a rolling planning time horizon (PTH) algorithm, and is depicted in **Figure 2**, which provides an overview of the rolling planning time horizon approach in the context of a 4-month PTH, which is nested within a 12-month study. The yellow area at the top of the figure represents the 12-month period for this modeling exercise. The brown arrow captures the entire decision-making period, which is longer (extended to the left of the 12-month period) by the number of months contained in the PTH – in this example, we envision a 4-month PTH, so food aid that is needed in January becomes visible as 'January demand' in October. The blue bars represent discrete but overlapping PTHs, which move forward in time at one-month time steps. The gray boxes identify the information that feeds into each PTH at the outset, and the outputs that emerge from the economic optimization algorithm for each PTH. The red triangles represent collections of model outputs associated with the first month of each PTH which are fixed (outcomes that can no longer be changed) as the planner shifts from one 4-month PTH to the next. Finally, the increasingly dark-shaded orange boxes represent the accumulated information on the costs that are associated with the optimal outcomes produced by the model.

A limited validation of different versions of the DM was done by carefully examining absolute and relative cost components, commodity flows, procurement and pre-positioning decisions. The relative magnitudes of these were compared to what we observed in the historical data. Furthermore, model logic was tested via extensive sensitivity analysis of parameters and constraints, making sure that changes in DM outputs make logical and directional sense given the imposed changes in parameters and constraints. A true validation can only be possible by implementing the suggested decisions and comparing the real-world impacts to those predicted by the DM, which is outside of the scope of this study.

Figure 2: 4-month Rolling Planning Time Horizon Overview



2.3. ADDING *UN*FORECASTABLE DEMAND FOR FOOD AID

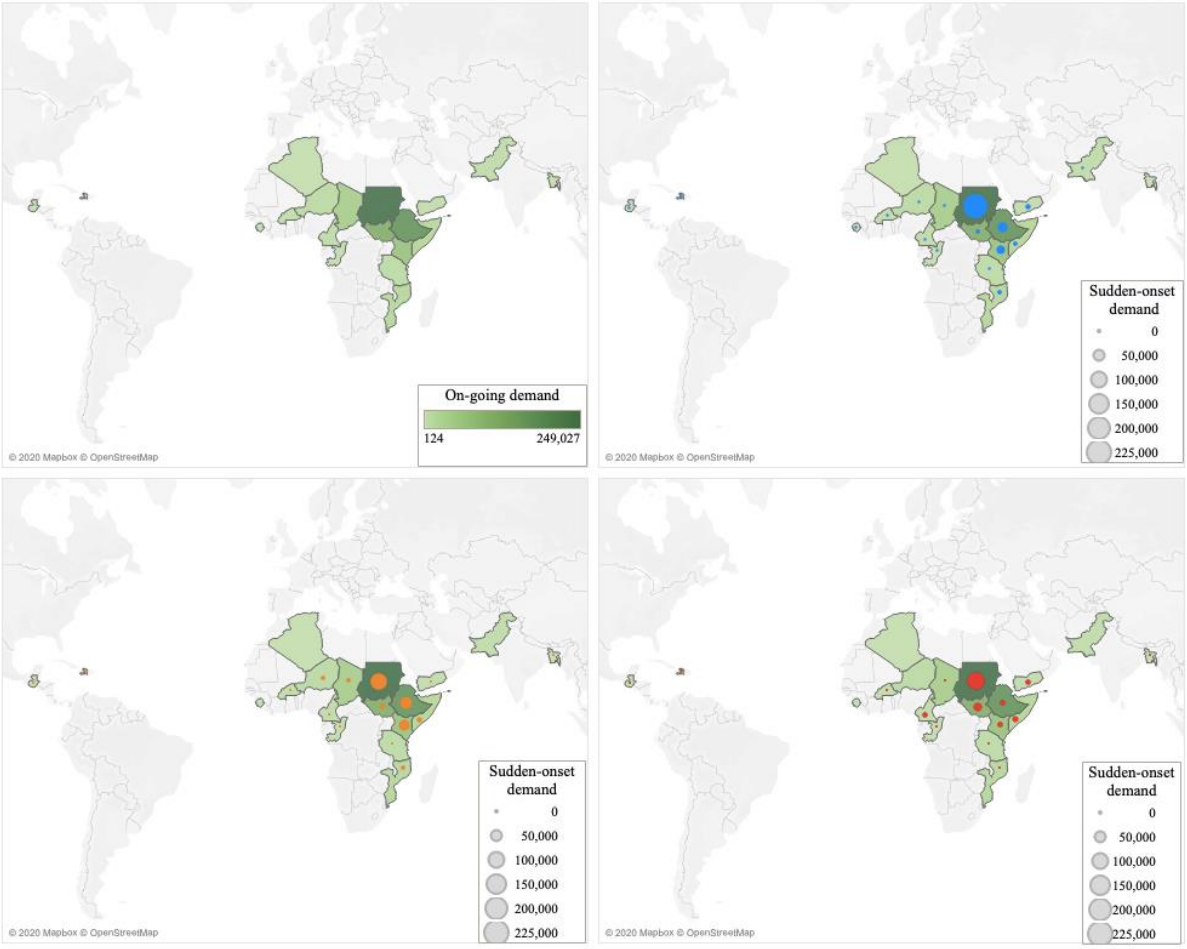
To adequately capture the nature of food aid needs, a second source of demand had to be added to the model – unforecastable or sudden-onset demand. Two steps were required. First, a definition of sudden-onset demand was needed, as was an empirical basis for estimating the location, volume, and timing of sudden-onset demand. Second, a two-stage decision-making process was introduced to the model – the stage-one decision focused on identifying the collection of warehouses to be opened/used to optimize the expected cost-effectiveness of the supply chain; the stage-two decision-making process focused on operating the stage-one supply chain optimally. We explain these two steps, below.

Sudden-onset demand, by definition, is a stochastic event in that we do not know when, where, or how large this unforecastable demand will be, but its location and volume could be related to the on-going demand. Therefore, we used historical delivery data from USAID (2011-2016) as a basis for generating country-level scenarios for sudden-onset demand based on the highest single-year country-level on-going demand over the sample period, e.g., sudden-onset demand for Ethiopia was based on the highest single-year amount of food aid provided to that country over the 2011-2016 period. Globally, three levels of sudden-onset demand were calculated – low (28% of peak food aid during the sample period), medium (37% of peak food aid during the sample period), and high (48% of peak food aid during the sample period) – and randomly distributed to different countries around

the globe. Each level of sudden-onset demand was equally likely to occur, i.e., each had a 1/3 chance of playing out.[4]

Figure 3 contains four quadrants that graphically depict total food aid demand under different assumptions about the levels of sudden-onset demand, but with constant underlying on-going demand for the simulations we employed. The upper-left quadrant depicts the level of on-going demand (only) by food assistance-receiving countries; darker-shaded countries have higher average levels of on-going demand. The remaining quadrants depict both on-going and sudden-onset demand by these same countries, but under different assumed levels of sudden-onset demand. The sizes of the country-specific dots reflect the volumes of sudden-onset demand; the colors of the dots identify the three levels of intensity/severity of sudden-onset demand. The upper-right quadrant represents the case of high (blue) sudden-onset demand. The lower-left quadrant reports the case of medium (orange) sudden-onset demand, and the lower-right quadrant reports the case of low (red) sudden-onset demand.

Figure 3: Spatial Distribution of Global On-going and Sudden-onset Demand, by Levels of Sudden-onset Demand – Volume-based Scenarios



[4] For details related to the generation of sudden-onset demand scenarios and the data underpinning them, see Annex 3.

Figures 4a-d report the same information, but in a somewhat different way. Each column reports on-going demand, or on-going *plus* sudden-onset demand, for specific countries and for three different levels of intensity/severity of sudden-onset demand. Again, if a country experiences any level of sudden-onset demand, then this demand volume is proportional to its historical average on-going demand. **Figure 4a** reports ongoing demand; these grey histograms are carried forward in **Figures 4b** through **4d**, and different color-coded levels of sudden-onset demand (blue = high-volume, yellow = mid-volume, red = low-volume) are added to them to depict total annual food aid demand, by country.

Figure 4a: Global On-going Demand in a 12-month Period, by Country

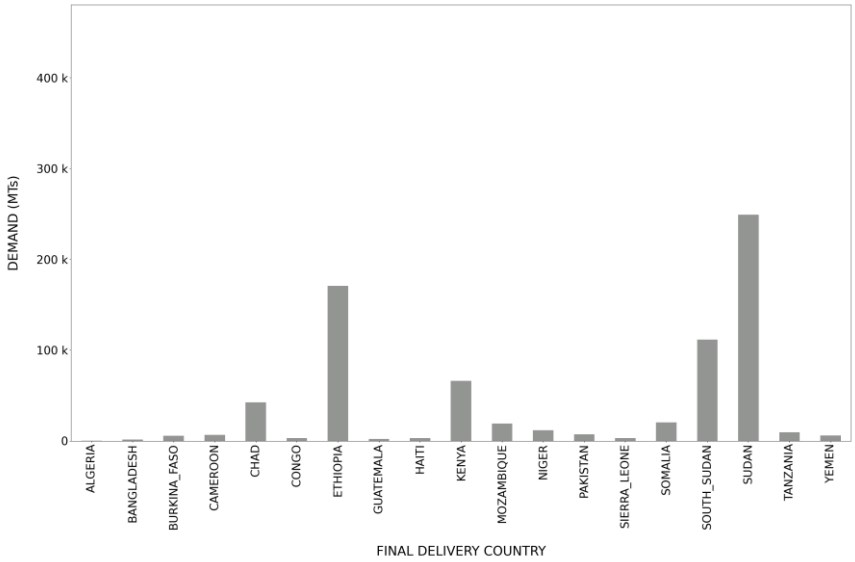


Figure 4b: Global On-going and Sudden-onset Demand in a 12-month Period, by Country – High-volume

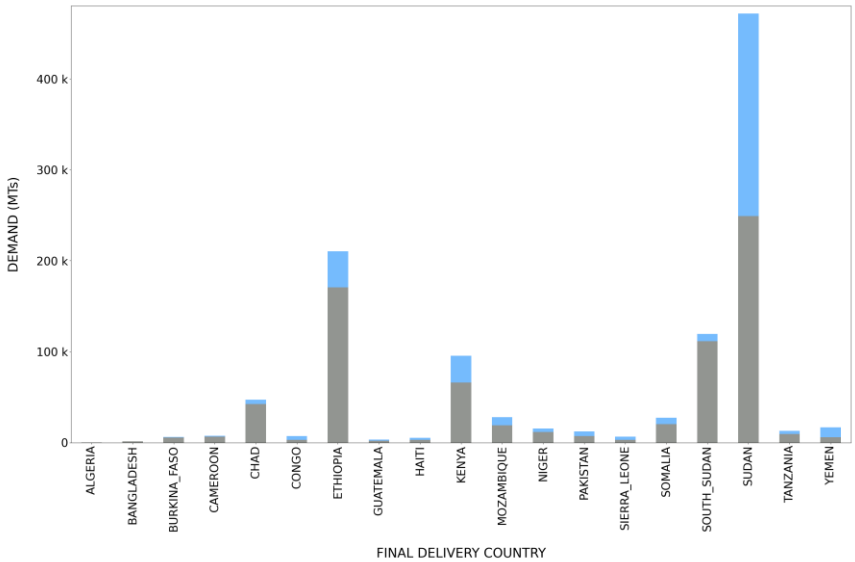


Figure 4c: Global On-going and Sudden-onset Demand in a 12-month Period, by Country – Mid-volume

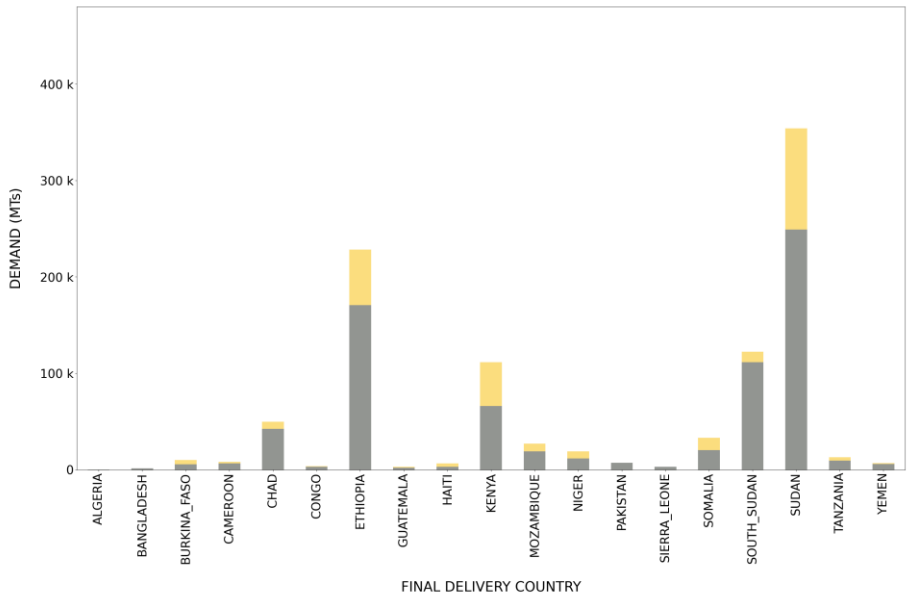
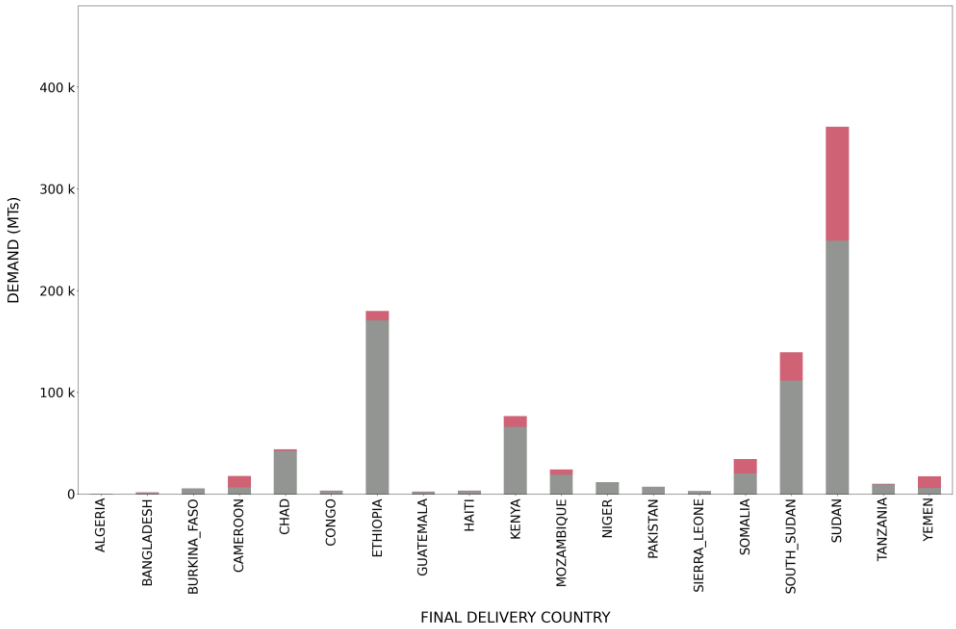


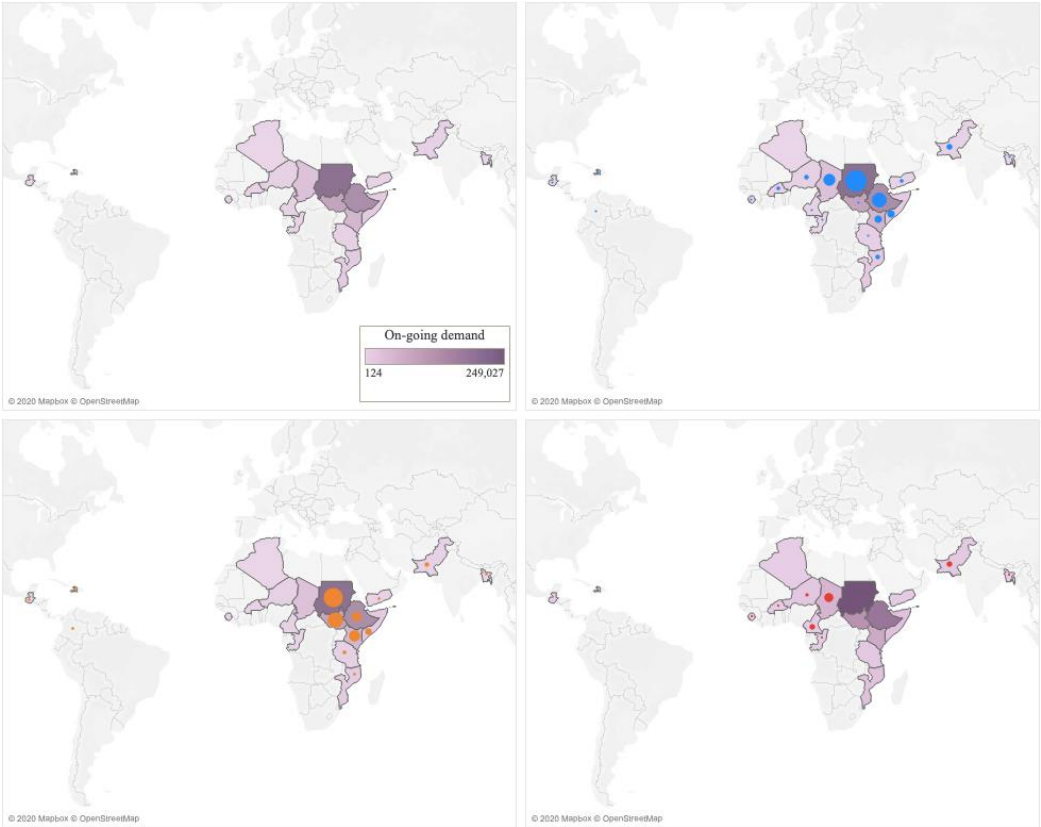
Figure 4d: Global On-going and Sudden-onset Demand in a 12-month Period, by Country – Low-volume



In a second set of simulations, sudden-onset demand was generated to spatially cluster in different regions. For example, **Figure 5**, in which the shades for each country represent the levels of average on-going demand; the sizes of the dots over each country represent the amount of sudden-onset demand. In the upper-left quadrant, average on-going demand is reported for food aid

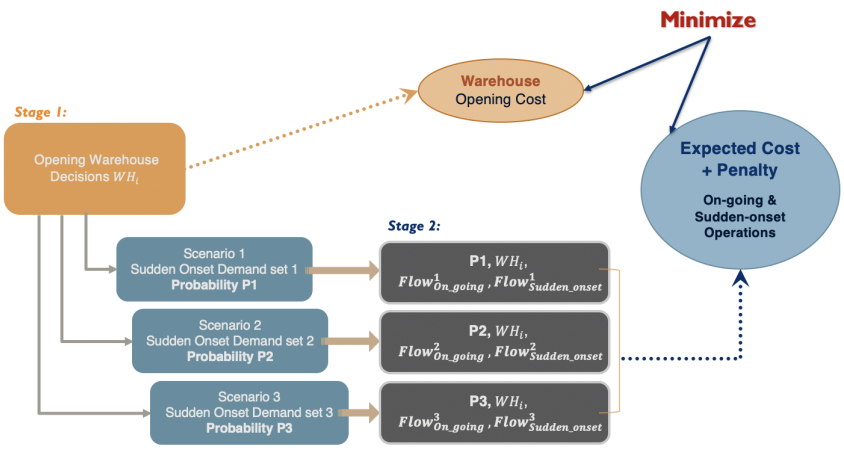
recipients. The upper-right quadrant depicts spatially uniform high-level (blue) sudden-onset demand, the bottom-left quadrant depicts medium-level (orange) demand that is skewed towards the Horn of Africa (perhaps associated with a regional drought), and the bottom-right quadrant depicts low-level (red) sudden-onset demand that is skewed towards the eastern part of Africa. Alternative clusterings are possible and could be used to experiment with (e.g.) sub-regional foci of civil strife.

Figure 5: On-going and Sudden-onset Global Demand, by Country and by Levels of Sudden-onset Demand – Region-based Scenarios



Next unforecastable or sudden-onset demand is introduced into the DM by adding a second stage to the model's decision-making process that would allow alternative (unforecastable) future events to influence key up-front (stage-one) supply chain investments (e.g., which warehouses facilities to open/maintain). **Figure 6** sets out the logic of the two-stage decision-making process. In the first stage (captured by the left-hand orange and light-blue boxes), the model reviews all possible combinations of country-level stochastic sudden-onset and (forecastable) on-going demand, with each sudden-onset demand scenario occurring with probability P. Having reviewed all possible outcomes, a stage-one decision is made regarding the structure of the supply chain, i.e., which warehouses to open. The second stage of the model's decision-making process then uses this (fixed) supply chain to minimize the cost associated with meeting the levels of on-going and sudden-onset demand that actually occur under each scenario, and subject to the penalties that apply for late-delivery of sudden-onset demand.

Figure 6: Two-stage Scenario-based Stochastic Programming Framework



With the structure of the model in place, we turn below to its application to address selected issues faced by USAID. Specifically, we use the DM to examine the effects of changes in the *visibility* of food aid demand, i.e., the planning time horizon that USAID personnel use when taking decisions regarding purchase, transportation, and prepositioning of food aid products. As will be seen, changing the planning time horizon can affect costs, on-time delivery, and the usefulness of preposition food aid products. Second, we use the model to assess the effects on transportation costs of the US flag carrier rule. Third, we use the tool to assess the costs of expanding the network of ports used by USAID to supply the Horn of Africa. Fourth, by also considering sudden-onset demand we determine locations of global warehouses for cost-effective and on-time food-aid delivery under different scenarios. These represent just a few of issues important to USAID that could be addressed by the DM and its underlying empirical base.

3. FORECASTABLE DEMAND: KEY RESULTS FROM SELECTED MODEL SIMULATIONS

3.1. INCREASING THE INSTITUTIONAL VISIBILITY OF FORECASTABLE DEMAND

We first examine the impacts of on-going demand visibility by setting different length of planning time horizon (PTH) during which USAID personnel can take advantage of the two key sources of efficiency gains, namely, seasonal fluctuations in commodity prices and in shipping costs. The longer the planning time horizon, the greater the potential for improving efficiency; efficiency gains can be achieved by any combination of shifting the timing of purchases, shifting shipping times, or modifications to the amounts and timing of prepositioned products. **Figure 7** reports the estimated total supply chain costs and demand satisfaction ratios for a single fiscal year for the case of yellow split peas (a major component of the overall Ethiopian food aid basket) procurement/delivery to the

Somali region of Ethiopia. Several insights emerge.[5] First, moving from a 3-month to a 4-month PTH significantly reduces overall supply chain costs by approximately 5% and increases (from 85% to essentially 100%) the demand satisfaction ratio, a key metric of food aid program success. [6] Second, extending demand visibility from 3 months to 6 months has the potential to generate up to 9.4 % annual cost savings over all supply chain activities. Over $6 million USD per year can be saved for a single commodity network for one region; additional cost savings would be expected for a similarly managed, multi-commodity global supply chain. Third, further extending the demand visibility from 6 to 12-months improves the cost-savings only by 0.3%. Therefore, from an efficiency perspective, all that planners need to see can be 'seen from a 6-month PTH. From an effectiveness perspective (on-time delivery), a 4-month PTH essentially guarantees on-time delivery of on-going food aid demand.[7]

The PTH also affects the potential usefulness of prepositioned food aid products. The colored horizontal bars in **Figure 7** represent different amounts and locations of preposition products; orange = no prepositioning, light blue = 40k MT at warehouses (WH), green = 40k MT spread equally across WHs and extended delivery points (EDP), grey = 40k MT at EDPs, yellow = 80k MT at WHs, red = 80k MT spread equally across WHs and EDPs, and dark blue = 80k MT at EDPs. The extent of on-time deliveries is reported above each bar. Shifting to a 4-month planning time horizon (in and of itself) dramatically improves on-time delivery, and holding more prepositioned products, and holding them closer to final delivery points, marginally improves on-time deliveries; the ability to manage the supply chain over a longer PTH reduces the benefits of prepositioned food aid products. Prepositioned products are not needed to secure 100% on-time delivery in the context of a 6-month (or longer) PTH; indeed, prepositioning in these contexts add to program costs but not to program effectiveness.

[5] Focusing on different food aid products may generate quantitative estimates of supply chain costs savings, etc. However, since the prices of all food aid products display seasonal variability, all products have expiration dates, on-time demand is important for all products, and all food aid products must be shipped using a system that displays seasonal fluctuations in prices, the *patterns* of the insights discussed here will be very similar for all food aid products.

[6] On-time demand satisfaction ratio is calculated as the percentage of total delivered commodity over total amount of requested demand at a particular time period.

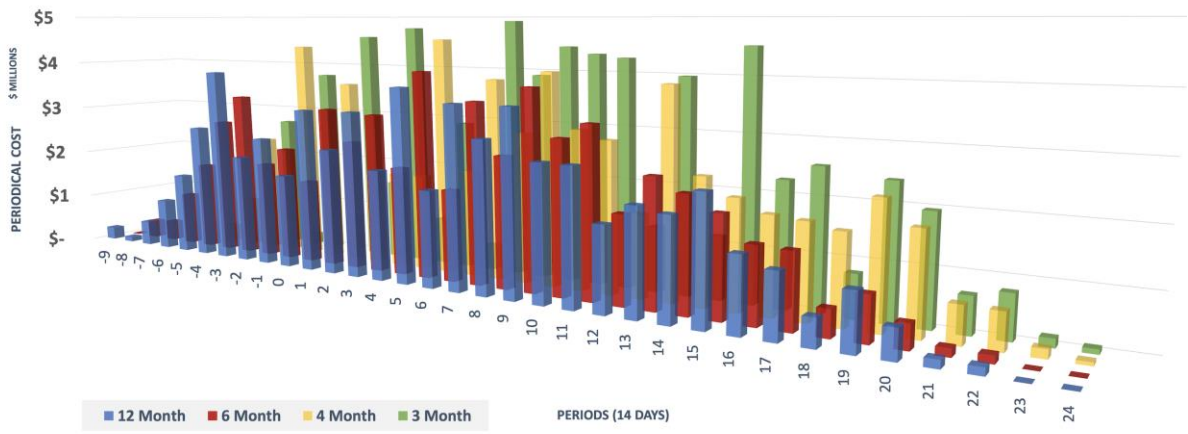
[7] The consensus among USAID collaborators is that the food aid program within USAID works a planning time horizon (PTH) that is roughly equivalent to the 3-month PTH captured in the DM. Extending the PTH will depend a number of issues, including preparing and using existing data to more accurately forecast food aid needs and extending the temporal extents of these forecasts, increased ability to buy forward food aid products, and increased ability to design and use longer-term contracts to purchase food aid products. These and other changes are possible, but may require changes in internal policies and legislation.

Figure 7: Supply Chain Costs and On-time Demand Satisfaction Ratios, by Planning Time Horizon, and Amount and Location of Prepositioned Products

Hence, to obtain efficiency gains by taking advantage of broader temporal windows for commodity purchases and oceanic shipping, at least a 6-month planning horizon should be aimed for, but even extending the current 3-month PTH by 1 month would reduce costs and improve effectiveness when coupled with the right prepositioning strategy.

Not detectable from summary annual cost savings estimates illustrated in **Figure 6** are the increasingly smooth purchasing/shipping/warehousing flows associated with longer PTHs. **Figure 8** presents periodic supply chain costs at two-week time steps for each of the PTHs examined in this simulation. The 3-month PTH cost series is much more jagged than any of the other PTH cost series – large purchase and shipping/overland transportation costs in some two-week periods, are followed by no or much smaller outlays in subsequent periods. The start/stop pattern that generally characterizes the USAID status quo may put great pressure on logistics personnel, equipment, etc. Shifting to a 4-month and especially to a 6-month and 12-month PTH would greatly smooth procurement, shipping, and overland transportation activities and hence reduce these pressures.

Figure 8: Total Supply Chain Costs at Two-week Increments, by Planning Time Horizon



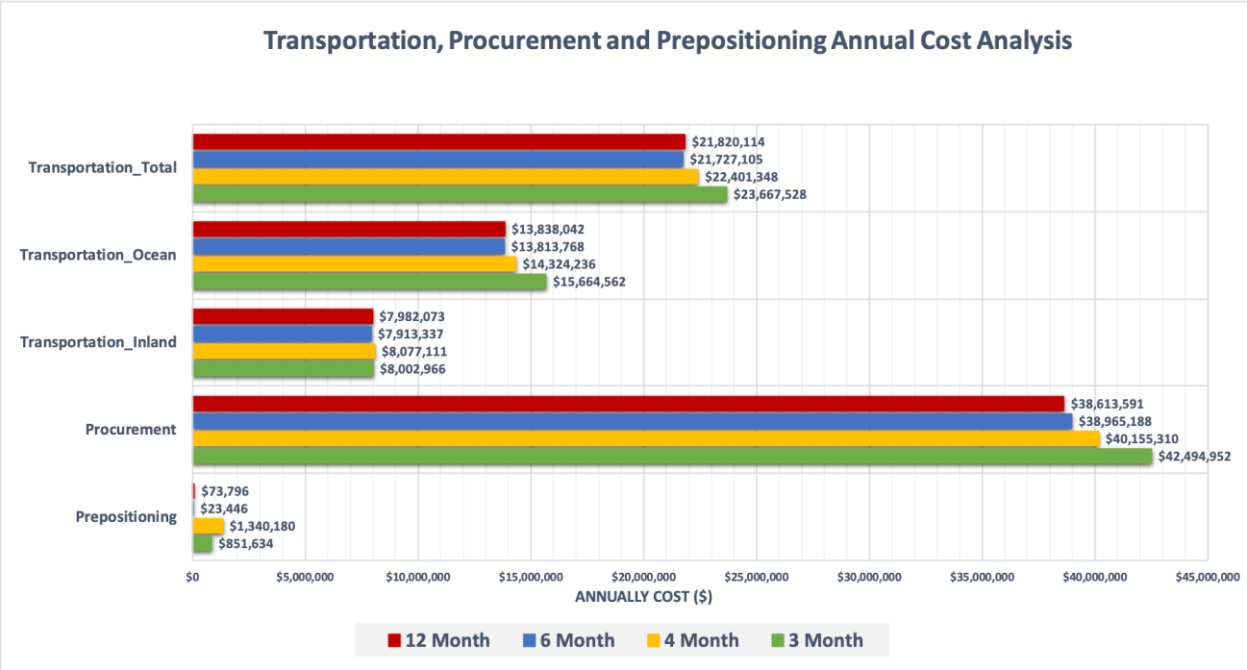
From a policy perspective, it can also be useful to identify the sources of cost savings associated with shifting from a 3-month PTH to a longer PTH. **Figure 9** reports costs for the one-year model simulation, and cost savings by comparing across PTHs, by cost categories – total transportation, its two components (ocean transport and overland transport), procurement, and prepositioning.

Overall and for all PTH scenarios, procurement costs are roughly double the costs associated with transportation. Therefore, it is no surprise that absolute savings associated with extending the PTH are greatest from fine-tuning the timing of procurement. There are potential savings in terms of transportation costs, but these savings are almost exclusively linked to ocean shipping – again, having the temporal flexibility to ship commodities when shipping rates are seasonally lower has the potential to bring about large savings.[8] Extending the PTH has essentially no effect on overland transportation costs in the geographic area captured by the model, since inland transportation in the current version of the DM is modeled at a very high-level spatial aggregation, and with essentially no capacity constraints and no seasonality in costs.[9] Finally, prepositioning costs are very small absolutely and especially relative to other cost categories, but these small outlays can generate both cost savings and improvements in on-time deliveries.

[8] The same may also be true for with-country ground transportation, especially in countries where road infrastructure suffers from seasonal breakdowns and when trucking services are in short supply. This will be especially true in countries with very high on-going and sudden-onset demand for food aid, the importation and movement of which may routinely require massive product transport efforts that stretch national resources very thinly. These details are not included in the current version of the DM, but they could easily be included if these data were available.

[9] Lower levels of spatial aggregation and in-land transportation capacity constraints could easily be included in the DM, if data were available.

Figure 9: Supply Chain Costs, by Cost Category (USD)



3.2. THE IMPACTS ON TOTAL SUPPLY CHAIN COSTS OF THE CARGO PREFERENCE ACT OF 1954

We now use the DM to address the issue of US-carrier flag rules in the context of each of the four PTHs. Again, the best strategy of initial inventory positioning for each PTH are chosen for examination. Simulations on five types of flag rule constraints are conducted: 100%, 75%, 50%, 25% and 0% minimum use of US-flagged carriers.[10] **Figure 10** reports the results for total global ocean shipping costs. In particular, the actual use of US-flagged carriers of 0% constraint scenarios varies between 19% and 12% for different PTH. Clearly, there are cost savings associated with reducing the amount of food aid that is required to be shipped by US-flagged carriers, regardless of the PTH scenario. The total annual cost savings associated with relaxing the 50% flag rule is approximately $1 million USD, regardless of the PTH. There are very large hypothetical cost reductions associated with moving from 100% to 50% implementation of the flag rule, but still significant cost reductions associated with moving below the current status quo 50% rule.

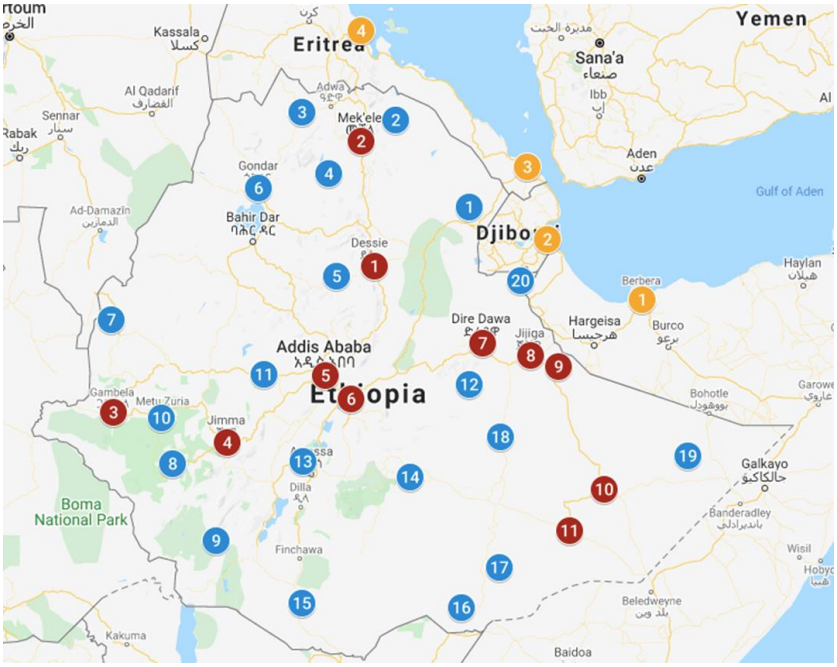
[10] In the current version of the model, this is not a carrier supply constraint issue. Rather, under some circumstances, US-flagged carriers are the most cost-effective option. That said, the model can be configured to use only a single carrier. When done this way, the supply of ships managed by this single carrier would dictate the period-specific shipping capacity constraints.

Figure 10: Ocean Shipping Costs, by Planning Time Horizon and by Degree of Adherence to the Prevailing P1 Flag Rule

3.3. THE IMPACTS ON COSTS OF EXPANDING THE PORT NETWORK IN THE HORN OF AFRICA

Ethiopia, one of the largest recipients of food assistance, is currently served by two ocean ports, Djibouti and Berbera. Since the peace accord was reached between Ethiopia and Eritrea, two additional ports (Assab and Massawa) could have been available with significant investments in infrastructure and management. Opening and using either or both of these ports would be costly, but may also be cost-effective, especially in meeting on-going food aid demand in northern Ethiopia. We used the DM to examine this issue.

Figure 11: Spatial Distribution of Ports in Ethiopia and Eritrea, and Delivery Points in Ethiopia



Key to figure: yellow = discharge port, red = extended delivery point, blue = final delivery point.

Figure 11 depicts the four candidate ports and all of the extended and final distribution points in Ethiopia; the DM contains estimated overland transportation times and costs associated with all of them. The question, then, is whether to open the two Eritrean ports and use them to redirect some of Ethiopia's food aid.

Table 1 reports the answer to that question in terms of cost savings (absolute and relative to the total cost of delivering one year's food aid to Ethiopia), by levels or relative costs of Djibouti versus the other three ports. Opening/using the two Eritrean ports did divert food aid shipments from the Djibouti port (thereby decreasing costs), however, even under circumstances of widely divergent handling costs, this choice never saves more than $2 million USD or roughly 3% of total cost.

Table 1: Savings Associated with Extending the Port Network in the Horn of Africa

HANDLING COSTS PER MT OF CARGO	COST SAVINGS	COST SAVINGS (%)
DJIBOUTI=0, OTHERS=0	$1.4M	2%
DJIBOUTI=$7, OTHERS=$3.5	$1.6M	2%
DJIBOUTI=$10.5, OTHERS=$3.5	$1.6M	2%
DJIBOUTI=$14, OTHERS=$3.5	$1.7M	3%
DJIBOUTI=$17.5, OTHERS=$3.5	$1.7M	3%
DJIBOUTI=$21, OTHERS=$3.5	$1.9M	3%

4. FORECASTABLE *AND* UNFORECASTABLE DEMAND: KEY RESULTS FROM SELECTED MODEL SIMULATIONS

We now use the DM to address issues associated with both on-going and sudden-onset demand for food aid products. We begin by using the model to identify the optimal set of USAID warehouses, when both costs and on-time delivery must be considered. Next, we use the DM to assess the effects of a large surge in sudden-onset demand in Ethiopia. Finally, we examine the effects of an important disruption in global supply chain – the unavailability of the Port of Mombasa.

4.1. ECONOMICALLY OPTIMAL LOCATIONS OF USAID WAREHOUSES

The locations and uses of warehouses for storing food aid products are continually discussed within USAID. Many options exist and choices must be made, and these choices will have cost and effectiveness implications. **Figure 12** provides a visual of the global set of candidate ports and

warehouses, and of the merged[11] demand sites. Which collection of ports and warehouses should be chosen in order to meet the on-going and sudden onset demands emerging from all demand sites (the green dots in **Figure 12**)? Intuitively, the answer will depend on the volume of on-going and sudden-onset demand and likelihood of sudden-onset demand emerging from each of the demand sites, the cost and capacities associated with the various candidate warehouses in the global system, and the urgency with which food aid needs are met. These are precisely the factors included in the DM.

Figure 12: Spatial Distribution of Candidate Ports and Warehouses, and Merged Demand Sites

There is no *single* answer to the above question. Depending on inventory holding/management costs[12] and the degree of urgency associated with meeting food aid needs, either no warehouses are needed at all, or, different warehouses or sets of warehouses are required. **Table 2** summarizes DM results on the economically optimal warehouses to be opened, at different levels of inventory costs and at different levels of urgency (as captured in the DM by penalties applied to the late-delivery of sudden-onset food aid products). The first row of **Table 2** (Base Case, brown row) reports warehouse needs associated with on-going demand *only* – if this very substantial demand can annually be forecasted (equivalent to assuming a 12 month PTH) with a good degree of accuracy by decision-

[11] Merged countries are collections of countries that have received relatively small average annual shipments of food aid products over the period 2011-2016.
[12] The inventory costs currently included in the model are those associated with moving food aid products from ports to warehouses and then to final destination points, and those associated with managing products in inventory (e.g., fumigation costs). However, other site-specific costs can be included in the model, including (e.g.) insurance costs and the transaction costs associated with opening and co-managing warehouse facilities. In some cases, these non-inventory costs may be very high, and therefore exclude sites from the set of economically optimal warehouse choices.

makers, it can always be met on-time, so no penalties apply in this case. At low inventory costs, the Mombasa warehouse is the only one in the global supply network that is opened. As inventory costs increase, no warehouses are needed at all to meet on-going demand in a timely way.

The results change markedly when sudden-onset demand (set of blue rows) is added to on-going demand. In only one case (low penalty for not meeting sudden-onset demand and high inventory cost) does the DM suggest that no warehouse be opened. As penalties rise and as inventory costs fall, more and different combinations of warehouses emerge as optimal choices. Generally, Mombasa is the first warehouse to open, followed by Djibouti, as urgency continues to rise and inventory costs continue to fall. Finally, under very high penalties for not completely meeting on-time delivery requirements, the Houston warehouse is opened.

Table 2: Economically Optimal Warehouse Choices, by Levels of Warehouse Costs and Late-delivery Penalties

		High Inventory Cost	Mid Inventory Cost	Low Inventory Cost
BASE CASE	No sudden-onset demand	none	none	M
Volume Scenario	Low Penalty (for sudden-onset demand)	none	M	M & D
Volume Scenario	Mid Penalty (for sudden-onset demand)	M	M	M & D
Volume Scenario	High Penalty (for sudden-onset demand)	M	M & D	M & D
Volume Scenario	Very high Penalty (for sudden-onset demand)	M & H	M & H	M & D & H

Key to Table: M = Mombasa, D = Djibouti, and H = Houston.

However, **Table 2**'s dichotomous reporting of which warehouses are open and under what circumstances masks important changes in the use of warehouses. For example, under the low-inventory cost scenario (far-right column) M&D appears for all but the last penalty scenario. Do the uses of Mombasa and Djibouti warehouses change as penalties for late delivery rise in this low-inventory-cost situation? Yes, and substantially. For example, average on-time delivery under the low-penalty scenario is ~35% with annual cost of inventory flowing through that warehouse of ~$478 million USD. If a mid-level penalty is applied, using the same warehouses on-time delivery *increases* to ~75% with total volume of ~$483 million USD – more, more expensive (fewer opportunities for tapping seasonal fluctuations in commodity prices and shipping costs are tapped), and differently-managed inventories allow for very significant improvements in on-time deliveries, but there are costs associated with these improvements in program effectiveness. Further increasing the

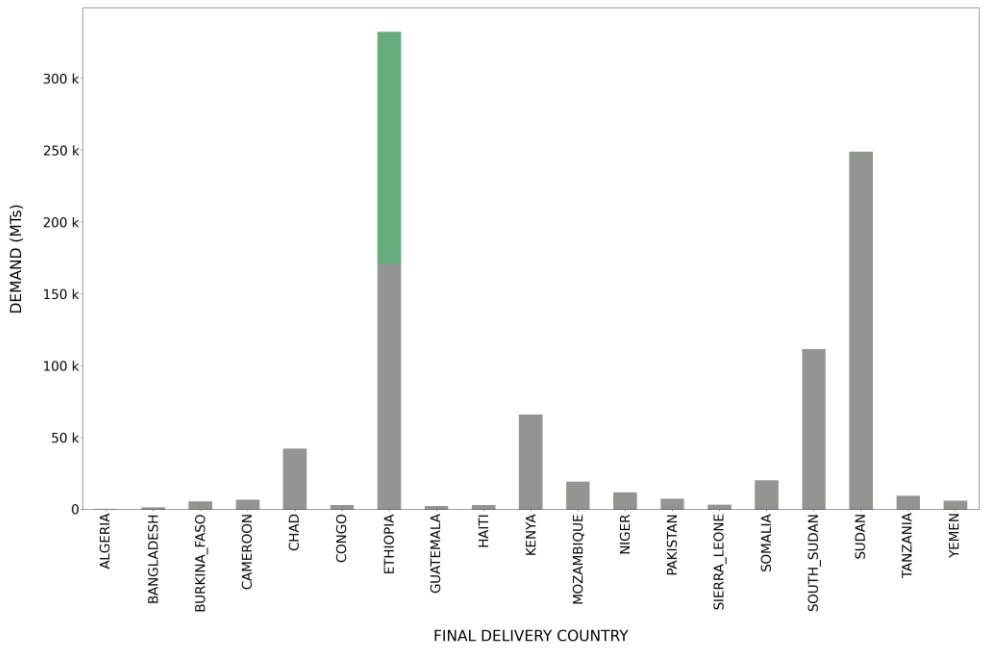
penalty to high-level improves on-time delivery to over 98%, but costs increase to $487 million USD – again, more and differently-managed inventories reach intended destinations on time. Finally, to guarantee 100% on-time delivery, the Houston warehouse is opened at a cost of $489 million USD.

4.2. RESPONDING TO VERY LARGE CHANGES IN UNFORECASTABLE DEMAND

One of the perennial challenges faced by USAID is responding to large sudden onset demand. This can arise from agroclimatic events (e.g., droughts), civil strife within countries, international disputes, etc., and the timing and magnitude of food aid needs associated with them are challenging to predict but nonetheless must be responded to. Moreover, these potential large unforecastable *changes* in sudden-onset demand need to be considered *alongside* all of the other potential sources and amounts of sudden-onset demand that form the underlying global food aid risk profile (NASEM 2020). The DM is designed to predict the impacts of such events (of any size, duration, or timing) on the structure of the supply chain (which collection of warehouses should be used) and its use (when to purchase products, and where to ship and store them). We use the DM to examine the risk of a major surge in Ethiopian sudden-onset demand together with the risk of the more widely distributed global high-, medium-, and low-sudden-onset demand.

Figure 13 depicts the simulated major increase in sudden-onset demand for Ethiopia (green bar) representing a roughly doubling of total food aid going to that country. Recall that this major surge in unforecastable food aid demand in Ethiopia is added to all of the other sources of unforecastable demand for global food aid.

Figure 13: Historical On-going Food Aid Demand and a Demand Surge in Ethiopia



The DM searches over all possible responses to this additional risk of a major increase in sudden-onset demand and identifies the most cost-effective collection of warehouses that should be opened to respond to it. As demonstrated above, the economically optimal set of warehouses will depend

on inventory costs and on the penalties assessed (within the DM) on late deliveries of food aid products. **Table 3** reports the results of this model simulation; the orange portion of the table identifies the economically optimal set of warehouses under different inventory cost and late-delivery penalties *without* the risk of Ethiopian demand surge, and the grey portion of Table 3 reports the optimal set of warehouses *with* the risk of demand surge, again under different inventory cost and penalty assumptions. Changes in warehouse selections associated with the sudden-onset demand surge appear in red. A clear set of patterns emerges. First, when inventory costs are high, inventories will be shifted from Mombasa to Djibouti. Second, at mid-level and low-level inventory costs, Djibouti is added to the regional warehouse network alongside Mombasa. Third, if late-delivery penalties are very high, then Djibouti is added alongside Mombasa and Houston in order to deal with the surge in sudden-onset demand in the timeliest manner (essentially guaranteeing 100% on-time delivery).

Table 3: Economically Optimal Warehouse Choices Given Surge in Ethiopian Sudden-onset Demand, by Levels of Inventory Costs and Late-delivery Penalties

		High Inventory Cost	Mid Inventory Cost	Low Inventory Cost
BASE CASE	No Sudden-onset Demand	none	none	M
Region 3-Scenario	**Low Penalty** (for sudden-onset demand)	none	M	M
Region 3-Scenario	**Mid Penalty** (for sudden -onset demand)	M	M	M & D
Region 3-Scenario	**High Penalty** (for sudden-onset demand)	M	M & D	M & D
Region 3-Scenario	**Very high Penalty** (for sudden-onset demand)	M & H	M & H	M & H
Region 4-Scenario	**Low Penalty** (for sudden-onset demand)	none	M	**M & D**
Region 4-Scenario	**Mid Penalty** (for sudden-onset demand)	**D**	M **& D**	M & D
Region 4-Scenario	**High Penalty** (for sudden-onset demand)	**D**	M & D	M & D
Region 4-Scenario	**Very high Penalty** (for sudden-onset demand)	**D** & H	**D &** M & H	**D &** M & H

Key to Table: M = Mombasa, D = Djibouti, and H = Houston.

4.3. RESPONDING TO DISRUPTIONS IN THE FOOD AID SUPPLY CHAIN

Another USAID concern is the structure of the global food aid supply chain – major changes in it can potentially compromise deliveries to an entire region, with human welfare consequences. The structure of the DM allows us to examine the consequences of disruptions in the supply chain and to identify cost-effective and timely ways to address them. In what follows, we examine the effects of the unavailability of the Mombasa warehouse and identify the economically optimal set of alternative warehouses that can be used, and the costs associated with these work-arounds.

Table 4 reports the economically optimal sets of warehouses with (orange) and without (green) the Mombasa warehouse, again under different warehouse cost and late-demand penalty situations. As noted earlier, when the Mombasa warehouse is available it appears in essentially every scenario; the lone exception if the high-cost/low-penalty situation, for which no warehouses are needed. Therefore, in virtually all of the baseline scenarios examined here, the Mombasa warehouse is pivotal. What happens if for some reason the Mombasa warehouse was not available? We put this question to the DM and the results are presented in the bottom (green) portion of **Table 4**. With Mombasa unavailable, Djibouti assumes a pivotal role in the region, with the (inland) Addis Ababa warehouse emerging as a cost-effective option if inventory costs are high and a mid-level late-

delivery penalty applies. Meeting on-time delivery is always possible, but the Houston warehouse plays a fundamental (and unique, under some inventory cost situations) role when late-delivery penalties are very high. If the Houston warehouse is not opened, sudden-onset demand in distant locations (such as Pakistan) cannot be satisfied on time. From a cost perspective, eliminating the Mombasa warehouse would increase expected total costs by up to $4 million USD.

Table 4: Economically Optimal Warehouse Choices *with* (orange) and *without* (green) the Mombasa Warehouse, by Levels of Inventory Costs and Late-delivery Penalties

	High Inventory Cost	Mid Inventory Cost	Low Inventory Cost
Low Penalty	none	M	M & D
Mid Penalty	M	M	M & D
High Penalty	M	M & D	M & D
Very High Penalty	M & H	M & H	M & D & H
Low Penalty	none	none	D
Mid Penalty	A	D	D
High Penalty	D	D	D & H
Very High Penalty	H	H	D & H

Key to Table: M = Mombasa, D = Djibouti, H = Houston, and A = Addis Ababa.

5. CONCLUSIONS AND THEIR IMPLICATIONS FOR PROGRAMMING

5.1. CONCLUSIONS

Given the volume and value of food aid provided to developing countries, even small changes in policies and practices can lead to large improvements in effectiveness and efficiency. Models such as the one presented here can be very useful in identifying *which* changes in policies and practices can be expected to generate the largest improvements in food aid supply chains in terms of cost-effectiveness and meeting food demands in a timely fashion.

Extending the planning time horizon and small investments in prepositioned products emerged from this analysis as very impactful candidate changes in policies and practices. For example, shifting from a 3-month planning time horizon (which roughly characterizes the current USAID *modus operandi*) to a 6-month planning time horizon could save up to approximately $6.3 million USD per year, and make supply chain operations much smoother and easier to manage. Relaxing the US Carrier Flag Rule has the potential to save another approximately $1 million USD per year.

Strategic use of prepositioned food aid products may increase costs but doing so can dramatically improve on-time delivery. For example, in one scenario outlined above, more, more expensive, and differently-managed inventories allowed on-time deliveries to improve from ~35% to ~75%; additional outlays of ~$5 million USD were required, but there are costs associated with these improvements in program effectiveness.

Some changes to the food aid supply chain should be avoided. For example, model simulations suggest that the unavailability of a Mombasa warehouse would increase total supply chain costs by over $4 million USD per year if on-time delivery were guaranteed by the more intensive use of other warehouses.

Other changes in the food aid supply chain may not be wise investments. For example, model results suggest that incorporating two Eritrean ports into the port network serving the Horn of Africa would generate only modest savings (~$1.5 million USD) and would not improve on-time deliveries.

The DM developed and discussed in the context of this Report, the details of which are reported in the technical Annexes, is not meant to *solve* any problem – no model ever is. Rather, the model is meant to enrich the evidence base available to decision-makers. What specifically can the supply chain optimization demonstration model do for USAID? Our response to that question is four-fold.

First, the DM can help put additional structure to the conceptual framework that already underlies USAID/BHA objectives and activities – how best to think about the competing objectives of efficiency and meeting the needs of food aid recipients in timely ways.

Second, the model can help inform discussions/decisions related to day-to-day operations and strategic investments, fine-tuning existing operations by providing answers to issues that may arise, including in the context of sudden-onset demand.

Third, USAID/BHA is not alone in determining which food aid products are shipped to which countries, and when. Bilateral discussions with countries play important roles in fine-tuning on-going and sudden-onset demand, and how and when that demand will be met. Moreover, these bilateral discussions change over time, as do the individuals participating in them. No model can include all of the details associated with these discussions or their effects on food aid decisions. However, the DM can identify efficient and effective supply chain management options that are *not* influenced by these bilateral discussions, and thereby provide an estimate of the efficiency and effectiveness losses associated with them. This information can be useful in managing bilateral discussions.

Finally, and perhaps most importantly, it can help USAID/BHA prepare for an increasingly needy, uncertain, and more volatile world. Climate change and civil unrest will likely increase the demand for, and the uncertainty associated with, food aid, and affect program costs. Moreover, disruptions in USAID global food aid supply chain (e.g., warehouse access) may be increasingly likely. How should USAID/BHA begin to prepare for this new world? Experiment. The demonstration model developed in the context of this project can be used to explore the impacts of increasing needs, uncertainty, and volatility (independently and jointly) on the costs and effectiveness of the current USAID food aid supply chain, and also provide insights into changes to the current supply chain that will make it

more effective and efficient. The model can also be used to assess the implications of supply chain disruptions and help to identify cost-effective work-arounds. One if its fundamental contributions will be found in the clustered results of many strategic simulations that help define a set of general food aid response contours – when particular sets of circumstances arise, the evidence base generated by these simulation results will provide guidance on what to do, and what to avoid, and estimates of the consequences of alternative choices in terms of their costs and the timeliness of food aid operations. No model can predict the future, but this model can examine the effects of alternative futures and thereby help USAID prepare for those that do emerge.

Every model has its strengths and its limitations; the supply chain optimization DM is no exception. The current version of the DM does not include, for example, an option for local and regional purchases of food aid – technically, it would not be challenging to include such options in the DM, but to our knowledge, the data (collected or modeled) are not currently available to do so. Related, the DM does not address general equilibrium effects of food aid, e.g., the impacts on market prices in receiving areas of the delivery of food aid products; if these effects are known and decision-makers wish to avoid them, constraints related to seasonal delivery of food aid products could be introduced into the model to accommodate these issues. Nor does the current version of the DM predict commodity prices.

The prices included in the model are based on historical price patterns (2011-2016); if future price patterns differ significantly from those of the relatively recent past (attributable, perhaps, to climate change or changes in the structure of industries along the supply chain), then the models' results and prescriptions may be somewhat less relevant. The current version of the DM contains the four most important commodities (by volume and by value) in the USAID portfolio of food aid products; more products could be added, thereby enriching the model. However, the products missing from the current model would have many of the same characteristics of those in the DM, so the patterns of DM simulation results would not be expected to change substantially. The model's current timeframe for analysis is 12 months; this could be expanded, but doing so would not change many results reported here. The model is not currently linked to real-time USAID or USDA data bases, and therefore at this time cannot be used to fine-tune daily food aid operation. That said, the model could be linked to these data sources and then used for such purposes. There are currently no push rules in the model that guarantee that commodities will be delivered by certain dates vis-à-vis their expiration or best-used-by dates; these rules could be easily introduced into the model, most likely in product-specific ways.

REFERENCES

Ahuja, K. R., Magnanti, L. T., & Orlin, B. J. (1993). *Network Flows: Theory, Algorithms, and Applications.* Englewood Cliffs, N.J. : Prentice Hall,.

Alexander, S., & Andy, P. (2007, March 21). *A Tutorial on Stochastic Programming.* Retrieved from isye.gatech.edu: https://www2.isye.gatech.edu/people/faculty/Alex_Shapiro/TutorialSP.pdf

Alvarenga, R., Ergun, O., Li, J., Mata, F., Shekhani, N., Slaton, D., . . . Vasudevan, A. ; Yang, E. (2010). *World Food Programme East African corridor optimization.* Atlanta, GA: Senior Design final report, H. Milton Stewart School of Industrial and Systems Engineering, Georgia Institute of Technology,.

Barret, C. B., & Maxwell, D. G. (2005). Food Aid After Fifty Years: Recasting Its Role. *London: Routledge.*

Barrett, C. B. (2017). *Testimony before the United States Senate Committee on Foreign Relations Hearing on "Modernizing the Food for Peace Program".*

Beamon, B., & Balcik, B. (2008). Performance measure in humanitarian relief chains. *International Journal of Public Sector Management*, 4-25.

Berling, M. J. (2016). Integrating supply chains for emergencies and ongoing operations in UNHCR. *Journal of Operations Management*, 57-72.

Bischi, A., Taccari, L., Martelli, E., Amaldi, E., Manzolini, G., Silva, P., . . . Macchi, E. (2019). A rolling-horizon optimization algorithm for the long term operational scheduling of cogeneration systems . *Energy, 184,*, pp. 73-90.

Cargo Preference Laws and Regulations. (2019, July 19). Retrieved from MARAD: https://www.maritime.dot.gov/cargo-preference/military-cargoes/cargo-preference-laws-and-regulations

Dimitris, B., & John, N. T. (1997). *Introduction to Linear Optimization.* Athena Scientific.

Duran S., E. Ö. (2013). *Humanitarian Logistics: Advanced Purchasing and Pre-Positioning of Relief Items. In: Bookbinder J. (eds) Handbook of Global Logistics. International Series in Operations Research & Management Science, vol 181.* New York, NY: Springer.

Duran, S., Gutierrez, A. M., & Keskinocak, P. (2011). Pre-Positioning of Emergency Items for CARE International. *INFORMS Journal on Applied Analytics*.

Ece, A., & Melih, Ç. (2019). Pre-positioning of relief items under road/facility vulnerability with concurrent restoration and relief transportation. *IISE Transactions*, 847-868.

Ergun, O., Keskinocak, P., & Swann, J. L. (2011). Introduction to the special issue on humanitarian applications: Doing good with good OR. *Interfaces, Informs 41(3)*, 215–222.

Ferrière, N., & Suwa-Eisenmannb, A. (2015). Does Food Aid Disrupt Local Food Market? Evidence from Rural Ethiopia. *World Development, Volume 76,*, Pages 114-131.

Gautam, Y. (2019). "Food aid is killing Himalayan farms". Debunking the false dependency narrative in Karnali, Nepal. *World Development, Volume 116*, Pages 54-65.

Google. (n.d.). *[Google Map of Ethiopia]*. Retrieved from May 25, 2019: https://goo.gl/maps/ToVp4WYhMW7K9drY6

Grossman-Cohen, B. (2012). *Saving Money and Lives: The Human Side of U.S. Food Aid Reform.* Oxfam America.

Habib, S. M., Lee, H. Y., & Memon, S. M. (2016). Mathematical Models in Humanitarian Supply Chain Management: A Systematic Literature Review. *Mathematical Problems in Engineering*, vol. 2016, Article ID 3212095, 20 pages,.

Jahre, M., Kembro, J., Rezvanian, T., Ergun, O., Håpnes, S. J., & Berling, P. (2016). Integrating Supply Chains for Emergencies and Ongoing Operations in UNHCR. *Journal of Operations Management, Volume 45,*, Pages 57-72.

Lantz, B. (2013). *Machine Learning with R.* Birmingham, UK: Packt Publishing.

Lentz, E. C., Passarelli, S., & Barrett, C. B. (2013). The timeliness and cost-effectiveness of the local and regional procurement of food aid. *World Development, 49 (C)*, pp. 9-18.

Melito, T. (2009). *Testimony Before the Subcommittee on Africa and Global Health, Committee on Foreign Affairs, House of Representatives Hearing on " International Food Aid : Local and Regional Procurement Provides Opportunities to Enhance*". U.S. GAO.

National Academies of Sciences, Engineering, and Medicine. 2020. *Strengthening Post-Hurricane Supply Chain Resilience: Observations from Hurricanes Harvey, Irma, and Maria.* Washington, DC: The National Academies Press. https://doi.org/10.17226/25490.

Nikulkov, A., Barrett, C. B., Mude, A. G., & Wein, L. M. (2016). Assessing the Impact of U.S. Food aid Delivery Policies on Child Mortality in Northern Kenya. *PLoS ONE 11(12): e0168432. doi:10.1371/journal.pone.0168432*.

Peters, K., Fleuren, H., den Hertog, D., Kavelj, M., Silva, S., Goncalves, R., . . . Soldner, M. (2016). "The Nutritious Supply Chain : Optimizing Humanitarian Food Aid,". *Tilburg: CentER, Center for Economic Research.*, (CentER Discussion Paper; Vol. 2016-044).

Research, I. f. (2020). *Mixed Integer Optimization.* Retrieved from ETH zurich institute of optimization: https://math.ethz.ch/ifor/research/mixed-integer-optimization.html

Ruttan, V. W. (1993). *Why Food Aid?* . Baltimore: John Hopkins University Press.

Sethi, S., & Sorger, G. (2011). A Theory of Rolling Horizon Decision Making. *Annals of Operations Research, Vol. 29, No. 1, December 2011*.

Shmueli, G., Bruce, P. C., & Patel, N. R. (2016). In *Data mining for business analytics: concepts, techniques, and applications in Microsoft Office with XLMiner(3rd ed.).* Hoboken, New Jersey: John Wiley & Sons.

Tasci, K. R., Talhouk, R., Ergun, O., Vosti, S., Walton, S., Webb, P., & Johnson, Q. (2019). *Analysis of Food Aid Supply Chain Data, April 2011- September 2016.* Boston,MA: Northeastern University .

UN. (2012, July). *Millennium Development Goals.* Retrieved from United Nations: wwww.un.org/millenniumgoals

USAID. (2013, March 27). *USAID*. Retrieved from USAID Web site: https://www.usaid.gov/what-we-do/agriculture-and-food-security/food-assistance/quick-facts/how-title-ii-food-aid-works

USAID- Agriculture and Food Security. (2018, July 31). Retrieved from USAID: https://www.usaid.gov/what-we-do/agriculture-and-food-security

Vielma, J. P. (2015). Mixed Integer Linear Programming Formulation Techniques. *SIAM Review*, 3-57.

Webb, P., Rogers, B., Rosenberg, I., Schlossman, N., Wanke, C., Bagriansky, J., . . . Narayan, A. (2011). *Delivering Improved Nutrition: Recommendations for Changes to U.S. Food Aid Products and Programs.* Boston, MA: Tufts University .

ANNEX 1: DATA PREPARATION

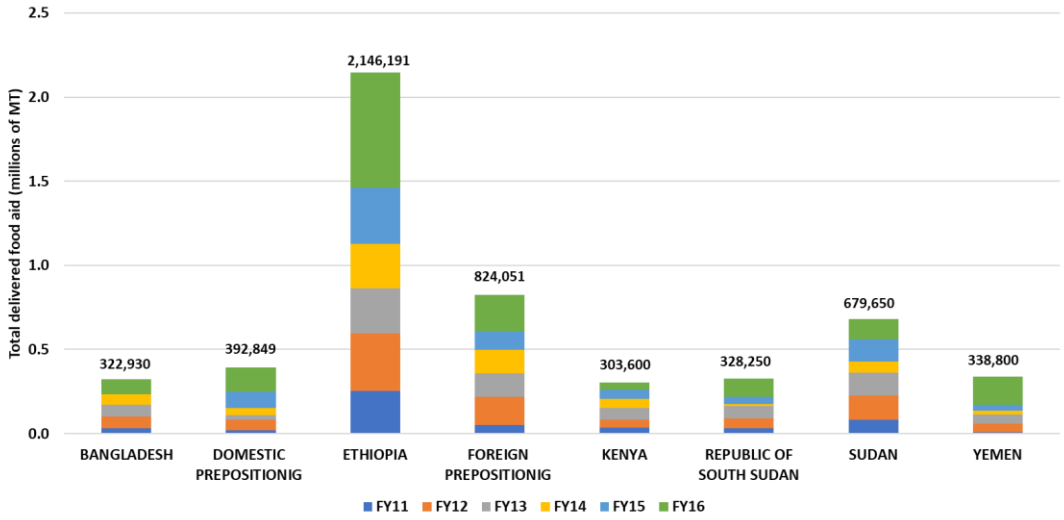
1.1. ETHIOPIA STUDY

In this study, we focus of our efforts geographically to the Somali region of Ethiopia and programmatically to packaged yellow split peas and justify these decisions. We then describe how these datasets were used to prepare the model parameters and decision variables that underpin the study's empirical scenarios.

1.1.1. COUNTRY, REGION, AND COMMODITY SELECTION

The USAID/FFP program, now BHA, delivered over 4.7 million tons of bulk commodities[13] (valued at over $1.2 billion USD) and approximately 2.2 million MT of packaged commodities[14] (valued at over $1.6 billion USD) to dozens of countries or regions within countries over the period 2011-2016. **Annex Figure 1** presents the total volume of food assistance delivered by USAID to all countries receiving over 300,000 MTs per year of assistance, for fiscal years 2011 through 2016.[15] Over two million MTs of food assistance were delivered to Ethiopia between April 2011 and September 2016, valued at more than $670 million USD. Approximately 85% of all foods, by volume, were commodities delivered in bulk form (e.g., sorghum and hard red winter wheat). The remaining approximately 15%, by volume, were packaged products including commodities (e.g., rice and whole/split peas), edible oils (delivered in cans), processed flours (e.g., corn/soy blends) and ready-to-use lipid-based food products.

Annex Figure 1: Volume of USAID/FFP Food Assistance Delivered to Major Recipient Countries, April 2011- September 2016, Metric Tons[16]



Source: USAID/FFP data; authors' calculations.

[13] These bulk commodities were primarily wheat and sorghum.
[14] These packaged products include an array of commodities, e.g., yellow split peas and rice, and other foods or food products, e.g., cooking oil, ready-to-use foods (RUF).
[15] The fiscal year for the U.S. government runs from October 1 through September 30.
[16] A figure depicting the total value of food assistance delivered to recipient countries would look very similar.

We chose to focus our initial modeling efforts on Ethiopia; even small efficiency gains for the largest recipient country could translate into significant overall savings. We further narrowed the geographic focus of our modeling efforts to Ethiopia's Somali region, a major recipient region, the supply chain within which was managed by large humanitarian agencies and collaborators.

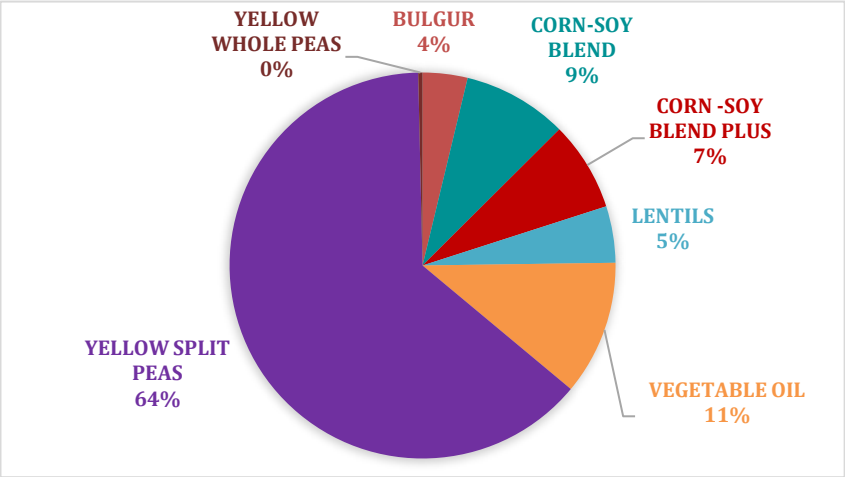
Annex Figure 2: In-country Food Assistance Distribution Network, Somali Region, Ethiopia

Source: In-country USAID partners' distribution facility location data.

The Somali region is supplied via two international ports (Djibouti and Berbera, Somalia), one international warehouse in Djibouti, four extended delivery points, and 46 final delivery points.

Over the 2011-2016 period, ten different food assistance products were delivered to Ethiopia. As noted earlier, bulk products such as wheat and sorghum represent the majority (in terms of volume and value) of the products delivered, but only a small proportion of these bulk products are prepositioned or stored in international warehouses; hence the supply chains for these products are more direct. Therefore, we chose to focus on packaged products (some of which included food commodities). **Annex Figure 3** presents the relative importance of the leading packaged foods provided to Ethiopia. Note the prominence of yellow split peas (YSP); over 165,000 MT were delivered to Ethiopia over the 2011-2016 period.

Annex Figure 3: Packaged Commodities Delivered to Ethiopia, April 2011- September 2016



Source: USAID data; authors' calculations.

For analytical purposes, then, we further narrowed our analysis to YSP, which were by far the most commonly requested commodity by Ethiopia in every fiscal year examined in this study, were heavily used in food assistance operations in a wide variety of developing countries and were prepositioned by USAID every fiscal year examined in this study. Moreover, YSP are always delivered as a packaged commodity and therefore are representative in terms of handling and storage of the 48 of the 58 commodities we analyzed in the USAID/FFP historical data. Finally, historical data indicate that YSP are available year-round in U.S. commodity markets, though procurement costs vary seasonally (Tasci, et al., 2019).

1.1.2. DATA DESCRIPTION AND PREPARATION FOR MODEL INPUT

Commodity procurement and ocean transportation data for the period between April 2011 and September 2016 were received from USAID and USDA. Partner organizations provided in-country distribution data. These datasets are used to create scenarios as inputs into the supply chain optimization demonstration model. During the input data preparation process, if historical data were incomplete or not available, predictive models, discussed in the following sections, were used to estimate required parameters. Throughout this report, the volume for YSP is given in metric tons (MT), cost currency is USD, and time is measured in days.

1.1.3. SUPPLY DATA PREPARATION

All YSP suppliers from which at least one procurement was made and shipped to discharge ports near Ethiopia over the 2011-2016 period were identified. The total supplied amount of YSP provided by supplier *i*, in month *m,* during fiscal year *y* ($\boldsymbol{supplied_{imy}}$) (see **Annex Table 1**) was calculated. The maximum of these values over the 2011-2016 period was set as the supply capacity for supplier *i* and month *m* ($\boldsymbol{capacity_{im}}$) (see **Annex Table 2**) for all months within the model.

In the USAID/FFP operational structure, once a purchase is made, the commodity supplier is responsible for delivery to a U.S. warehouse, trans-loading facility, or loading port; hence, the cost

and lead time of procurement includes cost and lead time for the U.S. inland transportation. We follow this structure and calculate a cost and a lead time[17] for each Month-Supplier-Loading Port (MSL), Month-Supplier, and U.S. Warehouse (MSUW) triplet.

To estimate the lead time to deliver YSP from a supplier *i* in month *m* to a loading port *j* ($\boldsymbol{leadtime_{ijm}}$) (see **Annex Table 2**), all historical lead times corresponding to the given (*i,j,m)* triplet over all the fiscal years in historical USAID data were averaged. This averaged value then is set as the model parameter $leadtime_{\boldsymbol{ijm}}$. To calculate the cost of procuring and delivering 1 MT of YSP from supplier *i* to loading port *j* in month *m* ($\boldsymbol{cost_{ijm}}$), we first calculated the overall average cost ($\boldsymbol{c_{ij}}$) (see Table 1) for a given supplier *i* and loading port *j* pair for YSP from the historical data. Then, monthly seasonality factors in the unit cost ($\boldsymbol{ysp\_seasonality_{\mathrm{m}}}$) (see **Annex Table 1**) of procurement and transportation to a loading port of YSP were calculated, again using the entire historical data series. Finally, the average unit cost for a given a Supplier-Loading Port pair ($\boldsymbol{c_{ij}}$) was multiplied by the cost seasonality factor ($\boldsymbol{ysp\_seasonality_{\mathrm{m}}}$) to determine the monthly procurement cost ($\boldsymbol{cost_{ijm}}$) (see **Annex Table 2**). Similar calculations were performed for procurement and transportation costs and lead times of YSP when the destination of the commodity was a U.S. Warehouse.

The following definitions, sets, and equations report the details associated with available YSP supply data and how they were used to estimate the parameters included in the optimization model.

Sets used to build input data for Ethiopia optimization model:

$\boldsymbol{M}$ = Set of months

$\boldsymbol{Y}$ = Set of fiscal years

$\boldsymbol{S}$ = Set of yellow split pea suppliers

$\boldsymbol{L}$ = Set of loading ports

$\boldsymbol{UW}$ = Set of warehouses located in U.S. soil

$\boldsymbol{D}$ = Set of discharge ports

$\boldsymbol{FDP}$ = Set of final delivery points

$\boldsymbol{S}$ = Set of suppliers

$\boldsymbol{F}$ = Set of flag types

[17] Lead time is the time interval from the beginning to the completion of an activity.

Annex Table 1: Calculated parameters from USAID data

$\boldsymbol{supplied_{imy}}$ = Total metric tons of yellow split peas sent from supplier *i* at month *m* in fiscal year *y*. $i \in S,\ m \in M$,and y$\in Y$.
$\boldsymbol{C_{ij}}$ = Average cost of transporting 1 MT of yellow split peas between *i* and *j*. $i \in S, j \in L \cup UW$
$\boldsymbol{ysp\_seasonality_m}$ **=** Procurement cost seasonality factor of yellow split peas at month *m*

Annex Table 2: Estimated parameters for Ethiopia optimization model

$\boldsymbol{capacity_{im}} = max(\boldsymbol{supplied_{imy}})\ for\ \forall i,m\ \ i \in S\ and\ \ m \in M$
$\boldsymbol{cost_{ijm}} = C_{ij} \times ysp\_seasonality_m\ \ for\ \forall\ i,j,m\ \ i \in S, j \in\ L \cup UW\ and\ \ m \in M$
$\boldsymbol{leadtime_{ijm}}$ = Average time for supplying yellow split peas from supplier $i \in S$ to loading port $j\ \in\ L \cup UW$ by starting at month *m*.

1.1.4. OCEAN SHIPPING

Ocean transportation parameters are also based on historical data provided by USAID and USDA. Month of the year, loading port, discharge port, vessel vendor, vessel type, and flag type are the attributes used to derive cost, lead-time, and capacity parameters included in the model. YSP delivered to Ethiopia are only transported by liner vessels; hence only liner vessel types were considered in this study. Cost, lead-time, and capacity parameters are calculated for each Month-Loading port-Discharge port-Vessel vendor-Flag type (MLDVF) quintuple.

More specifically, the average cost of shipping 1 MT cargo ($\boldsymbol{cost_{ldvf}}$) (see **Annex Table 3**) from loading port *l* to discharge port *d* via vessel vendor *v* with flag type *f* is calculated over all historically available data for a given *l, d, v, f* quadruple. Ocean transportation cost seasonality factors ($\boldsymbol{ocean\_seasonality_{mf}}$) (see **Annex Table 3**) for each month *m* are calculated for each flag type *f*. Finally, to calculate the final ocean transportation cost for shipping 1 MT cargo from loading port *l* to discharge port *j* via vessel vendor *v* with flag type *f* in month *m* ($\boldsymbol{cost_{mldvf}}$) (see **Annex Table 4**), we multiply the average cost ($\boldsymbol{cost_{ldvf}}$) (see **Annex Table 3**) by the seasonality factor for month *m* and flag type *f* ($\boldsymbol{ocean\_seasonality_{mf}}$).

The lead-time of shipping cargo from loading port *l* to discharge port *d* via vessel vendor *v* under flag type *f* in month *m* ($\boldsymbol{oceantime_{mldvf}}$) (see **Annex Table 4**) is assumed to be equal to the average of lead-times over ($\boldsymbol{lt_{mldvf}}$)(see **Annex Table 3**) all the years in historical data. If the data set has no shipment in a given month *m*, the lead-times over all *ldvf* quadruples are averaged ($\boldsymbol{lt_{mldf}}$)(see **Annex Table 3**) and assumed to be the lead-time for that month.

To determine the ocean transportation capacity between loading port *l* to discharge port *d* via vessel vendor *v* under flag type *f* for any month *m* ($\boldsymbol{capacity_{ldvf}}$) (see table 4), the total quantity of YSP supplied to Ethiopia for all *ldvf* quadruples for each month *m* overall fiscal years *y* ($\boldsymbol{A_{mldvfy}}$) (see **Annex Table 3**) is calculated and the largest value over the 2011-2016 period is taken as the maximum capacity for vendor *v* in route from loading port *l* to discharge port *d* under flag rule *f* for all months.

The following definitions, sets, and equations report the details associated with available YSP ocean shipping data and how they were used to estimate the economic optimization parameters.

Annex Table 3: Calculated parameters for Ethiopia optimization model

$\boldsymbol{A_{mldvfy}}$ = At month *m*, total transported MTs of yellow split peas from loading port *l* to discharge port *d* by vendor *v*, under flag type *f* in fiscal year *y*.
$\boldsymbol{cost_{ldvf}}$= Average cost of transporting 1 MT of any commodity from loading port *l* to discharge port *d* by vendor *v* under flag rule *f*.
$\boldsymbol{ocean\_seasonality_{mf}}$ = Ocean transportation cost seasonality factor is calculated under flag type *f* for month *m*
$\boldsymbol{lt_{mldvf}}$ = Average time required to transport any commodity from loading port *l* to discharge port *d* under flag type *f* for all vessel vendors for month *m*
$\boldsymbol{lt_{ldvf}}$ = Average time required to transport any commodity from loading port *l* to discharge port *d* under flag type *f* for vessel vendor v

Annex Table 4: Estimated parameters for Ethiopia optimization model

$\boldsymbol{capacity_{ldvf}} = \boldsymbol{max}\,(\boldsymbol{A_{mldvfy}})\ for\ \forall\ l, d, v, f\ \ l \in L, \quad d \in D, v \in V, \quad f \in F$
$\boldsymbol{cost_{mldvf}} = \boldsymbol{cost_{ldvf}} \times \boldsymbol{ocean\_seasonality_{mf}}$
$\boldsymbol{oceantime_{mldvf}} = \begin{cases} \boldsymbol{lt_{mldvf}}\ , & \boldsymbol{if\ \ there\ is\ historical\ shipment\ in\ month\ m} \\ \boldsymbol{lt_{ldvf}}\ , & \boldsymbol{else} \end{cases}$

1.1.5. INLAND TRANSPORTATION AND DISTRIBUTION POINTS

After commodities arrive at a given discharge port (DP), they are transported to either an international USAID warehouse (IWH) or an extended delivery point (EDP). EDP locations in this study are chosen to be the regional warehouses that are operated by USAID partner organizations in Ethiopia (see **Annex Figure 2**), and all EDP locations are assumed to be able to hold inventory. We further assume that the inventory holding capacity of all EDPs are sufficient for all of the scenarios we consider.

For each inland transportation link (DP-EDP, DP-IWH, IWH-EDP, EDP-FDP), we determine lead-times and unit costs per MT. These parameters are estimated using a mix of partner data and actual distance data gathered from Google-maps (Google, Google Maps Ethiopia, 2019).

P-value sections in **Annex Table 5, Annex Table 6, Annex Table 16, Annex Table 17, Annex Table 18** and **Annex Table 19** show the predictive power of each attribute on the model. The lower the P-value gets, the attribute becomes unlikely to be unrelated to the outcome attribute. R^2 value defines how well a model as a whole explains the values of dependent attributes. The closer the R^2 value is to 1.0 , the better the model perfectly explains the data. (Lantz, 2013, p. 183).

First, we find the lead time for each origin-destination pair:

> *Predicted lead time = intercept + coefficient*distance between location pairs with* $R^2 = 0.61$ *p-value: 2.793e-15*

Table 5 : Coefficients and P-values of predicted lead time model for inland transportation

	Coefficient	P-Value
Intercept	11.81	8.8e-06
Distance between location pairs	0.00257	0.00243

After estimating lead-times for all pairs, a neural network model and a multiple regression model were built and trained by distance and estimated lead time attributes to predict transportation unit costs. The multiple linear regression approach provided the least prediction error.

After adding the predicted lead time attribute to the data, we built a multiple linear regression model for cost estimation:

> *Predicted cost = intercept + coefficient*distance between location pairs + coefficient * predicted lead time with* $R^2 = 0.92$ *p-value: 2.793e-15*

Annex Table 6: Coefficients and P-values of predicted lead time model inland transportation

	Coefficient	P-Value
Intercept	16.952970	0.344
Distance between location pairs	0.055045	7.72e-08

Estimated lead time	-0.445691	0.748

Due to the lack of available historical data, seasonality factors for inland transportation costs could not be included in this study.

1.1.6. STORAGE AND HANDLING

A single, month-specific value for average cost per MT for combined handling and storage parameters for international and U.S. warehouses was derived from limited prepositioning data provided by USAID.[18]

1.1.7. DEMAND FOR YSP

We could determine the total amount of YSP delivered to Ethiopia's Somali region each month ($A_{Ethiopia,m}$) (see **Annex Table 7**) from historical USAID/FFP datasets. However, based on these datasets alone, we could not determine *how* or *when* this commodity was distributed across the various FDPs within the Somali Region. Therefore, monthly demand for YSP by each FDP was estimated based on USAID and partner organization data.

More specifically, while we do not know the number of beneficiaries served by each FDP, we do have some information regarding the amounts and timing of YSP deliveries to them each month over the past several years by all providers of food assistance (i.e., including non-USAID food assistance sources). We used these datasets first to calculate the total amount of YSP delivered to each final delivery point *j* from the partner's distribution data for *all* YSP regardless of source. Then, we calculated the percentage of all YSP shipped to Ethiopia that were ultimately delivered to each FDP (U_j) (see **Annex Table 7**). Therefore, the demand for YSP by FDP *j* in month *m* ($demand_{jm}$) (see **Annex Table 8**) is the percentage share of FDP *j* ($percentage_j$) (see **Annex Table 7**) multiplied by the average amount of YSP delivered from U.S. suppliers to Ethiopia at month *m-3* ($A_{Ethiopia,(m-3)}$).

Finally, regarding lead-time (the time between placing an order for YSP and expected arrival of the product at the FDP), conversations with USAID/FFP and in-country partners suggested that under current operational practices, lead-time is approximately three months.

Annex Table 7: Calculated metrics from USAID and partners' data for Ethiopia optimization model

U_j = Total distributed amount of YSP, by FDP *j*. $j \in FDP$.
$percentage_j$= Share of FDP *j* in overall Ethiopian demand. $percentage_j = \frac{U_j}{\sum_j Uj} \times 100, f\ or\ \forall\ j, j \in FDP$

[18] Capacity of USAID warehouses were set based on informal recommendations from USAID and was assumed to be sufficient to store all of the prepositioned product envisioned in the scenarios modeled here. Handling costs at all port facilities are equal and set to zero for this set of simulations.

$\boldsymbol{A_{Ethiopia,m}}$ = Average amount of YSP procured for Ethiopia in month *m*.

Annex Table 8: Estimated parameters for Ethiopia optimization model

$$\boldsymbol{demand_{jm}} = A_{Ethiopia,(m-3)} \times percentage_j \; for \; \forall j, m, m \in M, j \in FDP$$

1.2. WAREHOUSE STUDY

1.2.1. CANDIDATE WAREHOUSE LOCATION SET

This study considers 17 different locations globally, two on U.S. soil and 15 on international soil, to open warehouses for food assistance. The candidate warehouse location set is built by considering USAID's current and former warehouse locations as well as the Office of Foreign Disaster Assistance (OFDA) and United Nations Humanitarian Response Depot (UNHRD) recent warehouse locations. Also, Addis Ababa (Ethiopia) is added as the only candidate inland warehouse location because Ethiopia, Sudan, and South Sudan are the countries that received significant food assistance from USAID (Tasci, et al., 2019).

Annex Figure 4 shows the set of possible candidate locations by identifying the owning organization.[19] All locations shown in **Annex Figure 4**, except Addis Ababa represented by a purple circle in the map, are accepted to open in the same area as the international ports.[20] In the rest of the study, these ports are named as warehouse related ports.

Annex Figure 4: Candidate Warehouse Location Set for USAID In-Kind Food Assistance

[19] Where USAID and another agency has/had a warehouse in the same location, we mark that location as USAID's.
[20] Ports are always open. To open or close a connected warehouse does not affect the status of the port.

Annex Table 9 presents a list of all candidate warehouse locations and warehouse related ports they are linked.

Annex Table 9: Candidate Warehouse Locations and Related Ports

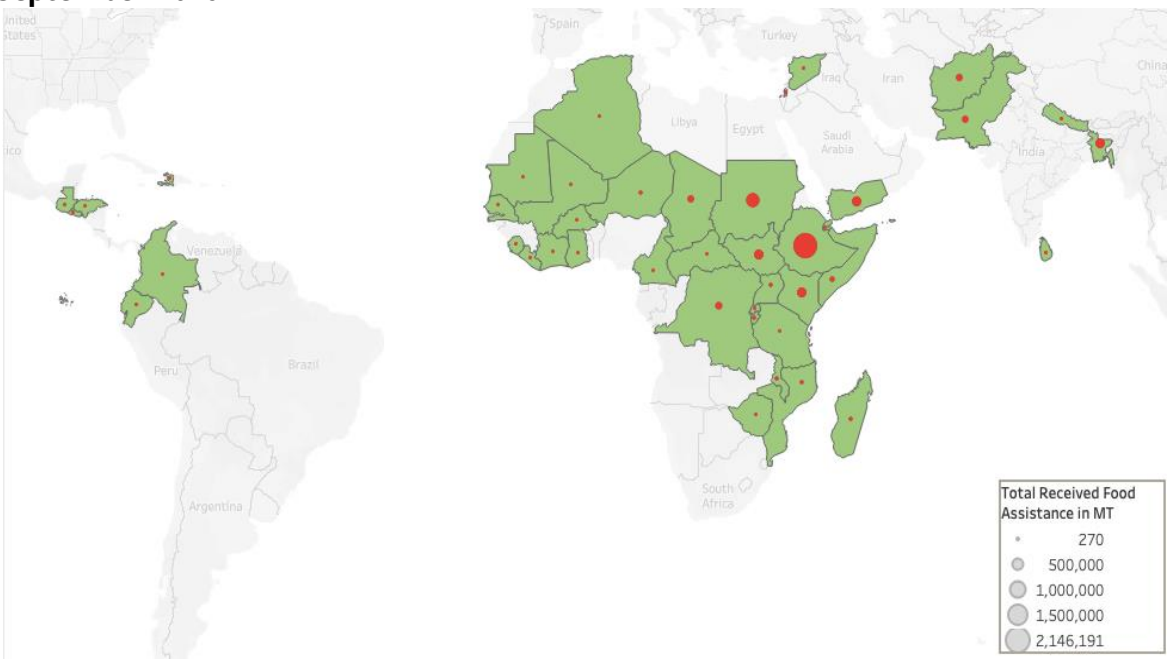
Located Country	Candidate Warehouse Location Name	Warehouse Related Port
US	Houston	Port of Houston
US	Miami	Port of Miami
South Africa	Durban	Port of Durban
Malaysia	Tanjung Pelepas	Port of Tanjung Pelepas
		Port of Singapore
Sri Lanka	Colombo	Port of Colombo
Kenya	Mombasa	Port of Mombasa
Togo	Lome	Port of Lome
Canary Island	Las Palmas	Port of Las Palmas
Italy	Brindisi	Port of Brindisi
Ghana	Accra	Port of Tema
Panama	Panama	Port of Balboa
Malaysia	Kuala Lumpur	Port of Klang
Italy	Pisa	Port of Livorno
Indonesia	Subang	Port of Tanjung Priok
Ethiopia	Addis	Port of Djibouti
UAE	Dubai	Port of Dubai

1.2.2. MERGING FINAL DELIVERY COUNTRIES

In this study, receiver countries are mapped as the final delivery points (FDPs). Some countries merged based on their geographical closeness, total received food volume, food variety, and food assistance receiving frequency. These countries received food assistance from USAID in-kind food

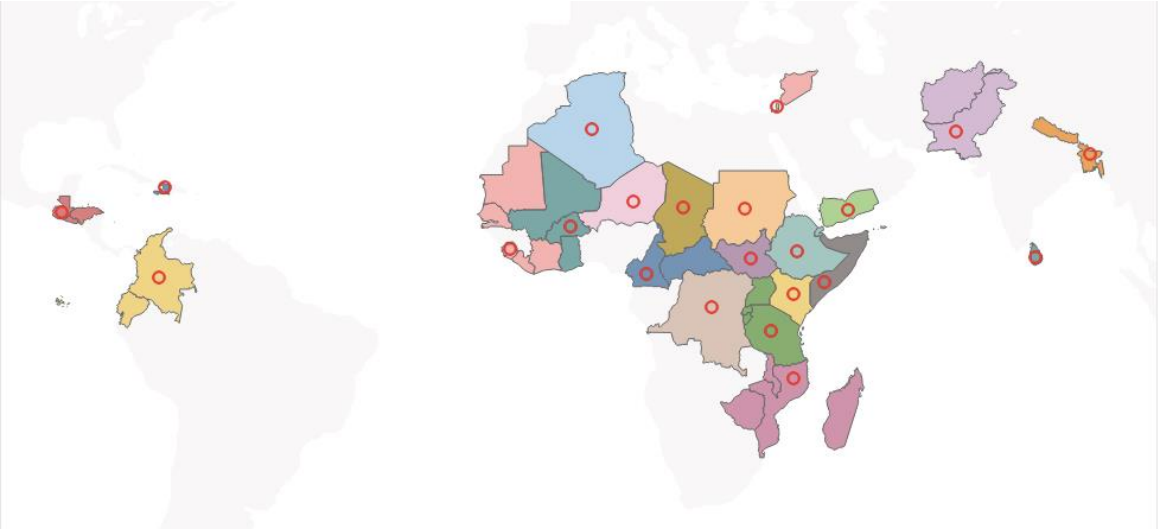
assistance at least one time between 2011-2016. The red dots on the countries shows the total volume of received food assistance.

Annex Figure 5: Countries who Received USAID/FFP Food Assistance, April 2011 - September 2016



All countries in **Annex Figure 5** are colored in **Annex Figure 6** based on their merging group. The red circle in each group indicates the representative country of the group. Generally, a few minor recipient neighbors are merged, or a minor country is added to its prominent recipient neighbor. The number of the countries decreased to half without missing any impactful detail. Even though Afghanistan and Pakistan are not minor countries in terms of volume of received food assistance, we merged them under Pakistan because of the similarities they bring into the operational system.

Annex Figure 6: Merged Country Groups and Representative Country



Annex Table 10 lists the merged country group and representative country for each group presented in **Annex Figure 6.**

Annex Table 10: Merged Counties and Chosen FDP Country

FDP COUNTRY NAME	MERGED COUNTRIES
ALGERIA	ALGERIA
BANGLADESH	BANGLADESH, NEPAL
BURKINA FASO	MALI, BURKINA FASO, GHANA
CAMEROON	CAMEROON, CENTRAL AFRICAN REP
CHAD	CHAD
CONGO	CONGO
ETHIOPIA	ETHIOPIA, DJIBOUTI
GAZA	SYRIA, GAZA
GUATEMALA	EL SALVADOR, HONDURAS, GUATEMALA
COLOMBIA	COLOMBIA, ECUADOR
HAITI	HAITI
KENYA	KENYA
MOZAMBIQUE	MOZAMBIQUE, ZIMBABWE, MADAGASCAR, MALAWI

NIGER	NIGER
PAKISTAN	AFGHANISTAN, PAKISTAN
SIERRA LEONE	MAURITANIA, SENEGAL, SIERRA LEONE, LIBERIA, IVORY COAST
SOMALIA	SOMALIA
SOUTH SUDAN	SOUTH SUDAN
SRI LANKA	SRI LANKA
SUDAN	SUDAN
TANZANIA	UGANDA, RWANDA, BURUNDI, TANZANIA
YEMEN	YEMEN

1.2.3. MERGING PORTS

1.2.3.1. MERGING U.S. LOADING PORTS

In historical data, loading ports used in the U.S. are recorded as loading points. We find the loading port, located city, and state for each loading point by checking World Port Source Website.[21] **Annex Figure 7** shows the loading ports located in cities based on the historical USAID data set. The U.S. loading ports are merged based on their geographical closeness and frequency of use.

The same-colored cities in **Annex Figure 7** are represented by one loading port in the study. Dark blue spots are merged under Port of Portland, orange spots are Port of Houston, green spots are Port of South Louisiana, purple spot is Miami, light blue spots are Port of Norfolk, red spots are Port of New York, and yellow spots are Port of Chicago. The gray point in the California region is ignored because California ports are used seldom.

[21] http://www.worldportsource.com/states.php World Port Source website gives information about all the ports around the world.

Annex Figure 7: U.S. Loading Port Cities from Historical USAID Data[22]

Annex Table 11 shows the U.S. ports' names recorded in the historical data, the ports' known name, located cities and states, and the port name they merged under in a list. Port cities in **Annex Table 11** are presented as colorful dots in **Annex Figure 7**.

Annex Table 11: List of U.S. Loading Ports from Historical Data with Related Information and The Representative Ports for Each

Representative Port Name	Port Name	Port City	Port State	Loading Port Name from Historical Data
Port of Chicago	Port of Chicago	Chicago	IL	BCHI-CHICAGO, IL
	Port of Chicago	Chicago	IL	L-LCHI-ALL-CHICAGO IL-BID POINT
Port of Houston	Port of Beaumont	Beaumont	TX	G-BEAU-ALL-BEAUMONT TX-BID POINT
	Port of Beaumont	Beaumont	TX	G-BEAU-LDC-BEAUMONT TX
	Port of Corpus Christi	Corpus Christi	TX	G-CC-ADM-CORPU CHRISTI TX

[22] Since California ports are rarely used in historical data, they are not involved in the global network.

	Port of Corpus Christi	Corpus Christi	TX	G-CC-ALL-CORPUS CHRISTI TX-BID POIN
	Port of Corpus Christi	Corpus Christi	TX	G-CC-INTER-CORPUS CHRISTI TX
	Port of Galveston	Galveston	TX	G-GALV-ADM-GALVESTON TX
	Port of Houston	Houston	TX	G-HOUS-BCC-BHOU-HOUSTON, TX
	Port of Houston	Houston	TX	G-HOUS-BCC-COOPER/T SMITH (AP MOELL
	Port of Houston	Houston	TX	G-HOUS-BCS-RHPP-PORT PACKAGING, TX
	Port of Houston	Houston	TX	G-HOUS-CAR-CARGILL-HOUSTON TX
	Port of Houston	Houston	TX	G-HOUS-HPP-PORT PACKAGING LLC
	Port of Houston	Houston	TX	G-HOUS-LDC-HOUSTON TX
	Port of Houston	Houston	TX	G-HOUS-MAN-AGRI-GULF LOGISTICS TX
	Port of Houston	Houston	TX	G-HOUS-PCW-GULF WINDS-PORT CROSSING
	Port of Houston	Houston	TX	G-HOUS-POA-PORTS AMERICA TEXAS WARE
	Port of Houston	Houston	TX	G-HOUS-SHI-SHIPPERS STEVEDORES TX
	Port of Houston	Houston	TX	G-HOUS-WSE-SHIPPERS STEVEDORES TX
	Port of Jacintoport	Houston	TX	G-JACI-ALL-JACINTO TX-BID POINT
Port of Miami	Port of Jacksonville	Jacksonville	FL	E-JACK-ALL-JACKSONVILLE FL-BID PT

Port of New York	Port of New York	New York	NEW YORK	E-NY-ALL-NEW YORK-NO FAS-BID PT
	Port of New York	New York	NEW YORK	E-NY-NEW YORK NY (NO FAS)
	Port of Elizabeth	Cumberland	NJ	E-PE-ALL-PORT ELIZABETH NJ-NO FAS-B
	Port of Newark	Newark	NJ	E-PNEW-ALL-NEWARK NJ-NO FAS-BID PT
Port of Norfolk	Port of Savannah	Savannah	GA	E-SAVA-ALL-SAVANNAH GA-NO FAS-BID P
	Port of Charleston	Charleston	SC	E-CHAR-ALL-CHARLESTON SC-NO FAS-BID
	Port of Norfolk	Norfolk	VA	E-NORF-ALL-NORFOLK VA-BID POINT
	Port of Norfolk	Norfolk	VA	E-NORF-NORFOLK VA
Port of Portland	Port of Portland	Portland	OR	W-PORO-COL-COLUMBIA GRAIN-PORTLAND
	Port of Portland	Portland	OR	W-PORO-IRV-TEMCO-IRVING-PORTLAND OR
	Port of Portland	Portland	OR	W-PORO-ODK-LDC-O DOCK-PORTLAND OR
	Port of Kalama	Kalama	WA	W-KALA-KEC-KALAMA EXPORT-KALAMA WA
	Port of Kalama	Kalama	WA	W-KALA-TEMCO-KALAMA WA
	Port of Seattle	Seattle	WA	W-SEAT-ALL-SEATTLE WA-BID POINT
	Port of Tacoma	Tacoma	WA	W-TACO-TACOMA WA
	Port of Vancouver	Vancouver	WA	W-VANC-UGC-UNITED GRAIN-VANCOUVER W

Port of South Louisiana	Port of Mobile	Mobile	AL	G-MOBI-ALL-MOBILE AL-NO FAS-BID PT
	Port of Lake Charles	Lake Charles	LA	G-LC-ALL-LAKE CHARLES LA-BID POINT
	Port of South Louisiana	Louisiana	LA	G-NO-AMA-A-ADM-AMA LA
	Port of South Louisiana	Darrow	LA	G-NO-DRW-DARROW LA
	Port of South Louisiana	Destrehan	LA	G-NO-DST-A-ADM-DESTREHAN LA
	Port of South Louisiana	Avondale	LA	G-NO-IMTAV-IMTT-AVONDALE LA
	Port of South Louisiana	St. Rose	LA	G-NO-IMTSR-IMTT-ST ROSE LA
	Port of South Louisiana	Myrtle Grove	LA	G-NO-MGR-C-CHS-MYRTLE GROVE LA
	Port of South Louisiana	Reserve	LA	G-NO-RSV-C-CARGILL-RESERVE LA
	Port of South Louisiana	Westwego	LA	G-NO-WTW-C-CARGILL-WESTWEGO LA
Not Included[23]	Port of Long Beach	Long Beach	CA	BLB-LONG BEACH, CA
	Port of Long Beach	Long Beach	CA	W-SNPD-ALL-SAN PEDRO CA-NO FAS-BID

1.2.3.1. MERGING INTERNATIONAL PORTS

There are 47 different international ports listed in USAID historical data. After merging countries, we merged some of these ports based on the countries they served, the frequency of appearing in historical data, volume of the cargo passed through, and necessity in the current global warehouse study network.

[23] Since CA ports are used only a few times in 5.5 years data, we do not include them into the network.

1.2.4. COMMODITY SELECTION

Commodity focus is extended from single commodity to multiple commodities in this study. Even though the procured volume of bulk commodities is significantly higher than packaged commodities, the variety of packaged commodities was remarkably much more in the 2011-2016 period. Yellow split peas in 50kg bag (YSP), vegetable oil 6/4 L can (OIL), corn-soy blend plus 25 kg HP bag (CSB+), sorghum bulk (SGM) are stated as impactful commodities in terms of large procurement quantity, price seasonality and involving broad country nutrition profile (Tasci, et al., 2019).

DATA PREPARATION FOR THE OPTIMIZATION MODEL

1.2.5. SUPPLY DATA PREPARATION

Supply data preparation is done for each commodity *k* separately but with the same methodology. First, all suppliers for commodity *k* over the 2011-2016 period were identified. The total supplied amount of commodity *k* provided by supplier *i* in month *m* during fiscal year y ($\boldsymbol{supplied_{kimy}}$) see **Annex Table 12**) was calculated. The maximum of these values over the 2011-2016 period was set as the supply capacity of commodity *k* for supplier *i* and month *m* ($\boldsymbol{capacity_{kim}}$) (see **Annex Table 13**), for all months within the model.

To estimate the lead time to deliver commodity *k* from a supplier *i* in month *m* to loading port *j* all historical lead times corresponding to the given *(k,i,j,m)* quadruple over all the fiscal years in historical USAID data were averaged. This averaged value is set as the model parameter $\boldsymbol{leadtime_{kijm}}$ (see **Annex Table 13**). To calculate the cost of procuring and delivering 1 MT of commodity *k* from supplier *i* to loading port *j* in month *m* ($\boldsymbol{cost_{kijm}}$), we first calculated the overall average cost ($\boldsymbol{av\_cost_{kij}}$) (see **Annex Table 12**) for a given supplier *i* and loading port *j* pair for commodity *k* from the historical data. Then, monthly seasonality factors in the unit cost ($\boldsymbol{k\_seasonality_{\mathrm{m}}}$) (see **Annex Table 12**) of procurement and transportation to a loading port of the commodity *k* were calculated, again using the entire historical data series. Finally, the average unit cost for a given a supplier-loading port pair ($\boldsymbol{av\_cost_{kij}}$) (see **Annex Table 12**) was multiplied by the cost seasonality factor ($\boldsymbol{k\_seasonality_{\mathrm{m}}}$) to determine the monthly procurement cost ($\boldsymbol{cost_{kijm}}$) (see **Annex Table 13**). Similar calculations were performed for procurement and transportation costs and lead times of commodity *k* when the commodity's destination was a U.S. Warehouse.

The following definitions, sets, and equations report the details associated with available commodity supply data for each commodity and how they were used to estimate the optimization model's parameters.

Sets used to build input data for global warehouse optimization model:

$\boldsymbol{K}$ = Set of commodities

$\boldsymbol{M}$ = Set of months

$\boldsymbol{Y}$ = Set of fiscal years

$\boldsymbol{L}$ = Set of loading ports

$\boldsymbol{UW}$ = Set of warehouses located in U.S. soil

$\boldsymbol{D}$ = Set of discharge ports

$\boldsymbol{FDP}$ = Set of final delivery points

$\boldsymbol{S}$ = Set of suppliers

$\boldsymbol{F}$ = Set of flag types

$\boldsymbol{W}$ = Set of candidate warehouse locations

$\boldsymbol{T}$ = Set of vessel types

Annex Table 12: Calculated metrics for USAID data for global warehouse optimization model

$\boldsymbol{supplied_{kmiy}}$ = Total metric tons of commodity *k* sent from supplier *i* at month *m* in fiscal year *y*. $k \in K$, $i \in S$, $m \in M$, and $y \in Y$.
$\boldsymbol{av\_cost_{kij}}$ = Average cost of transporting 1 MT of commodity *k* between *i* and *j*. $k \in K$, $i \in S$, $j \in L \cup UW$
$\boldsymbol{k\_seasonality_{km}}$ = Procurement cost seasonality factor of commodity *k* at month *m*.

Annex Table 13 : Estimated parameters for global warehouse optimization model

$\boldsymbol{capacity_{kim}} = max\left(\boldsymbol{supplied_{kmiy}}\right) for\ \forall k, i, m\ k \in K, i \in S\ and\ m \in M$
$\boldsymbol{cost_{kijm}} = \boldsymbol{av_{cost_{kij}}} \times \boldsymbol{k\_seasonality_{km}}\ for\ \forall\ k, i, j\ \ k \in K, i \in S, m \in M$ $and\ j \in L \cup UW$
$\boldsymbol{leadtime_{kijm}}$ = Required time for supplying commodity *k* from supplier $i \in S$ to loading port $j \in L \cup UW$ by starting at month *m*.

1.2.6. OCEAN SHIPPING

Ocean shipping data preparation is divided into two major parts in this study. The first part includes the data related to ocean shipments from a U.S. loading port to any discharge port located on foreign soil. The second part covers ocean shipment data from a global discharge port that is also a candidate location for a warehouse. Port handling capacity is ignored in this study, while port handling costs are differ based on various scenarios analyzed.

1.2.6.1. OCEAN SHIPMENT FROM U.S. TO FOREIGN SOIL (TRANSPORTATION LINKS THAT WERE USED HISTORICALLY)

There are seven U.S. loading ports considered in this study, and we assumed that U.S. ports only could be used as loading ports because of the nature of in-kind food assistance. Another assumption

about U.S. ports is that they all have ocean shipment links to each discharge port in the study. We used the methods explained in the following to set cost, lead time, and capacity parameters for existing links.

Port related parameters, including cost, lead-time, and capacity, are calculated as a function of month of the year, loading port, discharge port, vessel vendor, vessel type,[24] and flag type. Cost, lead-time, and capacity parameters are calculated for each Month-Loading port- Discharge port-Vessel vendor-Vessel Type -Flag type (MLDVTF) sextuple.

More specifically, the average cost of shipping 1 MT cargo ($av\_ost_{\boldsymbol{ldvtf}}$) (see **Annex Table 14**) from loading port *l* to discharge port *d* via vessel vendor *v* with vessel type *t* under flag type *f is calculated* over all historically available data for a given *l, d, v, t, f* quintuple. Cost seasonality factor of ocean transportation ($ocean\_seasonality_{\boldsymbol{mf}}$) (see **Annex Table 14**) for each month *m* are calculated for each flag type *f*. Finally, to calculate the final ocean transportation cost for shipping 1 MT cargo from loading port *i* to discharge port *j* via vessel vendor *v* with vessel type *t* under flag type *f* in month *m* ($cost_{\boldsymbol{mldvtf}}$) (see **Annex Table 15**) we multiply the average cost ($cost_{\boldsymbol{ldvtf}}$) by the seasonality factor for month *m* and flag type *f* ($ocean\_seasonality_{\boldsymbol{mf}}$).

The lead-time of shipping cargo from loading port *l* to discharge port *d* via vessel vendor *v* with vessel type *t* under flag type *f* in month *m* ($leadtime_{mldvtf}$) (see **Annex Table 15**) is assumed to be equal to the average lead-time overall observed historical data with the same attributes ($\boldsymbol{lt_{mldvtf}}$) (see **Annex Table 14**). If the data set has no shipment in a given month *m*, the lead-times over all *ldvtf* quintuples are averaged ($\boldsymbol{lt_{mldvtf}}$) (see **Table 14**) and assumed to be the lead-time for that month.

To determine the ocean transportation capacity between loading port *l* to discharge port *d* via vessel vendor *v* with vessel type *t* under flag type *f* for any month ($capacity_{\boldsymbol{ldvtf}}$) (see **Annex Table 15**), the total cargo for all *ldvtf* quintuples for each month *m* overall fiscal years *y* ($\boldsymbol{A_{mldvtfy}}$) (see **Annex Table 14**) is calculated and the largest value over the 2011-2016 period is taken as the maximum capacity for vendor *v* in route from loading port *l* to discharge port *d* with vessel type *t* under flag rule *f* for all months. In other words, we choose the maximum amount of cargo delivered by vendor *v* from U.S. port *p* to international port *j* with flag type *f* and vessel type *t* in a month for commodity *k*. Because if a vendor could do this once, we assume that that vendor has capacity for a given route under given conditions.

The following definitions, sets, and equations report the details of available ocean shipping data and how they were used to estimate the economic optimization model's parameters.

Annex Table 14: Calculated metrics for USAID data for warehouse location optimization model

$\boldsymbol{A_{mldvtfy}}$ = At month *m*, total transported metric tons of cargo from loading port *l* to discharge port *d* by vendor *v, with vessel type t,* under flag type *f* in fiscal year *y*.

[24] Bulk commodities are delivered via bunker type vessels, while packaged commodities delivered via liner type vessels.**Invalid source specified.**

$\boldsymbol{av\_cost_{ldvtf}}$= Average cost of transporting 1 MT of cargo from port *l* to port *d* by vendor *v* with vessel type *t* under flag rule *f*.
$\boldsymbol{ocean\_seasonality_{mf}}$ = Ocean transportation cost seasonality factor calculated for flag type *f* and month *m*
$\boldsymbol{lt_{mldvtf}}$ = Average time required to transport any commodity from loading port *l* to discharge port *d* starting in month *m* under flag type *f* for vessel vendor *v* with vessel type *t*.
$\boldsymbol{lt_{ldvtf}}$ = Average time required to transport any commodity from loading port *l* to discharge port *d* under flag type *f* for vessel vendor *v* with vessel type *t*.

Annex Table 15: Estimated parameters for warehouse location optimization model

$\boldsymbol{capacity_{ldvtf}} = \boldsymbol{max}\,(\boldsymbol{A_{mldvtfy}})\ for\ \forall\ l,d,v,t,f\ \ l \in L, d \in D, v \in V, t \in T\ \ f \in F$
$\boldsymbol{cost_{mldvtf}} = \boldsymbol{av\_cost_{ldvtf}} \times \boldsymbol{ocean\_seasonality_{mf}}$
$\boldsymbol{leadtime_{mldvtf}} = \begin{cases} \boldsymbol{lt_{ldvtf}}, & \boldsymbol{if\ there\ is\ no\ historical\ shipment\ at\ month\ m} \\ \boldsymbol{lt_{mldvtf}}, & \boldsymbol{else} \end{cases}$

1.2.6.2. OCEAN SHIPMENTS BETWEEN U.S. LOADING PORTS – DISCHARGE PORTS - (TRANSPORTATION LINKS THAT WERE NOT USED HISTORICALLY)

Adding new candidate warehouse locations and assuming all loading ports are connected to all discharge ports in the network required the creation of ocean links from U.S. loading ports to discharge ports that were not present in the historical data sets.

For these new ocean transportation options, capacity, cost, and lead time parameters had to be estimated for each Month-Loading port- Discharge port- Vessel Type -Flag type (MLDTF) quintuple.

The ocean transportation capacity between loading port *l* to discharge port *d* with vessel type *t* under flag type *f* for any month($capacity_{\boldsymbol{ldtf}}$) is set as maximum of all existing ocean transportation capacity ($\boldsymbol{max}\ capacity_{\boldsymbol{ldvtf}}\ \boldsymbol{for}\ \forall\ l,d,v,t,f\ \ l \in L,\ d \in D, v \in V, t \in T, f \in F$).

We used prediction models to estimate cost and lead time for the new ocean links between U.S. loading ports and discharge ports. Since the attributes from historical data are limited for the prediction model, we included a new attribute, the distance between loading-discharge port pairs[25]

[25] Always the shortest route is chosen as sea distance for pairs.

(sea distance). The sea distance attribute's values are calculated via the Sea Distance Website (https://sea-distances.org) for existing and new links.

Additionally, we included loading port, bulker vessel type, and U.S. flag type binary variables in our prediction model. We needed a training data set to teach or train the predictive model to capture the relationship between predictive attributes and outcome attributes (Shmueli, Bruce, & Patel, 2016, p. 20). Our finalized training data set consists of the following predictive attributes: sea distance, capacity, U.S. flag type[26], bulker vessel type, port of Chicago, port of Houston, Port of Norfolk, Port of New York, port of Portland, port of Louisiana.[27]

We examine several prediction algorithms, including regression trees, and multiple linear regression, to determine the model that provides the lowest error[28] to find lead time and cost data for new links between the U.S. loading ports and discharge ports. After reviewing the results, we decided to continue with the multiple linear regression method because of the training data set limitations and prediction accuracy. We used a backward elimination algorithm[29] to select significant attributes to calculate lead time values and arrived at the below-finalized model.

In this and following section, the R^2 values presented at the end of the model show how well the models explain the data, and global P-values give the likelihood of rejecting the relation between predictor attributes and the outcome attribute for the given model. The presented R^2 values are generally low, but the values can be increased by adding more insightful attributes to the data.[30]

*Predicted lead time = intercept + coefficient*sea distance + coefficient*bulker vessel type + coefficient* Port of New York + coefficient*Port of Norfolk, with* $R^2 = 0.13$ p-value: 3.304e-10

The presented R^2 in the predicted lead time model is very low; the model only covers 13% of the data variation. Not having enough data to build and observe logical relations between given attributes are the likely causes of this poor prediction. Even though the R^2 is low, the global p-value shows it is unlikely to reject the relation between predictive attributes and the lead time attribute.

Annex Table 16: Coefficients and P-values of predicted lead time model for ocean links between U.S. loading ports and discharge ports

	Coefficient	P-Value
Intercept	16.5385905	<2e-16

[26] All attributes except capacity and sea distance are binary. If they are equal to 1, it means the attribute is used; else, it is not used.
[27] When all of them are zero, it means that the cargo is loaded from port of Miami.
[28] Root mean square error rates are compared and the best model is chosen. Validations are done with randomly selected subset of the training data,
[29] In the backward elimination algorithm, first, all attributes are included in the model, and in each step, the algorithm eliminates the least useful attribute for prediction. The algorithm stops when all remaining attributes have a significant effect on the predictive model (Shmueli, Bruce, & Patel, 2016, p. 150).
[30] Please note that port merging process, not having vessel company names, and not having comprehensive data can cause low R^2 values.

Bulker Vessel Type	-3.4801051	3.23e-08
Port of New York	2.41592270	0.0337
Port of Norfolk	1.4060935	0.0641
Sea distance	0.0002332	0.0443

After adding predicted lead-times as a predictive attribute for new ocean links between U.S. port and international port data, we developed a new multiple linear regression model with a backward elimination algorithm to predict cost parameters for these links.

> Predicted *ocean shipping cost=intercept + coefficient*sea distance + coefficient*bulker vessel type + coefficient* U.S. flag type + coefficient* Port of Chicago + coefficient*Port of New York + coefficient*Port of Portland with* $R^2 = 0.35$) p-value < 2.2. e-16

The presented R^2 in the predicted ocean shipping cost model covers 35% of the data variations; however, we cannot reject the relation between predictive attributes and the ocean shipping cost attribute based on the given global low p-value.

Annex Table 17: Coefficients and P-values of predicted ocean shipping cost model for ocean links between U.S. loading ports and discharge ports

	Coefficient	P-value
Intercept	204.407444	<2e-16
Bulker Vessel Type	-69.741348	<2e-16
U.S. Flag Type	71.293432	<2e-16
Port of Chicago	22.057447	0.06807
Port of New York	36.283578	0.01035
Port of Portland	-28.512287	0.09233
Sea Distance	0.004084	0.00503

The predicted ocean shipping cost formula estimates the cost of transporting 1 MT cargo from loading port *l* to discharge port *d* with vessel type *t* under flag type *f* ($cost_{ldtf}$). Finally, to calculate the final ocean transportation cost for each Month-Loading port- Discharge port - Vessel Type -Flag type quintuple ($cost_{mldtf}$), we multiply the average cost ($cost_{ldtf}$) by the seasonality factor for month *m* and flag type *f* ($ocean\_seasonality_{mf}$).

1.2.6.3. NEW OCEAN LINKS BETWEEN INTERNATIONAL PORTS LOCATED AT POTENTIAL WAREHOUSE LOCATIONS AND DISCHARGE PORTS

We assume that all ports that are at potential warehouse locations can deliver commodities to any discharge port in the global network. Capacity, lead time, and ocean shipping cost values for all links between ports at potential warehouse locations and discharge ports are estimated because we did not have any historical shipment record from international soil to international soil. The previous section's training data set and output data set are combined to provide a larger data set for training. We only use the international flag vessel type subset of the combined data for training purposes because the Cargo preference rule does not apply for foreign soil shipment to foreign soil.

The ocean transportation capacity between international port *l* to discharge port *d* with vessel type *t* under international flag for any month is set as maximum of all existing ocean transportation capacity($\boldsymbol{max}\ capacity_{\boldsymbol{ldvtf}}\ \boldsymbol{for}\ \forall\ l, d, v, t, f\quad l \in L,\ d \in D, v \in V, t \in T, f \in F$).

In the rest of this section, ports at potential warehouse locations are considered as loading ports[31] as well as discharge ports. Sea distance,[32] bulker vessel type, and capacity were the attributes we considered for our initial prediction model. Loading ports are not used as attributes in these prediction models because they do not have a previous reference for supervised learning techniques. Similar methods as in the previous section were tried, and as before, multiple linear regression method with backward elimination algorithm was chosen as it gave the best fit to the training data.

First, we find the lead time for each origin-destination pair:

> *Predicted lead time = intercept + coefficient*sea distance + coefficient*bulker vessel type with Adjusted* $R^2 = 0.14$ *p-value: 2.793e-15*

The presented R^2 value shows that the model above only covers 14% of the data variation; this value can be increased by adding more attributes to the data or providing a more extensive training data set to the model. The global p-value shows these predictive attributes are related to the lead time attributes.

Annex Table 18: Coefficients and P-values of predicted lead time model for new ocean links between international ports located at potential warehouse locations and discharge ports

	Coefficient	P-value
Intercept	17.8856839	<2e-16
Sea distance	0.0001717	0.0447

[31] All warehouse related ports located outside of the U.S. are always considered as discharge ports. These warehouse-related ports are considered loading ports and discharge ports because of the global network's nature.
[32] Sea distance attribute is calculated from the same website (Sea-Distance.Org, n.d.).

Bulker Vessel type	-4.1203077	5e-16

After estimating the lead time attribute values, we add the lead time attribute to the training data set. We built another multiple linear regression model to predict the cost of delivering 1 MT of cargo from loading port *l* to discharge port *d* with vessel type under international flag rule ($cost_{\boldsymbol{ldt,international}}$):

*Predicted ocean shipping cost=intercept + coefficient*sea distance + coefficient*bulker vessel type + coefficient*estimated lead time, with* $R^2 = 0.42$ p-value < 2.2. e-16

The presented R^2 value in the ocean shipping cost model above covers 42% of the data variation; this value can be increased by adding more attributes to the data or providing a more extensive training data set to the model. The global p-value proves that given predictive attributes are related to the lead time attributes.

Annex Table 19: Coefficients and P-values of predicted ocean shipping cost model for new ocean links between international ports located at potential warehouse locations and discharge ports

	Coefficient	P-value
Intercept	198.040659	<2e-*16*
Sea Distance	-0.004487	1.09e-07
Bulker Vessel type	-68.327016	<2e-*16*
Estimated Lead Time	0.834479	0.076

Finally, to calculate the final ocean transportation cost for shipping 1 MT cargo from warehouse related international port *l* to discharge port *d* with vessel type *t* under international flag type in month *m* ($cost_{\boldsymbol{mldt,international}}$), we multiply the average cost ($cost_{\boldsymbol{ldt}}$)[33] by the seasonality factor for month *m* and international flag type *f* ($ocean\_seasonality_{\boldsymbol{m,international}}$). Even though we do not have historical data for these new ocean links between international ports located at potential warehouse locations and discharge ports, we used the seasonality cost factor calculated from USAID historical data.

[33] Please note that the model only predicts one general value for a origin-destination pair.

1.2.7. INLAND TRANSPORTATION

After commodities arrive at a given discharge port (DP), they are transported to either a USAID warehouse (WH) or a final delivery point (FDP) in this study. A single FDP location is chosen for each country or a group of merged countries.

For each inland transportation link between discharge port-final delivery point pairs (DP-FDP) and USAID warehouses-final delivery point pairs (WH-FDP), we determine lead-times and unit costs per MT by using the linear regressions presented in Annex 1.1.5. Ethiopia Study Inland Transportation and Distribution Point. Required actual distance data for origin-destination pairs are calculated from Google-maps (Google , 2020).

We assume no additional transportation cost between a warehouse and warehouse related port. Inland transportation costs between Djibouti port-Addis Ababa warehouse location pair and Port of Singapore-Tanjung Pelepas[34] warehouse is calculated as described above.

1.2.8. WAREHOUSE OPENING, STORAGE, AND HANDLING COST

USAID provided historic data on warehouse capacity in MT, capacity unit cost per MT, handling cost per MT, and annual warehouse opening cost data for Houston, Durban, Djibouti, and Tanjung Pelepas locations. We used given warehouses' data to estimate the rest.

All datasets from the Houston warehouse location is assumed to be the same for candidate Miami warehouse. Warehouse capacity ($\boldsymbol{wh\_capacity_w}$) of the rest is set to the average warehouse capacity of the given warehouses. Capacity unit cost[35] ($\boldsymbol{cap\_unit_w}$) is calculated by dividing opening cost by warehouse capacity for data-given warehouses. For the warehouses located in the same country with data-given warehouses, capacity unit costs are assumed to be the same as the data-given warehouses. For the warehouses located in Africa, the averaged capacity unit cost of Djibouti and Durban are set. Averaged capacity unit cost of four data-given warehouses is set as capacity unit cost for other warehouses. The opening cost of each warehouse ($\boldsymbol{open\_cost_w}$) is calculated by multiplying warehouse capacity ($\boldsymbol{wh\_capacity_w}$) and capacity unit cost ($\boldsymbol{cap\_unit_w}$). Additionally, warehouse handling cost[36] ($\boldsymbol{handling\_cost_w}$) is accepted as the same for the warehouses located in the same country. Durban and Djibouti's average handling cost is set as handling cost for the warehouses located in Africa. The average handling cost of four data-given warehouses is set for the rest. We assumed that warehouses and port handling capacity are enough for all operations and set to a single significant number.

[34] All candidate warehouse locations, except Tanjung Pelepas, are only linked to the port they are built in. Tanjung Pelepas can receive cargo from Port of Singapore and Port of Tanjung Pelepas.
[35] Opening cost for 1 MT of space in a warehouse.
[36] USAID states that given handling cost per MT includes drayage from port to warehouse, unload railcar/container, fumigation, daily storage, load container/truck, drayage from warehouse to port services.

Annex Table 20: Opening Cost, Capacity, Handling Cost of Each Candidate Warehouse Location.

Candidate Warehouse Name	Capacity in MT	Opening Cost (USD)	Warehouse Handling Cost per MT (USD)
Addis Ababa	20,000	1,567,498.87	25.22
Panama	20,000	1,464,400.00	31.59
Brindisi	20,000	1,464,400.00	31.59
Colombo	20,000	1,464,400.00	31.59
Djibouti	27,500	2,045,916.00	19.75
Dubai	20,000	1,464,400.00	31.59
Durban	17,000	1,400,000.00	30.69
Houston	27,000	3,000,000.00	58.60
Kuala Lumpur	20,000	1,464,400.00	31.59
Las Palmas	20,000	1,464,400.00	31.59
Pisa	20,000	1,464,400.00	31.59
Lome	20,000	1,567,400.00	25.22
Miami	27,000	3,000,000.00	58.60
Mombasa	20,000	1,567,498.87	25.22
Tanjung Pelepas	12,000	300,000.00	17.31
Subang	20,000	500,000.00	17.31
Tema	20,000	1,567,400.00	25.22

1.2.9. DEMAND PREPARATION

1.2.9.1. ON-GOING DEMAND FOR EACH COMMODITY BY FINAL DELIVERY POINT

Since we do not know the number of beneficiaries represented by each FDP location, we used historical USAID procurement data through 2011- 2016 to estimate on-going monthly demand for each commodity at each FDP location. First, we used these datasets to calculate the total amount of

procured commodity *k* and total supplied amount of commodity *k* to each FDP. Then, we calculated the percentage of all procured commodity *k* that were ultimately delivered to each FDP. We averaged the total procured amount of commodity *k* at month *m* over the 2011-2016 period. Therefore, the demand for commodity by FDP x in month m is the percentage share of FDP x multiplied by the average procured amount of commodity k from U.S. suppliers at month m+3.[37]

$$demand\ for\ commodity\ (k)\ at\ FDP\ (x)\ in\ month\ (m) = \%\ share * average\ procured\ commodity\ (k)\ at\ month\ (m+3)$$

1.2.9.2. SUDDEN-ONSET DEMAND

Sudden-onset demand data was produced based on the on-going demand dataset. A set of candidates of the maximum amount of demand for each period of each final delivery country were generated, opposed to using the average amount across the period 2011-2016. The following two risk profile datasets have been built based on the candidate set: volume-based scenarios and region-based scenarios.

Data 1: Volume-Based Scenarios Risk Profile

1. Take the on-going demand dataset and pick the maximum volume over the years for each commodity and each country of each period to generate a set of one-year range demand.
2. Assign weights to the log of demand volume, while the sum of all weights is 100%.
3. Randomly choose three sub-datasets from the above as sudden-onset demand for three scenarios:

    Scenario 1: sum (weights) = 20%, total demand volume: 379,320 MTs

    Scenario 2: sum (weights) = 15%, total demand volume: 276,900 MTs

    Scenario 3: sum (weights) = 10%, total demand volume: 189,510 MTs

Data 2: Region-Based Scenario Risk Profile

1. Repeat Data I: Volume-Based Scenarios Risk Profile Step 1) generation.
2. Before assigning weights to data, choose three sub-datasets of a mixed cluster of countries:

    Cluster 1: East Africa and its surroundings, West Africa and its surroundings, Asia, America.

    Cluster 2: East Africa and its surroundings, Asia, America.

    Cluster 3: West Africa and its surroundings, Asia, America.

[37] The time between placing order for a commodity and expected arrival of the product at FDP is stated as approximately 3 months in the beginning of this Appendix.

3. Assign weights to log of demand volume for each Cluster dataset, while the sum of all weights is 100%.

4. Randomly choose three sub-datasets from Cluster dataset 1, 2, 3, respectively, as sudden-onset demand for three scenarios:

   Scenario 1: sum (weights) = 20%, total demand volume: 380,080 MTs

   Scenario 2: sum (weights) = 20%, total demand volume: 324,000 MTs

   Scenario 3: sum (weights) = 20%, total demand volume: 60,780 MTs

ANNEX 2: MATHEMATICAL MODELS

2.1. ETHIOPIA STUDY

2.1.1. ABBREVIATIONS:

MT: Metric Ton

USS: Suppliers Located in the United States

USW: Warehouses Located in the United States

LP: Loading Port

DP: Discharge Port

IW: Warehouses Located Outside the US (Within Africa)

EDP: Extended Delivery Point

FDP: Final Delivery Point

TC: Total Cost of Supply Chain

2.1.2. SETS:

$\mathcal{N}$ = Set of all Nodes

$\mathcal{N}_{US}$ = Set of US Suppliers

$\mathcal{N}_{P}$ = Set of Procurement Nodes ($\mathcal{N}_{US}$)

$\mathcal{N}_{UW}$ = Set of US Prepositioning Warehouses

$\mathcal{N}_{IW}$ = Set of International Prepositioning Warehouses

$\mathcal{N}_{W}$ = Set of Prepositioning Warehouses ($\mathcal{N}_{UW} \cup \mathcal{N}_{IW}$)

$\mathcal{N}_{LP}$ = Set of Loading Ports

$\mathcal{N}_{DP}$ = Set of Discharge Ports

$\mathcal{N}_{T}$ = Set of Transshipment Nodes ($\mathcal{N}_{LP} \cup \mathcal{N}_{DP}$)

SL= Set of Service Level for Ocean Transportation ($s \in SL$)

VV= Set of Vessel Vendors ($v \in VV$)

$\mathcal{N}_{EDP}$ = Set of Extended Delivery Points

$\mathcal{N}_{FDP}$ = Set of Final Delivery Points

$\mathcal{K}$ = Set of Commodities ($k \in \mathcal{K}$) (Yellow Split Pea is chosen in this study)

$\mathcal{T}$ = Set of Bi-weekly Periods ($t \in \mathcal{T}$)

Arc_P = Set of all Existing Procurement Arcs ($i \in \mathcal{N}_S,\ j \in \mathcal{N}_{LP} \cup \mathcal{N}_{UW}$)

Arc_{Oce} = Set of all Existing Ocean Transportation Arcs ($i \in \mathcal{N}_{LP},\ j \in \mathcal{N}_{DP}, \mathrm{v} \in \mathrm{VV}, s \in \mathrm{SL}$)

Arc_T = Set of all Existing Inland Transportation Arcs ($i \in \mathcal{N}_W \cup \mathcal{N}_{DP} \cup \mathcal{N}_{EDP}, j \in \mathcal{N}_W \cup \mathcal{N}_{LP} \cup \mathcal{N}_{EDP} \cup \mathcal{N}_{FDP}, v \in \mathrm{VV}, s \in \mathrm{SL}, i \neq j$)

Arc_{inv} = Set of all Existing Nodes that can Hold Inventory at the Arc (i, i) ($i \in \mathcal{N}_W \cup \mathcal{N}_{EDP}$)

2.1.3. PARAMETERS:

$\boldsymbol{dem_{tjk}}$ = Requested amount of commodity k at FDP j at time t.

$\boldsymbol{cap^S_{ikt}}$ = Procurement capacity (in MT) of commodity k from source $i \in \mathcal{N}_{US}$ at time t.

$\boldsymbol{cap^{pre}_i}$ = Available storage capacity (in MT) of node i. ($i \in \mathcal{N}_W \cup \mathcal{N}_{EDP}$)

$\boldsymbol{cost^s_{ik}}$ = Storage costs (in \$/MT/month) of commodity k at node i. ($i \in \mathcal{N}_W \cup \mathcal{N}_{EDP}$, $k \in \mathcal{K}$)

$\boldsymbol{cap^H_i}$ = Handling capacity (in MT) at node i. ($i \in \mathcal{N}_W \cup \mathcal{N}_{LP} \cup \mathcal{N}_{DP} \cup \mathcal{N}_{\mathrm{EDP}}$)

$\boldsymbol{cost^H_{ik}}$ = Handling cost (in \$/MT) of commodity k at node i. ($i \in \mathcal{N}_W \cup \mathcal{N}_{LP} \cup \mathcal{N}_{DP} \cup \mathcal{N}_{EDP}$)

$\boldsymbol{cap^T_{ijt}}$ = Transportation capacity (in MT) from node i to node j at time t.

$\boldsymbol{cost^T_{ijkt}}$= Transportation cost (in \$/MT) of transferring commodity k from node i to node j at time t.

$\boldsymbol{cap^P_{ijkt}}$ = Transportation capacity (in MT) of commodity k from node $i \in \mathcal{N}_{US}$ to node j at time t.

$\boldsymbol{cost^P_{ijkt}}$= Procurement and transportation cost (in \$/MT) of commodity k from node $i \in \mathcal{N}_{US}$ to node j at time t.

$\boldsymbol{cap^V_{ijvst}}$ = Transportation capacity (in MT) of vessel vendor v with service level s from loading port i to discharge port j at time t.

$\boldsymbol{cost^f_{ijvskt}}$= Ocean transportation cost (in \$/MT) of moving commodity k from loading port i to discharge port j with vessel vendor v and service level s at time t. ($i \in \mathcal{N}_{LP},\ j \in \mathcal{N}_{DP}$, $s \in SL$, $v \in VV$, $k \in \mathcal{K}$)

$\boldsymbol{inv_{ik}}$= Initial and ending inventory level of commodity k at warehouse i.

$\boldsymbol{LT^L_{ijkt}}$ = Lead Time of inland transportation, transferring commodity k from node i to node j at time t.

$\boldsymbol{LT^O_{ijvskt}}$ = Lead Time of ocean transportation, transferring commodity k from loading port i to discharge port j with vessel vendor v and service level s at time t.

$$\mathbf{T_{land(t,i,k)}} = \{(t^*, j^*, i, k) : t^* + LT^L_{t^*,j^*,i,k} = t\} \ \forall k, t, i.$$

$$\mathbf{T_{oce(t,i,k)}} = \{(t^*, j^*, i, \mathrm{v}, \mathrm{s}, k) : t^* + LT^O_{t^*,j^*,i,v,s,k} = t\} \ \forall k, t, i.$$

[$\mathbf{T_{land(i,k,t)}}$ and $\mathbf{T_{oce(i,k,t)}}$ are two searching methods that create arc sets given a time t, a node i and a commodity k. They contain the indices of all possible flow variables $F_{j^*ikt^*}$ and $F_{j^*ikt^*vs}$ that arrive at node i at time t for commodity k.]

$\boldsymbol{\beta}$= Required percentage of the carriers to have P1 flags (50% organizational requirement).

$\boldsymbol{pen_k}$= Penalty for one MT of unsatisfied demand for commodity k at each time period.

$\boldsymbol{t_{start}}$ = Starting time for each planning horizon.

$\boldsymbol{t_{end}}$ = Ending time for each planning horizon.

2.1.4. VARIABLES:

$\boldsymbol{F_{ijkt}}$ = Metric tons of commodity k sent from node i to node j at time t. (when $i = j$: F_{iikt} indicates the inventory level of commodity k at time t at node i.)

$\boldsymbol{F_{ijsvkt}}$ = Metric tons of commodity k transported by vendor v with service level s from loading port i to discharge port j at time t.

$\boldsymbol{Latedem_{jkt}}$ = The number of metric tons of commodity k that cannot be delivered on time to node j at time t.

2.1.5. OBJECTIVE:

The supply chain optimization demonstration model aims to minimize the total cost of the current supply chain (TC).

$$Min\ TC \tag{1}$$

$$TC = \sum_{(i,j)\in \mathrm{Arc}_P} \sum_{k,t} cost^P_{ijkt} \times F_{ijkt} \tag{2}$$

$$+ \sum_{(i,j)\in \mathrm{Arc}_T} \sum_{k,t} cost^T_{ijkt} \times F_{ijkt} \tag{3}$$

$$+ \sum_{i\in \mathcal{N}_W \cup \mathcal{N}_{EDP}} \sum_{k,t} cost^S_{ik} \times F_{iikt} \tag{4}$$

$$+ \sum_{i \in \mathcal{N}_W \cup \mathcal{N}_{LP} \cup \mathcal{N}_{DP} \cup \mathcal{N}_{EDP}} \sum_{k,t} cost_{ik}^{H} \times F_{iikt} \quad (5)$$

$$+ \sum_{(i,j,v,s) \in \mathrm{Arc}_{Oce}} \sum_{k,t} cost_{ijvskt}^{f} \times F_{ijsvkt} \quad (6)$$

$$+ \sum_{j \in \mathcal{N}_{FDC}} \sum_{k,t} Latedem_{jkt} \times pen_{k(j)} \quad (7)$$

Total cost includes the following components: (2) Procurement cost for purchased commodities (this also includes the transportation cost from the supplier to loading port or US warehouse); (3) In-land transportation cost; (4) Storage cost; (5) Handling cost; (6) Ocean transportation cost between loading ports and discharge ports; (7) Penalty cost for commodities not delivered to FDPs on scheduled time. Note that (7) is only added to the model while doing supply chain optimization. There is no such cost in real life so, this part is not concerned as part of total cost in the output.

2.1.6. CONSTRAINTS:

FLOW BALANCING CONSTRAINTS

FDPs (Demand Satisfaction):

$$\sum_{(j^*,i,k,t^*) \in T_{land(t,i,k)}} F_{i^*jkt^*} = dem_{tjk} - Latedem_{jkt} \quad (8)$$

$$for\ t = t_{start}, \quad \forall j \in \mathcal{N}_{FDP}\ \forall k.$$

$$\sum_{(j^*,i,k,t^*) \in T_{land(t,i,k)}} F_{i^*jkt^*} = dem_{tjk} + Latedem_{jk(t-1)} - Latedem_{jkt} \quad (9)$$

$$for\ t \neq t_{start}, \quad \forall j \in \mathcal{N}_{FDP}\ \forall k.$$

Constraints (8) and (9) indicate that the total amount of commodity k delivered to FDP j at time t equals the summation of required demand amount at time t and unsatisfied demand amount from last period (t-1) minus the unsatisfied demand amount at time t.

Warehouse and EDP (Inventory management):

$$F_{iikt} = inv_{ik}, \quad for\ t = t_{start}\ and\ (t_{end} + 1), \forall (i,i) \in Arc_{inv}, \forall k. \quad (10)$$

$$F_{iik(t+1)} + \sum_{j \in \mathcal{N}_{LP} \cup \mathcal{N}_{EDP}} F_{ijkt} = F_{iikt} \quad (11)$$

$$for\ t = t_{start}, \forall (i,i) \in Arc_{inv}, \forall k$$

$$F_{iik(t+1)} + \sum_{j \in \mathcal{N}_{LP} \cup \mathcal{N}_{FDP}} F_{ijkt} = F_{iikt} + \sum_{(j^*,i,k,t^*) \in T_{land(t,i,k)}} F_{j^*ikt^*} \quad (12)$$

$$for\ \forall (i,i) \in Arc_{inv}, \forall t \neq t_{start}\ and\ t_{end}, \forall k$$

$$F_{iik(t+1)} = F_{iikt} + \sum_{(j^*,i,k,t^*) \in T_{land(t,i,k)}} F_{j^*ikt^*} \quad (13)$$

$$for\ t = t_{end}, \forall (i,i) \in Arc_{inv}, \forall k$$

Constraints (10)-(13) are traditional flow balance constraints for the warehouses to ensure that the summation amount of commodity k shipping out of warehouse/EDP i and the remaining amount of inventory held for the next time period (t+1) equals the total amount of incoming shipments of commodity k arriving at warehouse i at time t plus its inventory level at time t.

Ports (connecting between inland and ocean transportation flow):

$$\sum_{j,v,s} F_{ijvskt} = \sum_{(j^*,i,k,t^*) \in \mathrm{T}_{\mathrm{land}(t,i,k)}} F_{j^*ikt^*} \quad \forall i \in \mathcal{N}_{LP}, \forall k, t \quad (14)$$

$$\sum_{j} F_{ijkt} = \sum_{(t^*,j^*,i,\mathrm{v},\mathrm{s},k) \in \mathrm{T}_{oce(t,i,k)}} F_{j^*ikt^*} \quad \forall i \in \mathcal{N}_{DP}, \forall k, t \quad (15)$$

Constraint (14) and (15) are flow balance constraints for the loading port and discharge port, respectively. They ensure the total amount of commodity k shipping out of the port at time t equals to what it has received during the time t (since it is assumed that ports are transshipment node and cannot hold inventory).

CAPACITY CONSTRAINTS

Procurement (Supplier source availability):

$$\sum_{j} F_{ijkt} \leq cap^{S}_{ikt}\ for\ \forall i \in \mathcal{N}_{US}, \forall k, t. \quad (16)$$

Constraint (16) states that the total procured amount of commodity k at time t from suppliers i cannot exceed its availability at the moment.

Transportation:

$$F_{ijkt} \leq cap^{P}_{ijkt}\ for\ \forall (i,j) \in \mathrm{Arc}_P, \forall\ k, t. \quad (17)$$

Constraint (17) states that the flow of commodity k at time t from supplier i shipped to its next stop by inland transportation cannot exceed the capacity of the arc.

$$\sum_{k} F_{ijkt} \leq cap_{ijt}^{T} \;\; for \;\; \forall i(i,j) \in \mathrm{Arc}_{T}, \forall t \tag{18}$$

Constraint (18) states that the total flow of all commodities on an inland transportation arc (not including the ones of procurement) cannot exceed the capacity of the arc.

$$\sum_{k} F_{ijktvs} \leq cap_{ijvst}^{V} \;\; \forall (i,j,v,s) \in \mathrm{Arc}_{Oce}, \forall t \tag{19}$$

Constraint (19) states that the total flow over all commodities on an ocean transportation arc cannot exceed the capacity of the vessel vendor.

Storage (inventory holding availability):

$$\sum_{k} F_{iikt} \leq cap_{it}^{pre} \;\; \forall (i,i) \in \mathrm{Arc}_{inv}, \forall t \tag{20}$$

Constraint (20) shows the total amount of inventory at time t of all commodities at warehouses and EDPs cannot exceed its storage capacity.

Handling:

$$\sum_{k} \sum_{(j^*,i,k,t^*) \in T_{land(t,i,k)}} F_{j^*ikt^*} \leq cap_{it}^{H} \quad \forall i \in \mathcal{N}_{W} \cup \mathcal{N}_{EDP}, \forall t \tag{21}$$

$$\sum_{k} \sum_{(j^*,i,k,t^*) \in T_{land(t,i,k)}} F_{j^*ikt^*} \leq cap_{it}^{H} \;\; \forall i \in \mathcal{N}_{LP}, \forall t. \tag{22}$$

$$\sum_{k} \sum_{(t^*,j^*,i,v,s,k) \in T_{oce(t,i,k)}} F_{j^*ivskt^*} \leq cap_{it}^{H} \;\; \forall i \in \mathcal{N}_{DP}, \forall t \tag{23}$$

Constraints (21)-(23) show that the total amount of commodities arriving at EDPs, Warehouses, and Ports at time *t* cannot exceed their handling capacity.

Regulation Constraint —US Flag Rule:

$$\sum_{i,j,s=P1,v,k,t} F_{ijktsv} \geq \beta \times \sum_{i,j,k,t,s,v} F_{ijktsv} \quad [(i,j,v,s) \in \mathrm{Arc}_{Oce}] \tag{24}$$

Constraint (24) guarantees that at least β percent of the total commodity amount should be shipped by vessels carrying the P1 flag, satisfying the requirement of the USAID flag rule on ocean transportation. β is initially set to 50%. While running different simulations, we also used 0%, 25%, 75%, and 100% for specific scenario analysis.

Non-negativity Constraints:

$$F_{ijkt} \geq 0 \qquad \forall (i,j) \in \mathrm{Arc}_T \cup \mathrm{Arc}_P \cup \mathrm{Arc}_{inv}, \forall\, k,t \tag{25}$$

$$F_{ijsvkt} \geq 0 \qquad \forall\ (i,j,\mathrm{s},\mathrm{v}) \in \mathrm{Arc}_{Oce}, \forall\, k,t \tag{26}$$

$$Latedem_{jkt} \geq 0 \qquad \forall j \in \mathcal{N}_{FDP}, \forall\, k,t. \tag{27}$$

2.2. WAREHOUSE STUDY

2.2.1. ABBREVIATIONS

MT: Metric Ton

USS: Suppliers Located in the United States

USP: US Loading Port

INTP: International Port

PW: Port Warehouses

IW: Inland Warehouses

FDP: Final Delivery Point (Country Level)

TC: Total Cost of Supply Chain

2.2.2. SETS

N_{Sce} = Set of all Scenarios $(c \in N_{Sce})$

N = Set of all Nodes $(i \in N)$

N_{US} = Set of US Suppliers

N_P = Set of Procurement Nodes (N_{US})

N_{PW} = Set of Prepositioning Port Warehouses

N_{IW} = Set of International Prepositioning Inland Warehouses

N_W = Set of Prepositioning Warehouses $(N_{PWH} \cup N_{IWH})$

N_{USP} = Set of US Loading Ports

N_{INTP} = Set of International Ports

N_{FDP_OG} = Set of Final Delivery Points with On-going Demand

N_{FDP_SO} = Set of Final Delivery Points with Sudden-onset Demand

N_h = Set of Nodes with Handling Cost ($N_{IW} \cup N_{USP} \cup N_{INTP}$)

SL = Set of Service Level for Ocean Transportation ($s \in SL$)

VV = Set of Vessel Vendors ($v \in VV$)

T = Set of Periods (in 15 days) of Planning

T_{check}= Set of Periods to Check Inventory Level at Warehouse

Arc_{Bulk} = Set of all Existing Ocean Transportation Arcs for Bulk Commodity ($i \in N_{USP} \cup N_{INTP},\ j \in N_{INTP}, v \in VV, s \in SL$)

Arc_{Liner} = Set of all Existing Ocean Transportation Arcs for Liner Commodity ($i \in N_{USP} \cup N_{INTP},\ j \in N_{INTP}, v \in VV, s \in SL$)

Arc_{Oce} = Set of all Existing Ocean Transportation Arcs ($Arc_{Bulk} \cup Arc_{Liner}$)

Arc_{flag} = Set of all Existing Ocean Transportation Arcs Shipping from US Port ($i \in N_{USP}$, $j \in N_{INTP}, v \in VV, s \in SL$)

Arc_h = Set of all Existing Nodes can Hold Inventory as the Arc (i, i). ($i \in N_W$)

Arc_T = Set of all Existing Inland Transportation Arcs

Arc_P = Set of all Existing Procurement Arcs ($i \in N_{US},\ j \in N_{USP}$)

Arc_{em} = Set of all Sudden-onset Delivery Arcs ($i \in N_{IW} \cup N_{INTP},\ j \in N_{FDC}$)

Arc_{port} = Set of all Existing Arcs from/to a Port

2.2.3. PARAMETERS

$\boldsymbol{\beta}$ = Required percentage of the carriers (only for ocean transportation departing from US port) to have P1 flags.

$\boldsymbol{Max_{total\_inventory\_cost}}$ = USAID annual budget for all prepositioning events: US$15 million.

$\boldsymbol{dem_{tjk}}$ = Requested demand amount of commodity k at FDP j at time t.

$\boldsymbol{em\_dem_{tjkc}}$ = Stochastic sudden-onset demand (based on historical data) for the amount of commodity k at FDP j at period t.

$\boldsymbol{cap^S_{ikt}}$ = Procurement capacity (in MT) of commodity k from source $i \in N_{US}$ at period t.

$\boldsymbol{cost^P_{ijkt}}$= Procurement and transportation cost (in $/MT) of commodity k from node $i \in N_{US}$ to node j $i \in N_{USP}$ at period t.

$\boldsymbol{cap^{pre}_i}$ = Available storage capacity (in MT) of node i. ($i \in N_W$)

$\boldsymbol{cost_{ik}^{S}}$ = Storage costs (in \$/MT/month) of commodity k at node i. ($i \in N_W$, $k \in K$)

$\boldsymbol{cap_{i}^{H}}$ = Handling capacity (in MT) at node i. ($i \in N_W \cup N_{USP} \cup N_{INTP}$)

$\boldsymbol{cost_{i}^{H}}$ = Handling cost (in \$/MT) of node i. ($i \in N_W \cup N_{USP} \cup N_{INTP}$)

$\boldsymbol{cap_{ij}^{T}}$ = Transportation capacity (in MT) from node i to node j.

$\boldsymbol{cost_{ij}^{T}}$= Transportation cost (in \$/MT) of transferring commodity k from node i to node j.

$\boldsymbol{cap_{ijvst}^{B/L}}$ = Ocean transportation capacity (in MT) of vessel vendor v with service level s from port i to port j at period t for Bulk/Liner commodity. ($i, j, v, s \in Arc_{Bulk}/Arc_{Liner}$)

$\boldsymbol{cost_{ijvst}^{B/L}}$= Ocean transportation cost (in \$/MT) of moving Bulk/Liner commodity from port i to port j with vessel vendor v and service level s at period t. ($i, j, v, s \in Arc_{Bulk}/Arc_{Liner}$)

$\boldsymbol{inv_{ik}}$= Initial and ending (at time t_{start} and t_{end}) inventory level of commodity k at warehouse i.

$\boldsymbol{t_{start}}$ = Starting time for each planning horizon.

$\boldsymbol{t_{end}}$ = Ending time for each planning horizon.

$\boldsymbol{LT_{ijkt}^{In}}$ = Lead Time of inland transportation, transferring commodity k from node i to node j at period t.

$\boldsymbol{LT_{ijvst}^{B/L}}$ = Lead Time of Bulk/Liner ocean transportation, transferring commodity from port i to port j with vessel vendor v and service level s at period t.

$$\boldsymbol{T_{land(t,i,k)}} = \left\{(t^*, j^*, i, k) : \ t^* + LT_{t^*,j^*,i,k}^{L} = t\right\} \ \forall k, t, i.$$

$$\boldsymbol{T_{land\_em(t,i,k)}} = \left\{(t^*, j^*, i, k) : \ t^* + LT_{t^*,j^*,i,k}^{L} = t\right\} \ \forall k, t, (j^*, i) \in Arc_{em}$$

$$\boldsymbol{T_{oce(t,i,k)}} = \left\{(t^*, j^*, i, v, s, k) : \ t^* + LT_{t^*,j^*,i,v,s,k}^{O} = t\right\} \ \forall k, t, i.$$

[$\boldsymbol{T_{land(i,k,t)}}$ and $\boldsymbol{T_{oce(i,k,t)}}$ are two methods that create arc sets given a period t, a node i, and a commodity k. They contain the indices of all possible flow variables $F_{j^*ikt^*}$ and $F_{j^*ikt^*vs}$ that arrive at node i at period t for commodity k.]

$\boldsymbol{Opr_i}$ = Opening annual cost for warehouse i.

$\boldsymbol{Preset\_wh_i}$ = Open/Close preset-decision of warehouse i.

$\boldsymbol{Probability_c}$ = Probability of scenario c.

$\boldsymbol{pen_k}$ = Penalty cost for one MT of unsatisfied demand for commodity k for one period.

2.2.4. VARIABLES

Linear Variables:

$\boldsymbol{F_{ijktc}}$ = MTs of commodity k transported (through inland transportation) from node i to node j at period t of scenario c.

$\boldsymbol{F_{iiktc}}$ = Inventory level (MTs) at WH i for commodity k at period t for scenario c.

$\boldsymbol{F_{ijsvktc}}$ = MTs of commodity k transported (through ocean transportation) by vendor v with service level s from port i to port j at period t of scenario c .

$\boldsymbol{EM_{ijktc}}$ = MTs of commodity k transported from international port/warehouse i to FDP j at period t of scenario c. (only for sudden-onset delivery)

$\boldsymbol{Inflow_{iktc}}$ = Inflow volume that will be stored at warehouse i for commodity k at period t for scenario c.

$\boldsymbol{Late\_em\_dem_{jktc}}$ = The proportion of the sudden-onset delivery of commodity k that arrived 'late' at the final delivery point (FDP) in time t of scenario c, namely, defined as late delivery.

Binary Variable:

WH_i = Open/Close decision of warehouse i.

2.2.5. OBJECTIVE

The objective is to minimize the expected total cost (TC) of given scenarios, associated with three parts: a) Fixed cost of opening warehouses in the first stage, where $\boldsymbol{Opr_i}$ represents the annually opening cost of warehouse i ; b) Variable cost incurred in the second stage from procurement to delivery of food assistance products via inland or ocean transportations, where; k represents commodities, t represents time, i and j represent index locations of suppliers, warehouses, loading and discharge ports, and final delivery points (FDPs), for scenario c, and additionally, for ocean transportation, v represents vessel venders and s represents service level; c) Penalty cost pen, multiplied by the total amount of late delivery, which is a fictitious cost added to TC, to indirectly adjust the level of on-time delivery.

$$Min\ E[TC] = \tag{1}$$

$$\sum_{i \in N_W} Opr_i \times WH_i \tag{2}$$

$$+ \sum_{(i,j) \in Arc_P} \sum_{k,t,c} cost^P_{ijkt} \times F_{ijktc} \times Probability_c \tag{3}$$

$$+ \sum_{(i,j) \in Arc_T} \sum_{k,t,c} cost^T_{ij} \times F_{ijktc} \times Probability_c \tag{4}$$

$$+ \sum_{(i,j,v,s)\in Arc_{Bulk}/Arc_{Liner}} \sum_{k,t,c} cost_{ijvst}^{B/L} \times F_{ijvsktc} \times Probability_c \quad (5)$$

$$+ \sum_{(i,j)\in Arc_{em}} \sum_{k,t,c} cost_{ij}^{T} \times EM_{ijktc} \times Probability_c \quad (6)$$

$$+ \sum_{i\in N_W} \sum_{k,t,c} cost_{ik}^{s} \times F_{iiktc} \times Probability_c \quad (7)$$

$$+ \sum_{i\in N_W} \sum_{k,t,c} cost_{ik}^{H} \times Inflow_{iktc} \times Probability_c \quad (8)$$

$$+ \sum_{i,j\in Arc_{port}} \sum_{k,t,c} cost_{ik}^{PH} \times F_{ijktc} \times Probability_c \quad (9)$$

$$+ \sum_{j\in N_{FDC\_SO}} \sum_{k,t,c} Late\_em\_dem_{jktc} \times pen_k \times Probability_c \quad (10)$$

Total cost includes the following components: annual fixed cost for opening warehouses (2), the procurement cost for purchased commodities (this also includes the transportation cost from the supplier to US port/WH, when the supplier is located in the US) (3), inland transportation cost (4), ocean transportation cost (5), inland transportation cost for sudden-onset delivery (6), inventory cost at WHs (7), handling cost at WHs (8), handling cost at Ports (9), and penalty cost of late delivery for sudden-onset demand (10).

2.2.6. CONSTRAINTS

FLOW BALANCING CONSTRAINTS

Final Delivery Countries: On-going Demand

$$\sum_{(j^*,i,k,t^*)\in T_{land(t,i,k)}} F_{i^*jkt^*c} = dem_{tjk} \quad \forall j \in N_{FDP\_OG}\ \forall t,k,c. \quad (11)$$

Final Delivery Countries: Sudden-onset Demand

$$\sum_{(j^*,i,k,t^*)\in T_{land\_em(t,i,k)}} EM_{i^*jkt^*c} = em\_dem_{tjkc} - Late\_em\_dem_{jktc} + Late\_em\_dem_{jk(t-1)c} \quad (12)$$

$$\forall j \in N_{FDP\_SO}\ \forall t,k,c$$

Constraint (11) indicates that the summation of commodity k delivered through the supply chain to FDP j at time t must equal to the required amount of on-going demand for each scenario c. Constraint (12) indicates that the total amount of commodity k delivered to FDP j at time t equals the summation of required sudden-onset demand amount at time t and unsatisfied demand amount from last period (t -1) minus the unsatisfied demand amount at time t.

Warehouses:

$$F_{iiktc} = inv_{ik} \times WH_i \quad for\ t = t_{start} \text{ and } t_{end}, \forall i \in N_w, \forall k\ . \tag{13}$$

International Inland Warehouse:

$$F_{iik(t+1)c} + \sum_j F_{ijktc} + \sum_j EM_{ijktc} = F_{iiktc} + \sum_{(j^*,i,k,t^*)\in T_{land(t,i,k)}} F_{j^*ikt^*c} \quad for \quad \forall i \in N_{IW}, \forall k, t, c \tag{14}$$

US Port Warehouse:

$$F_{iik(t+1)c} + \sum_{Arc_{Oce}} F_{ijvsktc} = F_{iiktc} + \sum_{(j^*,i,k,t^*)\in T_{land(t,i,k)}} F_{j^*ikt^*c} \quad for\ \forall i \in N_{USP}, \forall k, t, c. \tag{15}$$

International Port Warehouse:

$$F_{iik(t+1)c} + \sum_j F_{ijktc} + \sum_j EM_{ijktc} + \sum_{Arc_{Oce}} F_{ijvsktc} = F_{iiktc} + \sum_{(j^*,i,k,t^*)\in T_{land(t,i,k)}} F_{j^*ikt^*c} + \sum_{(t^*,j^*,i,v,s,k)\in T_{oce(t,i,k)}} F_{j^*ivskt^*c} \quad for\ \forall i \in N_{USP}, \forall k, t, c. \tag{16}$$

Constraint (13)-(16) are traditional flow balance constraint for the warehouses (international inland warehouse, US port warehouse and International port warehouse) to ensure that: for each scenario c, the summation of commodity k shipping out of warehouse i and the remaining amount of inventory left for the time period (t +1) equals to the total amount of incoming shipments of commodity k that arrives at warehouse i at time t and its current inventory level at time t.

Ports (without Warehouses):

US Ports:

$$\sum_{Arc_{Oce}} F_{ijvsktc} = \sum_{(j^*,i,k,t^*)\in T_{land(t,i,k)}} F_{j^*ikt^*c} \qquad for\ \forall i \in N_{USP}, \forall k, t, c \tag{17}$$

International Ports:

$$\sum_j F_{ijktc} + \sum_j EM_{ijktc} + \sum_{Arc_{Oce}} F_{ijvsktc} = \sum_{(j^*,i,k,t^*)\in T_{land(t,i,k)}} F_{j^*ikt^*c} + \sum_{(t^*,j^*,i,v,s,k)\in T_{oce(t,i,k)}} F_{j^*ivskt^*c} \quad for\ \forall i \in N_{INTP}, \forall k, t, c \tag{18}$$

Constraint (17) and (18) are flow balance constraints for US and International Ports (without warehouses), respectively, to ensure the total amount of commodity k shipping out of the port equals to what it has been received during the time t, for each scenario c.

CAPACITY CONSTRAINTS

Source Availability:

$$\sum_{j} F_{ijktc} \leq cap_{ikt}^{S} \;\; for \;\; \forall i \in N_s, \forall k, t, c. \tag{19}$$

Constraint (19) states that the total procured amount of commodity k at time t from supplier i (to all destinations) of scenario c, cannot exceed its availability at the moment.

Transportation Capacity:

Ocean Transportation:

$$\sum_{k \in Bulk/Liner} F_{ijktvsc} \leq cap_{ijvst}^{B/L} \;\; \forall (i,j,v,s) \in Arc_{Oce}, \forall\, t, c \tag{20}$$

Constraint (20) states that the total flow of all Bulk/Liner commodities on an ocean transportation arc between two ports i, j cannot exceed the capacity of given vessel vendor v and service level s, for each scenario c.

Inland Transportation:

$$\sum_{k} F_{ijktc} + \sum_{k} EM_{ijktc} \leq cap_{ij}^{T} \quad for \;\; \forall (i,j) \in Arc_T, \forall t, c \tag{21}$$

$$\sum_{k} F_{ijktc} + \sum_{k} EM_{ijktc} \leq cap_{ij}^{T} \times WH_i \quad for \;\; \forall (i,j) \in Arc_T \;\; if \; i \in N_{IW}, \forall t, c \tag{22}$$

Constraint (21) and (22) state that the total flow over all commodities on an inland transportation arc cannot exceed the capacity of the arc for each c. (If an international inland warehouse is not open, commodities cannot be transported through the given arc.)

Warehouse Capacity:

Inventory Holding:

$$\sum_{k} F_{iiktc} \leq cap_{i}^{pre} \times WH_i \qquad \forall i \in N_W, \forall\, t, c. \tag{23}$$

Constraint (23) shows that, if the warehouse is opened, the total amount of inventory of all commodities at time t at warehouse i cannot exceed its inventory holding capacity for each scenario c; else if the warehouse is closed, it cannot be used to preposition any commodity.

Warehouse and Port Handling:

$$\sum_{k} Inflow_{iktc} \leq cap_i^H \quad \forall i \in N_W, \forall\, t, c. \tag{24}$$

$$\sum_{k} \sum_{(j^*,i,k,t^*) \in T_{land(t,i,k)}} F_{j^*ikt^*c} \leq cap_i^H \;\; \forall i \in N_{USP}, \forall\, t, c. \tag{25}$$

$$\sum_{k} \sum_{(t^*,j^*,i,v,s,k) \in T_{oce(t,i,k)}} F_{j^*ivskt^*c} + \sum_{k} \sum_{(j^*,i,k,t^*) \in T_{land(t,i,k)}} F_{j^*ikt^*c} \leq cap_{it}^H \;\; \forall i \in N_{INTP}, \forall\, t, c. \tag{26}$$

Constraint (24) shows the total amount of commodities arriving at warehouses at time t cannot exceed its handling capacity, for each scenario c. Constraint (25) and (26) are corresponding to port handling capacities, which are not considered in the model due to lack of data.

REGULATORY CONSTRAINTS

Flag Rule:

$$\sum_{i,j,s=P1,v,k,t} F_{ijktsvc} >= \beta \times \sum_{i,j,k,t,s,v} F_{ijktsvc} \quad \forall\, c \tag{27}$$

Constraint (27) guarantees that there would be at least β of the total amount of commodity shipped by the vessels carrying US flag (P1) for each scenario c, preventing violation of the USAID flag rule of ocean transportation that is departing from US ports.

Pre-set Warehouse Decisions:

$$WH_i = Preset\_wh_i \qquad \forall i \in N_W \; if \; Preset_{wh_i} = OPEN \; or \; CLOSE \tag{28}$$

Constraint (28) provides user with choices to make pre-decisions for each warehouse; 'OPEN' assigns '1' as model input, 'CLOSE' assigns '0' as model input. If no value input is given, the open/close decision for the warehouses will be left for the model to determine.

Warehouse and Prepositioning Budget Constraint:

$$\sum_{i \in N_W} \sum_{k,t} cost_i^S \times F_{iiktc} + \sum_{i \in N_W} \sum_{k,t} cost_i^H \times Inflow_{iktc} + \sum_{i \in N_W} Opr_i \times WH_i <= Max_{total\_inventory\_cost} \tag{29}$$

Constraint (29) follows the USAID current annual budget on all prepositioning related events.

OTHER CONSTRAINTS

Inventory Inflow Definition:

$$Inflow_{iktc} >= F_{iik(t+1)c} - F_{iiktc} \tag{30}$$

Constraint (30) and nonnegative constraint (36) define the inventory inflow of commodity k at warehouse i at period t for scenario c, which equals the difference of inventory level of the period $(t+1)$ and period t, if, and only if, it is positive.

Sudden-Onset Demand Visibility:

$$\sum_{(i,j)\in Arc_{em}} \sum_{t_s<t} EM_{ijkt_sjc} \leq \sum_{t_s<t} em\_dem_{t_sjkc} \qquad \forall j,k,c. \tag{31}$$

Constraint (31) shows the assumption that the model can only start to mobilize and schedule the delivery after sudden-onset events occurs. In other words: planning is only allowed after the sudden-onset demand occurs.

Non-negativity and Binary state:

$$F_{ijktc} \geq 0 \qquad \forall (i,j) \in Arc_T \cup Arc_P \ \forall\, k,t,c \tag{32}$$

$$F_{ijsvktc} \geq 0 \qquad \forall\ (i,j,s,v) \in Arc_{Oce}, \forall\, k,t,c \tag{33}$$

$$EM_{ijktc} \geq 0 \qquad \forall (i,j) \in Arc_{em}\ \forall\, k,t,c \tag{34}$$

$$F_{iiktc} \geq 0 \qquad \forall\, i \in N_w\ \forall\, k,t,c \tag{35}$$

$$Inflow_{iktc} \geq 0 \qquad \forall\, i \in N_w\ \forall\, k,t,c \tag{36}$$

$$Late\_em\_dem_{jktc} \geq 0 \qquad \forall j,k,t,c. \tag{37}$$

$$WH_i \in [0,1] \qquad \forall\, i \in N_w \tag{38}$$

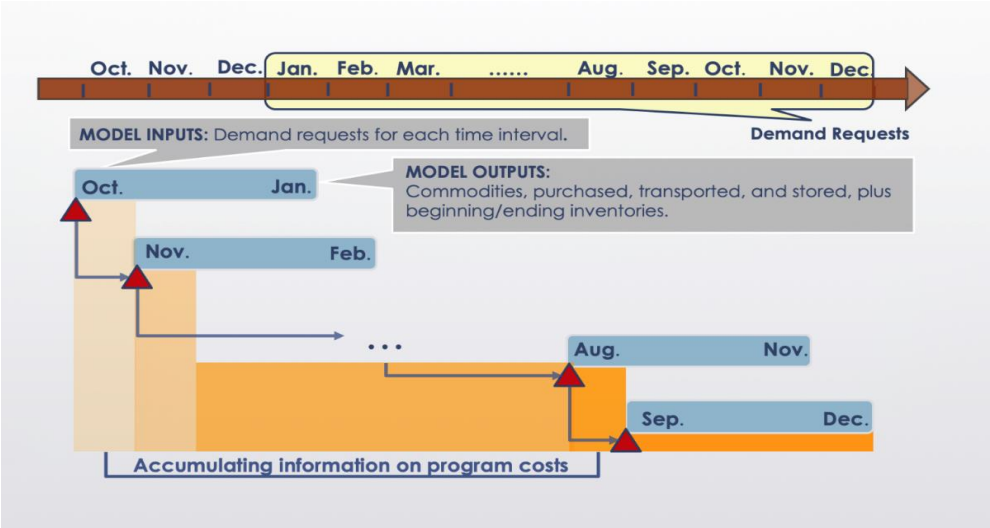
ANNEX 3: SOLUTION METHODOLOGIES

3.1. ETHIOPIA STUDY METHODOLODY

The mathematical model developed roots from a traditional of Minimum Cost Network Flow (MCNF) (Ahuja, Magnanti, & Orlin, 1993) linear programming (LP) (Dimitris & John, 1997) problem, with policy- and context-specific modifications to the objective function and constraint sets. An innovative rolling planning time horizon (PTH, the number of months into the future that planners can make decisions for) algorithm was developed, following (Sethi & Sorger, 2011) and (Bischi, et al., 2019), to capture the current decision-making process used by FFP and to examine the effects of alternative PTHs.

Annex Figure 8 provides an overview of the rolling planning time horizon approach in the context of a 4-month PTH, which is nested within a 12-month study. The yellow area at the top of the figure represents the 12-month period for this modeling exercise. The brown arrow captures the entire decision-making period, which is longer (extended to the left of the 12-month period) by the number of months contained in the PTH – in this example, we envision a 4-month PTH, so food aid that is needed in January becomes visible as 'January demand' in October. The blue bars represent discrete but overlapping PTHs, which move forward in time at one-month time steps. The gray boxes identify the information that feeds into each PTH at the outset, and the outputs that emerge from the economic optimization algorithm for each PTH. The red triangles represent collections of model outputs associated with the first month of each PTH which are fixed (outcomes that can no longer be changed) as the planner shifts from one 4-month PTH to the next. Finally, the increasingly dark-shaded orange boxes represent the accumulated information on the costs that are associated with the optimal outcomes produced by the model.

Annex Figure 8: 4-month Rolling Planning Time Horizon Overview



A step by step algorithm describing the implemented rolling horizon framework is given below.

Algorithm

1. Set periodical planning periods K = [1, 2, 3, 4, … 11, 12]. Define the current planning horizon problem as M_k. Define the optimal variable outputs of problem M_k as Opt_k.
2. Step 1: Solve each sub-problem M_k for k in K, generate Opt_k.
3. Step 2: Output data manipulation and rewriting Opt_k:
    a) Tracking lead times calculate the arrival time and location of the commodity flow corresponding to the first two planning periods within Opt_k. Save the results in $past\_arrival\ (i, t)$.
    b) Extract variable $Latedem_{jt}$ output corresponding to the first two planning periods within Opt_k. Save the results in delay$_demand\ (j, t)$.
    c) Extract variable F_{iit} output corresponding to the third planning period within Opt_k. Save the results in $new\_initial\ (i)$.
    d) Update Opt_k by extracting all variable output corresponding to the first two planning periods.
4. Step 3: Rewriting the constraint sets:
    a) Add $past\_arrival\ (i, t)$ as a parameter at all nodes which can receive commodities.
    b) Add delay$_demand\ (j, t)$ to dem_{tj} and apply to all FDP flow balance constraints.
    c) Replace the parameter inv_i with $new\_initial\ (i)$ in the warehouse and EDP flow balance constraint (10).
5. Step 4: Go back to step1.
    Use the rewritten constraint sets to solve all following sub-problems.
6. Step 5: Finalize the optimal output:
    If $Opt_{k=12}$ is generated
    Then stop, combine the results of $Opt_k\ for\ k\ in\ K$, save as Opt_{all}.
7. Step 6: Objective calculation:
    Re-calculate the objective function without considering penalty cost.

The algorithm tracks and reorganizes the output of one 4-month planning horizon solution which serves as input into the next 4-month planning horizon's decisions. In **Annex Figure 8**, the first PTH runs from October through January (four months), during which the model identifies the most cost-effective set of strategies for meeting the demand for food assistance that are visible to the decision-maker. Once that set of optimal choices have been identified, the rolling planning time horizon takes one step forward to February and drops October, decisions, which are at this point considered fixed (and fixed in the cost analysis). The model then runs another optimization routine over this new 4-month PTH that covers previous months (November-January) for which decisions taken during the first iteration of the model can now be revisited and revised, and one new month (February) which brings with it newly visible food assistance demand, new relative prices of available commodities, new seasonal ocean shipping rates, etc. The rolling time horizon continues to march toward the 12-month endpoint of the overall timeframe for analysis, one month at a time. For each month and for each prepositioning facility, beginning and ending stocks are managed so as to guarantee that a pre-established minimum (at least) of the food assistance commodity is available.

For descriptive purposes, we used a 4-month PTH to present the rolling time horizon method in **Annex Figure 8**. We experiment with changing the length of this PTH from 3 to 4 to 6 months, with each change altering the 'visibility' of food assistance demand and also changing the time horizon for making decisions regarding purchase, prepositioning, transportation routes and carrier choices, etc. These shifts in demand visibility and decision-making timeframe may affect overall supply chain costs and on-time delivery rates as reported.

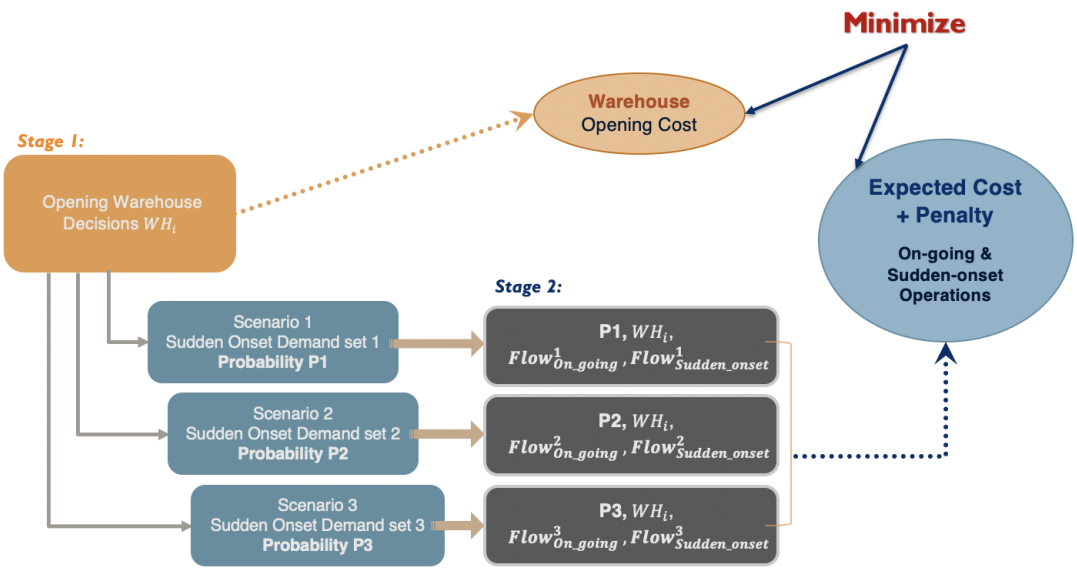
3.2. WAREHOUSE STUDY WITH UNFORCASTABLE DEMAND METHODOLOGY

Stochastic programming (Alexander & Andy, 2007) is a framework used generally for optimization problems that involve uncertainty. Deterministic optimization problems, such as the one modeled in the Ethiopia study, are formulated with known parameters and on-going forecastable demand. However, when considering more realistic contexts some unforeseen parameters, sudden-onset demand in this case, should be included. The goal of stochastic optimization is to find a feasible set of decisions and policies for all possible realizations and minimize the expectation of total cost over all these realizations. In each of our simulations, we developed three independent sudden-onset demand scenarios to represent the risk profiles faced by the agency over a year.

To better assess annual open/close contracts for a set of global warehouse locations, a mixed-integer programming (MIP) (Vielma, 2015) model is introduced to enable joint decision-making for not only supply chain flows but also locating global warehouses.

Then, a two-stage stochastic mix-integer problem is developed to simultaneously make optimal decisions for two types of variables to minimize the expected cost: 1) In stage 1, several decision variables are fixed, these apply for all scenarios despite the uncertainty of the risk profile. 2) In stage 2, based on stage 1 decisions, an independent plan within each scenario is devised given the realization of previously uncertain events. 3) The expected cost is calculated over all scenarios, composed of both stage 1 and stage 2 costs. **Annex Figure 9** provides an overview of the scenario-based two-stage stochastic programming framework in the context of the global warehouse location model within a 12-month supply chain modeling framework.

Annex Figure 9: Two-Stage Scenario-based Stochastic Programming Framework



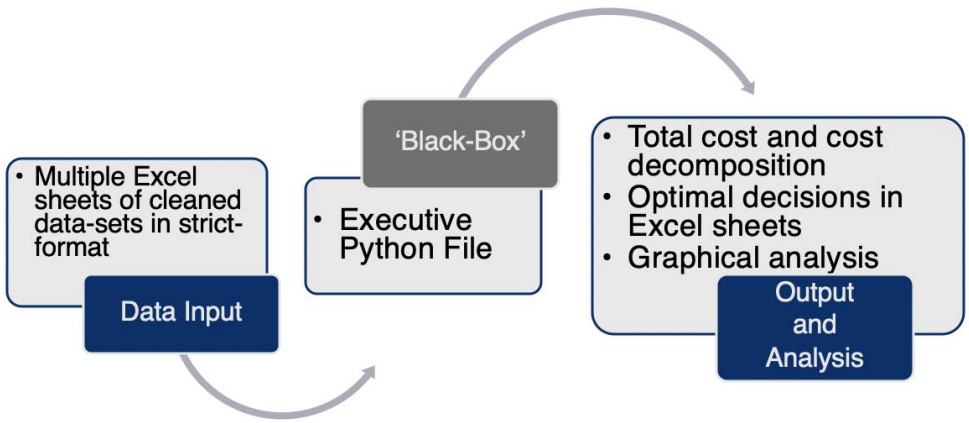
The framework of how we applied two-stage stochastic mix-integer programming is shown in **Annex Figure 9**. First, as a stochastic problem, the uncertainty is represented with multiple likely scenarios. Each scenario corresponds to a realization of risk: we use three independent Scenarios 1-3 with a different set of sudden-onset demand. The Probability P1-P3 represents the likelihood of a given scenario to happen, shown in the blue boxes in the bottom left of **Annex Figure 9**. Then, we set Stage 1 decisions applied to all Scenarios 1-3 (shown in the top orange box): Opening Warehouse Decision, WH_i. This suggests the binary state (OPEN/CLOSE) of a warehouse i.

In Stage 2 (the dark grey boxes in **Annex Figure 9**), the model sets scenario-sensitive decisions giving the flexibility to transport and allocate commodities differently for on-going demand and the particular realization of sudden-onset demand. The objective is set to minimize the total cost, composed of two parts: 1) Stage 1 cost: the warehouse opening cost; 2) Expected Stage 2 cost: the expected supply chain cost from purchasing to the delivery; plus the penalty for the proportion of demand that has not been delivered on-time, over three scenarios.

3.3. SOFTWARE AND SOLVER

Both the Ethiopia Study Demonstration Model and Warehouse Study Demonstration Model are implemented using open-source Python-PuLP software and solved by the GNU Linear Programming Kit (GLPK) open-source solver. The input data of the models are shaped in strict format and stored in multiple Excel sheets. For each scenario, a Python file has been executed and solved. The optimal decisions are saved in several Excel spreadsheets as output tables, which contain detailed results regarding cost components, decisions variable values (e.g.: commodity flows at each time period, warehouse decisions and inventory flow, etc.) and on-time delivery ratios. Complementary graphical analysis are saved in the format of png.

Annex Figure 10: Demonstration Model Overview



3.4. TECHNICAL OVERVIEW OF DM FOR WAREHOUSE STUDY

3.4.1. PREPARATION

The demonstration model works in a specific python environment with pre-installed modules. One way of building that environment is using PyCharm, an open-source integrated development environment (IDE). The following is the reference list for all software/packages the DM requires:

1) Programming Language: Python (open-source) https://www.python.org/downloads/
2) IDE: PyCharm https://www.wikiwand.com/en/PyCharm , https://www.jetbrains.com/pycharm/
3) Optimization Solver: GNU Linear Programming Kit (GLPK) (open-source), the kit for windows system is given in the final product package: 'winglpk-4.65.zip'.

   Introduction link: https://www.wikiwand.com/en/GNU_Linear_Programming_Kit

   Download link: https://www.gnu.org/software/glpk/

4) Python Modules:

   i. PuLP: A Linear Programming(LP) modeler written in Python. Used to generate LP files and call GLPK to solve linear problems. https://pypi.org/project/PuLP/
   ii. Numpy: The fundamental package for scientific computing with Python https://numpy.org/
   iii. Pandas: A software library written for Python, for data manipulation and analysis. https://www.wikiwand.com/en/Pandas_(software)

   https://pandas.pydata.org/pandas-docs/stable/getting_started/install.html

   iv. Openpyxl & et_xmlfile & xlrd: Help the DM to interpret Excel input and output in python language. Openpyxl is A Python library to read/write Excel 2010 xlsx/xlsm files: https://openpyxl.readthedocs.io/en/stable/ ; et_xmlfile is a low memory library for creating large XML files: https://pypi.org/project/et_xmlfile/ It is used to be part of the openpyxl module, but in the latest versions, they were separate modules, hence, we need both installed to make the DM work[38] ; xlrd is the Library for developers to extract data from Microsoft Excel (tm) .xls spreadsheet files https://pypi.org/project/xlrd/)
   v. Matplotlib and Seaborn: Visualization with python language, generate graphical analysis based on DM's outputs: https://matplotlib.org/ , https://seaborn.pydata.org/

3.4.2. SET-UP STEPS

1) Download and install Microsoft Excel, Python3.7 and PyCharm (community version)
2) Download and install optimization solver (GLPK).
   KEEP TRACK OF THE DIRECTORY WHERE GLPK IS INSTALLED. One line of DM code needs to be adjusted based on the User's preference.
   a. Windows user: detailed graphical instruction given in separate document in the final product package: 'GLPK installation guide.docx'
   b. Install Installation process might be different for Mac OS. See below options:
      – https://formulae.brew.sh/formula/glpk
      – http://hichenwang.blogspot.com/2011/08/fw-installing-glpk-on-mac.html

38 The DM works in the setting of environment built on current versions of software/packages. Slight adjustment to the DM might be needed if user wished to keep all their package up to date.

3) Build PyCharm environment:
    a. Create a Project file and Set Python3 as the project interpreter
    b. Open Preference and manage packages under Project interpreter directory
    c. PyCharm should be equipped with the built-in 'pip install' if downloaded properly (Otherwise User might have to build the environment in cmd/terminal manually).
    d. Click the '+' sign at the left bottom corner of the sub-window and type in required package/module names one at a time
    e. Click the 'Install Package' box at the left bottom corner, wait till installed successfully
    f. Repeat step d. & e.to install the next package
    g. Click 'OK' box at the right bottom corner to save the set-up when all of the following packages have been installed successfully: PuLP, Pandas, Numpy, openpyxl, et_xmlfile, xlrd, matplotlib, and seaborn.
4) Claim directory and run DM:
    a. From the final product package, download the model input file 'GWH.py' and data input file GWH_xxx.xlsx[39] under the same directory. Users have the freedom to create/choose any current working directory (cwd) to save these files; after running the DM, all outputs will be automatically generated and saved under this given directory.
    b. Go to PyCharm menu bar 'File', click 'Open' and select the DM file 'GWH.py' from cwd.
    c. As noted in step (2), users have the freedom to install the GLPK package in the customed directory; hence, the directory where DM could call for the solver must be claimed. Users need to input the customed directory in DM python file line 48 manually.
    d. Go to PyCharm menu bar 'Run' and select 'Run', click the DM file 'GWH.py' in the pop-up window. Wait until optimal solutions are found and all results/analysis being saved: 'Process finished with exit code 0' shows up in the terminal window suggests that no error has occurred during the process and outputs are ready to view at cwd.

3.4.3. DM MODEL INPUT

For the DM model input, Users will only need to update their customed GLPK solver directory once (refer to section 3.4.2-3.4.4.). No more changes are needed except adjustments for fundamental package/software updates.

3.4.4. DM DATA INPUT

3.4.4.1. PARAMETER OVERVIEW

Each DM input excel file has 20 sheets. Each sheet contains an index (single-index & multi-index) and its corresponding parameter(s):

1. Commodity sheet:
   Index: commodity no.
   Parameter: vessel type

39 Each study only has one model input file, while the data input file varies by scenarios.

2. US supplier sheet
   Index: commodity no. – period – supplier
   Parameter: Capacity (MTs/period)

3. Warehouse overview sheet
   Index: name
   Parameter: a) Opening cost ($/year); b) Pre decision

4. International inland warehouse sheet
   Index: name
   Parameter: a) Handling Capacity (MTs/period); b) Handling Cost ($/MT); c) Storage Capacity (MTs/period)

5. US Ports & US Warehouse sheet
   Index: name
   Parameter: a) Handling Capacity(warehouse) (MTs/period); b) Handling Cost(warehouse) ($/MT); c) Storage Capacity(warehouse) (MTs/period); d) Port handling cost ($/MT)

6. International Port & International Warehouse
   Index: name
   Parameter: a) Handling Capacity (MTs/period); b) Handling Cost ($/MT); c) Storage Capacity (MTs/period)

7. Inventory sheet
   Index: commodity no. – name
   Parameter: a) Initial inventory (MTs); b) Inventory cost ($/MT/period)

8. Final Delivery Country Sheet
   Index: country
   Parameter: a) Handling Capacity (MTs/period); b) Handling Cost ($/MT)

9. On-going Demand Sheet
   Index: commodity no. – period – country
   Parameter: On-going demand (MTs)

10. Sudden-onset Demand Sheet
    Index: scenario – commodity no. – period – country
    Parameter: Sudden-onset demand (MTs)

11. US Supplier-US Port Sheet (Inland Transportation)
    Index: commodity no. – period – origin – destination
    Parameter: a) Capacity (MTs/period); b) Cost ($); c) Lead time (day)

12. US Port-International Port Sheet (Ocean Transportation) for Vessel Type **LINER**
    Index: period – origin – destination – Vessel company –Service level

Parameter: a) Capacity (MTs/period); b) Cost ($); c) Lead time (day)

13. US Port-International Port Sheet (Ocean Transportation) for Vessel Type **BULK**
    Index: period – origin – destination – Vessel company –Service level
    Parameter: a) Capacity (MTs/period); b) Cost ($); c) Lead time (day)

14. International Port-International Port Sheet (Ocean Transportation) for Vessel Type **LINER**
    Index: period – origin – destination – Vessel company –Service level
    Parameter: a) Capacity (MTs/period); b) Cost ($); c) Lead time (day)

15. International Port-International Port Sheet (Ocean Transportation) for Vessel Type **BULK**
    Index: period – origin – destination – Vessel company –Service level
    Parameter: a) Capacity (MTs/period); b) Cost ($); c) Lead time (day)

16. International Port-International Port Sheet (Inland Transportation)
    Index: origin – destination
    Parameter: a) Capacity (MTs/period); b) Cost ($); c) Lead time (day)

17. International Port -Final Delivery Country Sheet (Inland Transportation)
    Index: origin – destination
    Parameter: a) Capacity (MTs/period); b) Cost ($); c) Lead time (day)

18. International Port-International Inland Warehouse Sheet (Inland Transportation)
    Index: origin – destination
    Parameter: a) Capacity (MTs/period); b) Cost ($); c) Lead time (day)

19. Inland Warehouse-Final Delivery Country Sheet (Inland Transportation)
    Index: origin – destination
    Parameter: a) Capacity (MTs/period); b) Cost ($); c) Lead time (day)

20. Scenario information sheet
    Index: scenario
    Parameter: a) Probability; b) Penalty($/period/MT)

3.4.4.2. DATA INPUT MODIFICATION/UPDATE

For the DM input file, users can not add/delete columns in Excel sheets since it will sabotage the links between the data input file and the model input file. However, users can add/delete rows and modify existing inputs in the given 20 excel sheets while abiding by the following critical data-modeling rules carefully:

1) Do not change column names; otherwise the model input file has to be modified as well.
2) No space between characters.
   Python recognizes space input as '_', the initial flow output calculated by DM is unimpacted. The post cost analysis will still be impacted due to the inconsistency of naming between input and

output files. Tip: Search and replace space with '_' in the modified data input file before running DM.

3) Duplication of data causes the termination of DM with index error. (e.g., two rows of data with the same index but two different parameter value) Tip: clean the new data before adding it to the data input file.
4) Typos could ruin the model without a sign.
   DM is a data-driven model; different input represents a different node in the network, especially the same node among different sheets. E.g., if there is a typo 'P_LIVERNO' in sheet' INTERNATIONAL _PORT&WH', but 'P_LIVORNO' shows up correctly in sheet 'BULK_US_PORT_INT_PORT', the connectivity of the global network will be ruined since 'P_LIVERNO' and 'P_LIVORNO' are different locations to the model. Users might still be notified with 'optimal solution found', but it will not be a realistic solution. Tip: If new data have been added, after running the model and getting the optimal decisions, users can simply perform a summation function in excel sheet to check whether the overall purchased commodity amount matches with the total demand.
5) Keep the naming short.
   The module used to interpret the problem: PuLP, has limitations on index length. The variable name index in the model is a long list containing information of the following: at what time, from which location, (via which vender, in what service level), to which location, for which commodity, in which scenario that the commodity is scheduled to transfer. Hence, in some occasions it might exceed the maximum length the module can handle. If an error occurs while creating model variables: consider replacing relative long names (e.g., supplier/vessel company) with numbers or abbreviations and build the corresponding reference list.
6) Using 6-digit product number/letter to represent different commodities.

3.4.5. DM OUTPUT

3.4.5.1. MODEL OUTPUT – EXCEL OUTPUT FILE

In the final product zip file, the following excel sheets have been given:

a. Decision variable output file: 'WH_SCE_RESULTS.xlsx'

   Sheet1: Open warehouse decision

   Sheet2: Sudden-onset late delivery

   Sheet3: Supply chain inland transportation flow & inventory flow (except sudden-onset delivery)

   Sheet4: Sudden-onset delivery flow

   Sheet5: Supply chain ocean transportation flow

   Sheet6: Warehouse inventory in-flow

b. Objective output file: 'COST_ANALYSIS.xlsx'

Sheet1: Total cost

Sheet2: Total cost decomposition (procure, inventory related, inland/ocean transportation)

Based on the excel output, users can convert data into different format and perform further data analysis.

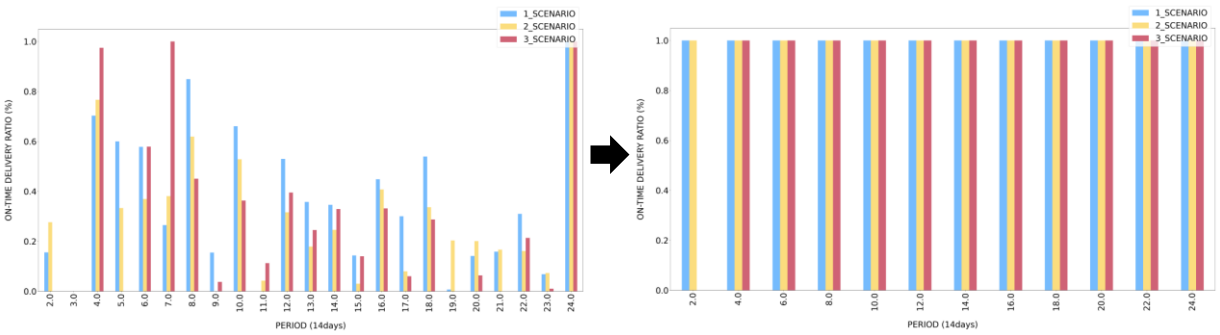
3.4.5.2. GRAPHICAL OUTPUT

In the final product zip file, the following graphical analysis for selected scenarios (volume-based risk profile, $5 USD inventory holding cost) have been given:

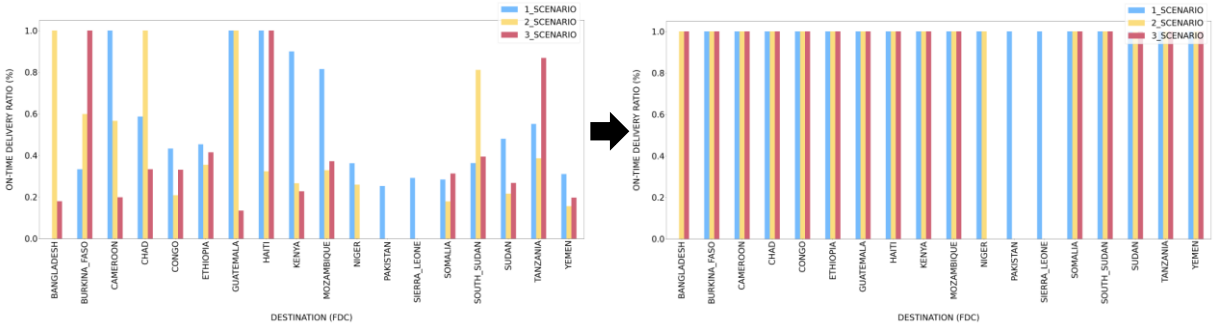
- In each of the following graphs, the color of blue, yellow, and red represents scenario1~high-volume, scenario2~mid-volume and scenario 3~low-volume sudden onset demand.
- Under the assumption of 12-month demand visibility and set period one as the first demand occurrence time, in the horizontal axis of graphs in sections I-IV, the period starts with negative numbers.

I. The on-time delivery ratio for sudden-onset demand – Improvement of the average on-time sudden-onset delivery ratio when the late delivery penalty level increases from low to high:

The following graphs present the average on-time sudden-onset delivery ratio at each period for all commodities at all final delivery locations of three scenarios. The horizontal axis is measured by period (14 days); the vertical axis suggests the ratio from 0~100%.

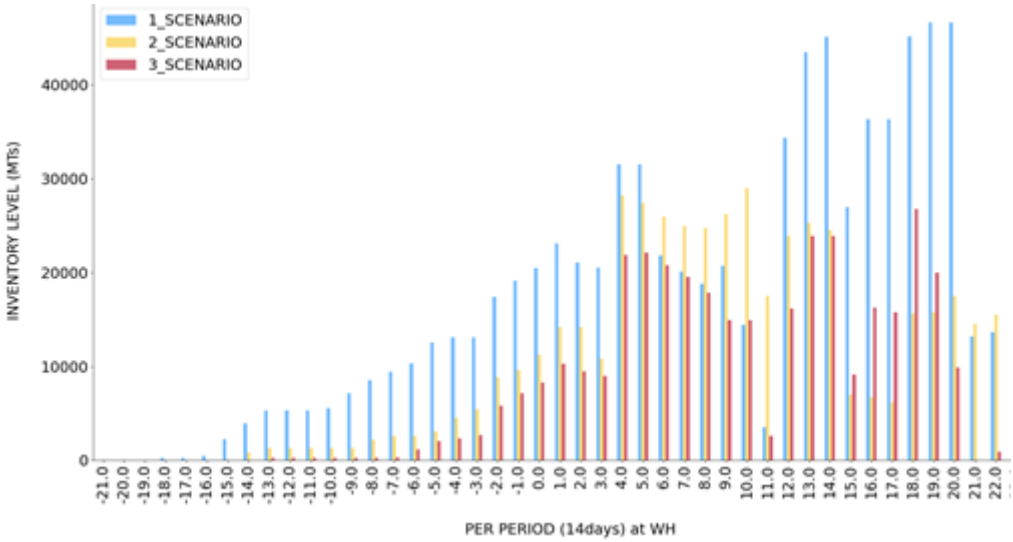


The following graphs present the average on-time sudden-onset delivery ratio at each final delivery country for all commodities across all planning periods of three scenarios. The horizontal axis represents different final delivery countries; the vertical axis suggests the ratio from 0~100%.



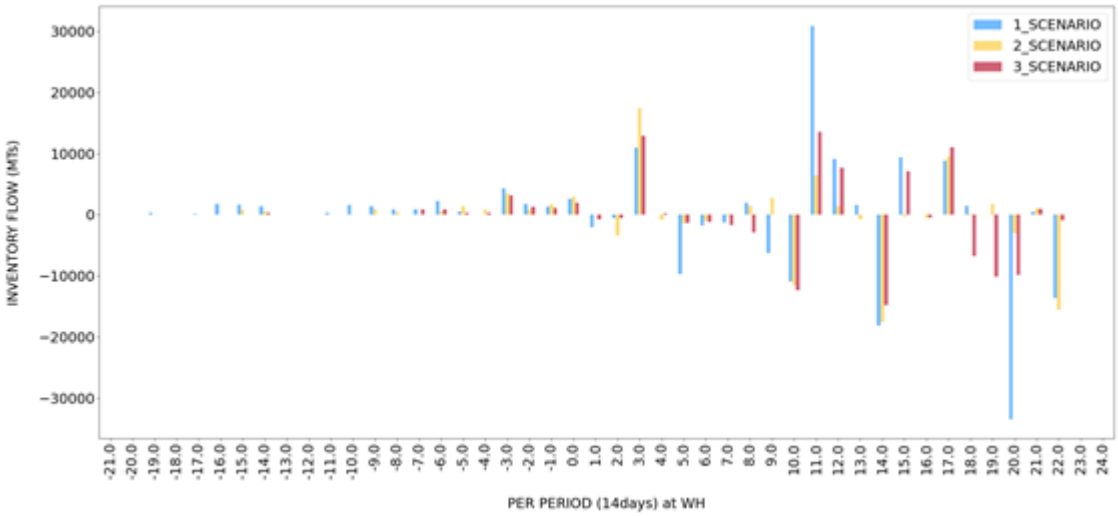
II. Inventory level of all warehouses – High penalty level for late delivery:

The following graph presents the total inventory level for all commodities at all warehouse locations for each planning period of three scenarios. The horizontal axis is measured by period (14 days), the vertical axis shows the inventory level in MTs.



III. Inventory inflow/outflow of all warehouses – High penalty level for late delivery:

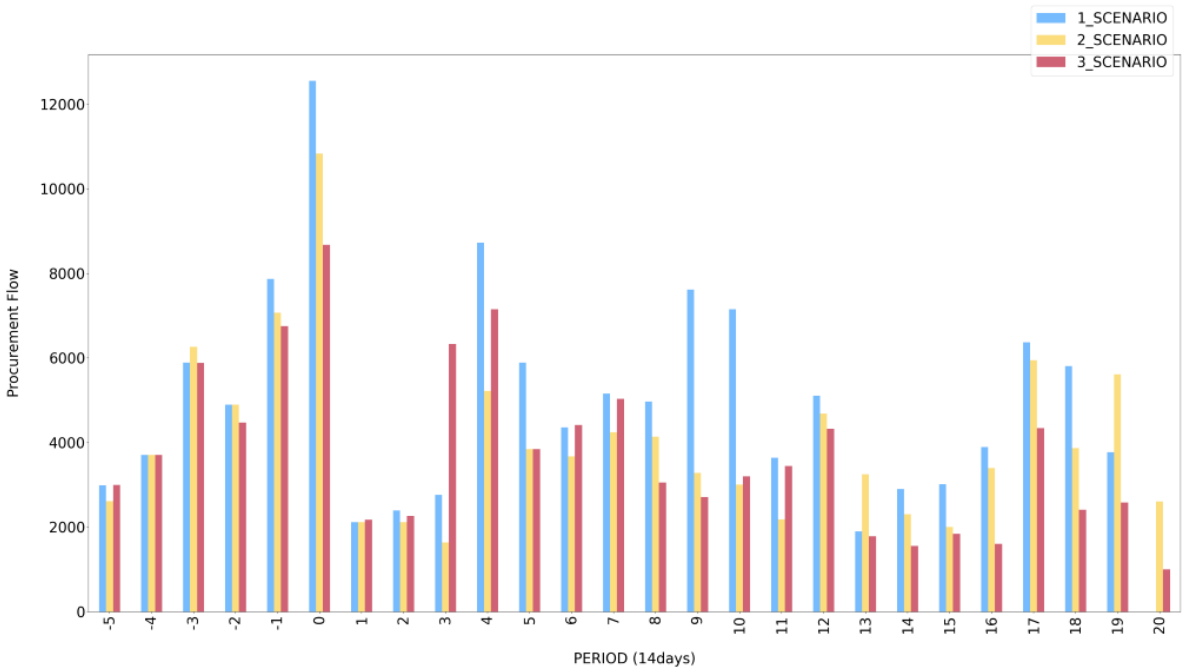
The following graph presents the inventory flows for all commodities at all warehouse locations for each planning period of three scenarios. The horizontal axis is measured by period (14 days). The vertical axis shows the inventory flows in MTs. Positive numbers represent the inventory inflow from all previous locations; negative numbers represent the inventory outflow towards the next destinations.



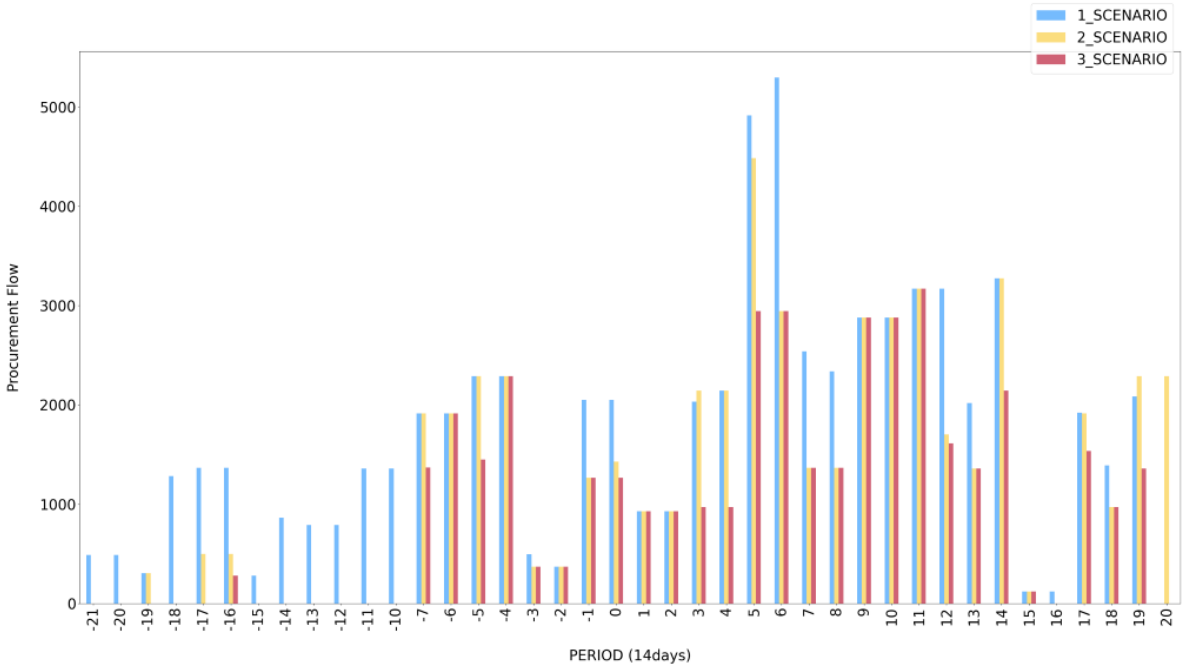
IV. Procurement flow – High penalty level for late delivery:

The following graphs present the total procurement flows for each commodity from all suppliers for each planning period of three scenarios. The horizontal axis is measured by period (14 days), the vertical axis shows the total procurement flow in MTs.

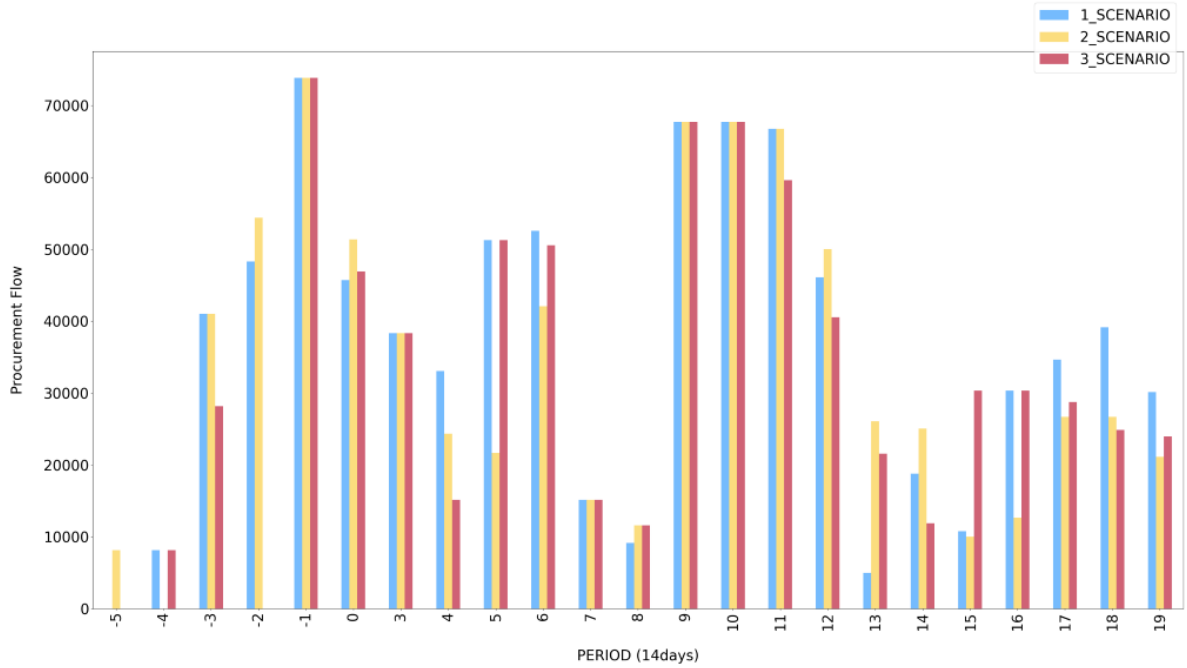
For commodity 100555(YSP):



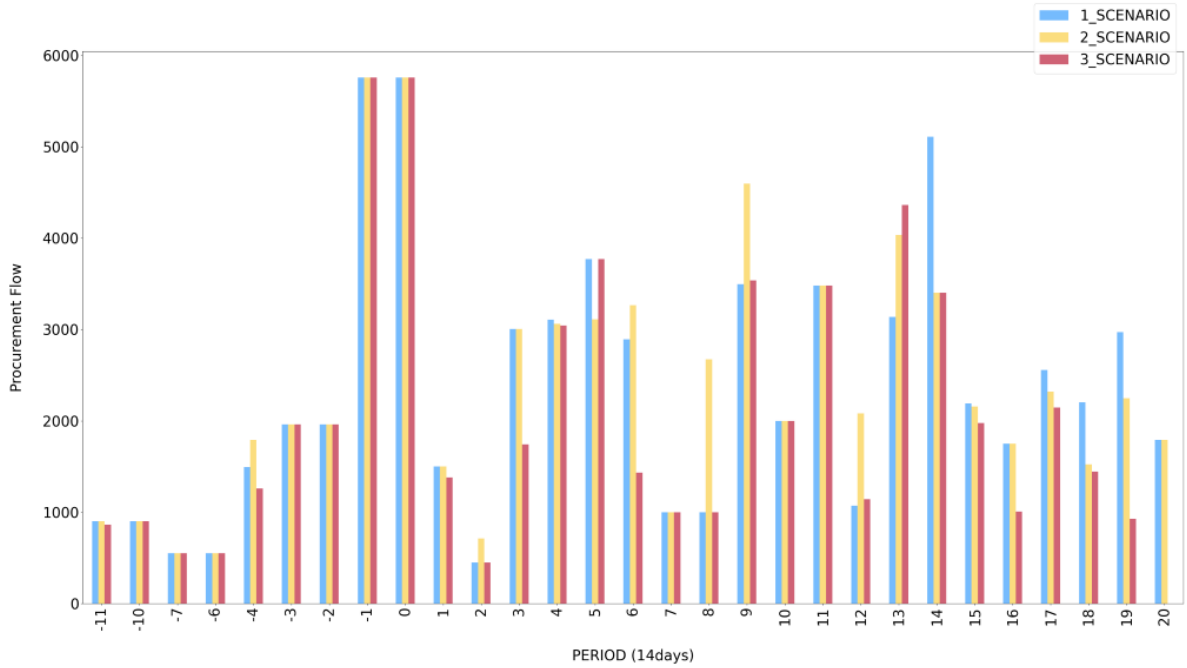
For commodity 100566(OIL):



For commodity 100597(SGM):

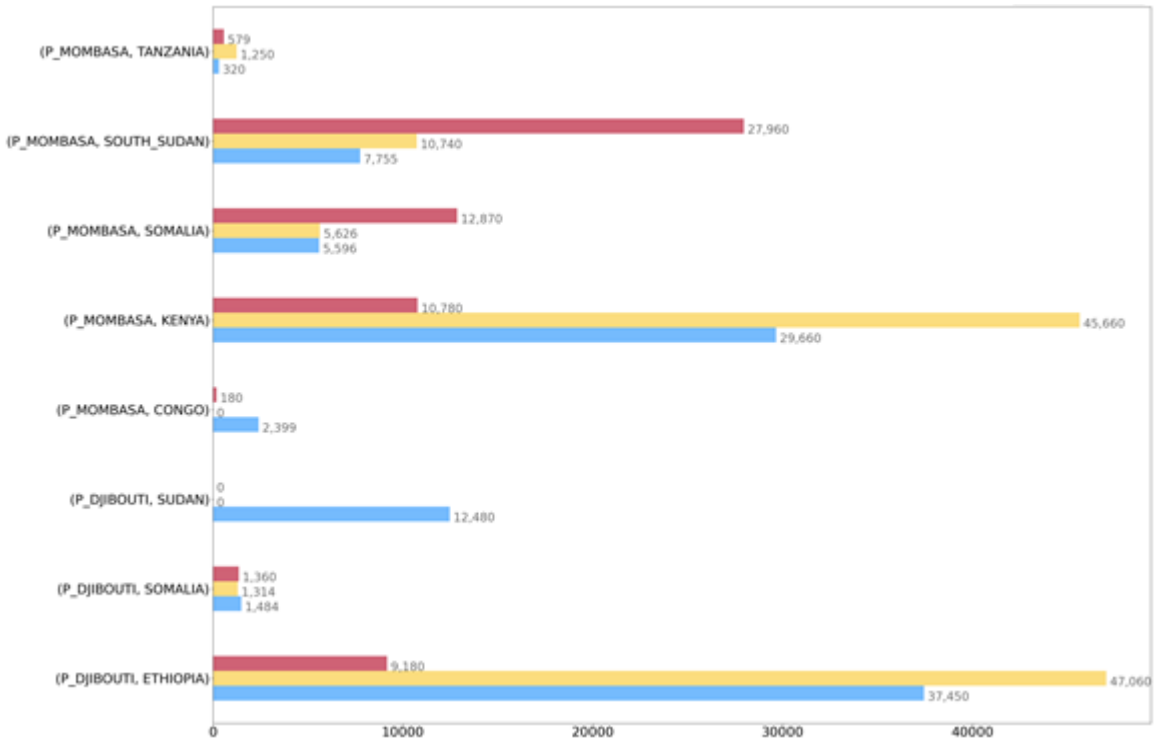


For commodity 110200(CSB+):



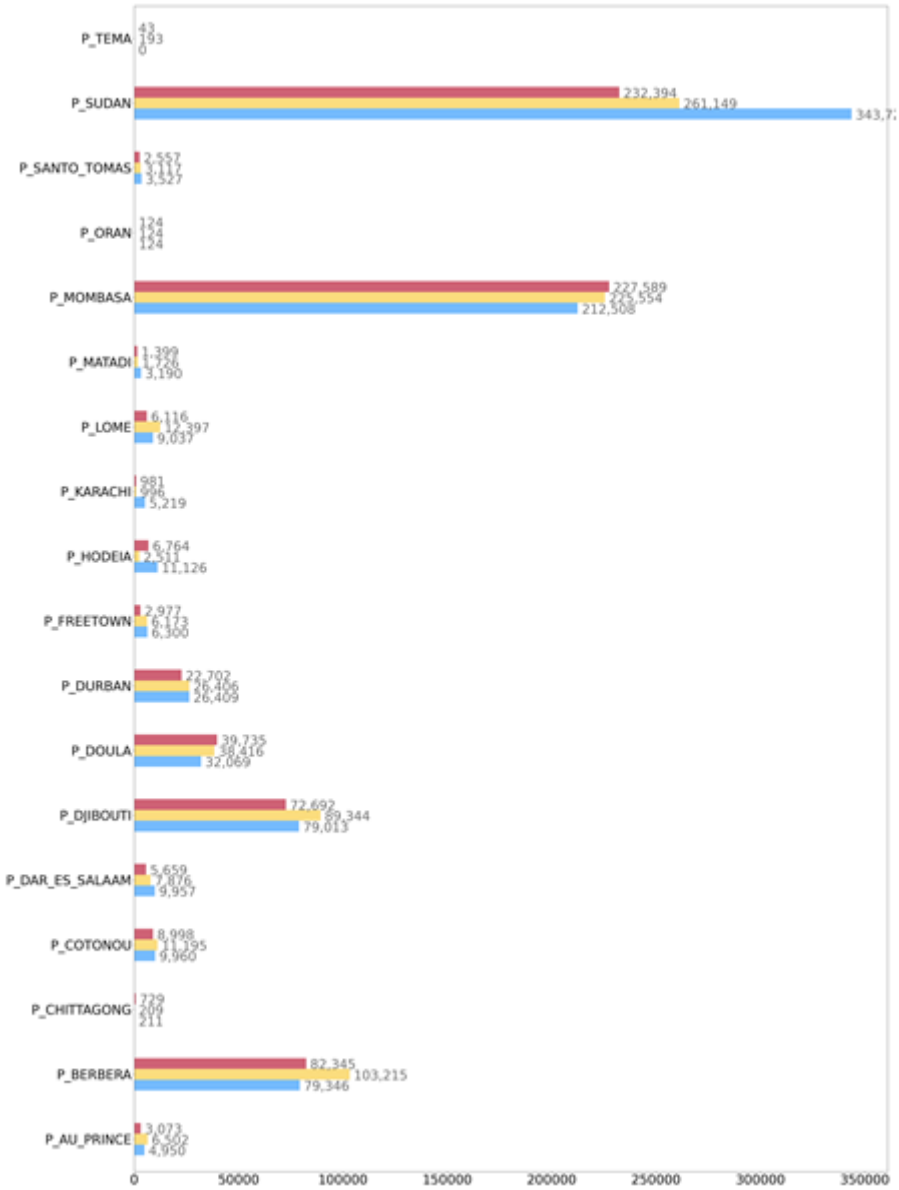
V. Mombasa & Djibouti Port outflow for sudden onset delivery – High penalty level for late delivery:

The following graph presents the total sudden onset delivery from Mombasa & Djibouti for all commodities and all periods of three scenarios. The vertical axis shows the existing port-final delivery destination pairs; the horizontal axis shows the corresponding delivery flow in MTs.



VI. Houston Port outflow – High penalty level for late delivery:

The following graph presents the outflow towards international ports from Houston port for all commodities and all periods of three scenarios. The vertical axis shows the destination discharge port; the horizontal axis shows the corresponding ocean transportation flow in MTs.


P_TEMA
43
193
0
P_SUDAN
232,394
261,149
P_SANTO_TOMAS
2,557
3,117
3,527
P_ORAN
124
124
124
P_MOMBASA
227,589
225,554
212,508
P_MATADI
1,399
1,726
3,190
P_LOME
6,116
12,397
9,037
P_KARACHI
981
996
5,219
P_HODEIA
6,764
2,511
11,126
P_FREETOWN
2,977
6,173
6,300
P_DURBAN
22,702
26,406
26,409
P_DOULA
39,735
58,416
32,069
P_DJIBOUTI
72,692
89,344
79,013
P_DAR_ES_SALAAM
5,659
7,876
9,957
P_COTONOU
8,998
11,195
9,960
P_CHITTAGONG
729
209
211
P_BERBERA
82,345
103,215
79,346
P_AU_PRINCE
3,073
6,502
4,950
0
50000
100000
150000
200000
250000
300000
350000